Lecture Notes on

Wireless HealthCare Research

Kevin Patrick and Mu-Chun Su,
Editors

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(Editors)

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Preface

This volume contains the lecture notes from the first Workshop on Wireless Healthcare which was held between March 23 and 24, 2012 at National Central University and the second one which was then held at UC San Diego between November 29 and 30, 2012 . These joint meetings were meant to provide the opportunities for researchers from UCSD and the University System of Taiwan (UST) - which is a consortium of four research universities in Taiwan: National Central University, National Chiaotung University, National Tsinghua University and National Yang Ming University - to discuss and to develop projects of common interest. Because of the rapid changes in the global demography because of progresses in the healthcare systems and social conditions, wireless health care research has become more and more important. The related biomedical applications cover a wide range of scientific topics from detector technology, signal processing techniques, to behavior dynamics. In addition, many emerging issues could only be tackled by interdisciplinary and international cooperation. These urgent needs are particularly felt in Taiwan. Looking forward to the immediate future and the possibility of establishing a long-lasting partnership in education and research on wireless health care, UST was very happy to sponsor these two UST-UCSD workshops with the wish that such bilateral academic activity will continue and increase to the point that not just academic exchange but also industrial cooperation can be sustainable. Finally, I would like to thank all the participants and authors in the workshops for their valuable contributions. The tutorial chapters and lecture notes are all presentations of the state-of-the art development in various areas of importance. They will be useful reference materials for many years to come. It has been a wonderful experience to work with Professor Kevin Patrick and Prof. Mu-Chun Su who made this volume possible. Ms Jeniffer Yang was indispensable in organizing the workshops. Finally, I would like to thank Ms Mei-Hei (Bella) Chu for accomplishing the pains-taking task of editing the chapters.

Wing-Huen Ip

The Application of Hilbert-Huang Transform for Biomedical Research

Norden E. Huang[1],Men-Tzung Lo[1], Chung-Kang Peng[1,2]

1.Research Center for Adaptive Data Analysis
Center of Dynamical Biomarkers and Translational Medicine
National Central University
Zhongli, Taiwan
2.Research Center for Adaptive Data Analysis
Margret and H.A. Rey Institute for Nonlinear Dynamics in Physiology & Medicine
Beth Israel Deaconess Medical Center
Harvard Medical School
Boston, MA 02215 USA

(e-Mail:norden@ncu.edu.tw)

Abstract — Analyzing data from real world is a challenge; we have to face the limitations imposed by reality: nonstationarity, nonlinearity and the availability of information. Traditional methods, strictly adhesive to rigorous mathematical rules, cannot fully circumvent these restrictions. As a result, data analysis is reduced to merely data processing, and truth remains concealed. Many of the difficulties could actually be traced back to the lack of correct definition for frequency, a critical physical quantity. In fact, once the frequency can be properly defined and extracted from the data, many difficulties such as quantification of degree of nonlinearity and nonstationarity and determination of the trend could be achieved easily. As we will discuss in this review, a proper definition of frequency has to be based on an adaptive approach. A possible solution is the Hilbert–Huang transform (HHT), which consists of empirical mode decomposition (EMD) and the Hilbert spectral analysis (HSA) methods. Many new advances in HHT are made in recent years, including the nonlinear matching pursuit method, ensemble empirical mode decomposition (EEMD), instantaneous frequency computations, trend determination, time-dependent intrinsic correlation (TDIC), density representation of Hilbert spectrum, and the extension of the time series analysis method to multi-dimensional data. Although these advances have made the HHT method much more robust and mature, many

mathematical problems remain to be resolved. Meanwhile, applications of HHT are progress and had produced viable results. In this review, we will also discuss applying the HHT technique to quantify the dynamic cerebral autoregulation, an important mechanism to regulate blood flow in the brain.

Keywords — Hilbert-Huang Transform, Empirical Mode, Decomposition Instantaneous Frequency, Hilbert Spectral Analysis, Intrinsic Correlation, Fourier Analysis

1. Background

Data analysis is indispensable to every science and engineering endeavor; it is the critical step to convert the cold numbers to yield physical meaning and gain understanding of the underlying driving processes. For this reason, the data analysis method should produce physically meaningful prospective rather than mathematical parameters. Data from natural phenomena are highly variable, and often are from nonstationary and nonlinear processes. This poses a severe challenge to the existing data analysis methods, e.g., probability theory and spectral analysis, that are all developed for idealized conditions that are both linear and stationary. In pursue of mathematical rigor, we are forced to make unrealistic assumptions and live in a pseudo-real linear and stationary world. But the world we live in is neither stationary nor linear. For example, spectral analysis is synonymous with the Fourier based analysis. As Fourier spectrum can only give meaningful interpretation to linear and stationary processes, its application to data from nonlinear and nonstationary processes is problematic. Furthermore, probability distributions can only represent global properties, which imply homogeneity (or stationarity) in the population. As scientific research getting increasingly sophisticated, the inadequacy becomes glaringly obvious. Even with some modifications, the available data analysis methods could be applied to nonstationary but linear processes such as wavelet and Wigner–Ville distribution [1] or nonlinear but stationary and deterministic processes. For both nonlinear and nonstationary processes, our tool is totally inadequate. The only alternative is to break away from these limitations; we should let data speak for themselves so that the results could reveal the full range of consequence of the true underlying driving mechanisms. To do so, we need new paradigm of data analysis methodology without a priori basis to fully accommodate the variations of the physical processes. The answer is an adaptive data analysis method, based on the Empirical Mode Decomposition (EMD) and Hilbert Spectral Analysis, officially designated by NASA as Hilbert–Huang Transform (HHT) [2]. The result is presented in a time–frequency–energy representation. In fact, we can only define true frequency with adaptive method, which would lead to a new definition of nonstationarity and nonlinearity, and to determine the elusive trend of nonstationary data.

Since HHT was introduced in 1998, it has been used widely in science and engineering research. Over the years, new improvement such as the ensemble EMD (EEMD) was introduced, which greatly improve the robustness of the method. Further extension also made the method extended to multi-dimensional and multi-variant data sets. Based on the very properties of instantaneous frequency, new approaches to define the degree of nonlinearity and nonstationarity were also proposed. With EMD, the elusive trend also got a good definition and a method to extract it objectively was developed.

The advantages of the HHT have been appreciated in many studies of different physiological systems such as blood pressure hemodynamics [3], cerebral autoregulation [3,4], cardiac dynamics [5,6] respiratory dynamics [7], and electroencephalographic activity [8]. In this review, we focus on the computational challenge on the quantification of interactions between two nonstationary physiologic signals. To demonstrate progress in resolving the generic problem related to nonstationarities, we review the recent applications of nonlinear dynamic approaches based on HHT to one specific physiological control mechanism—cerebral autoregulation (CA) of blood flow. In this short review, we will summarize the method and give strong evidence that CA may be active in a much wider frequency region than previously believed and that the altered multiscale CA in different vascular territories following stroke may have important clinical implications for post-stroke recovery.

This short introduction paper is based mostly on a recent review papers authored by us on the basic HHT method[9].

2. Empirical Mode Decomposition Method

The problem of traditional data analyses could be simply traced to the poor definition of frequency. The most fundamental definition of frequency, ω, is based on period, T, of a wave:

$$\omega = \frac{1}{T} \qquad (1)$$

This definition is certainly correct dimensionally, but it is crude and could only serve as a mean value over the entire period of a wave. All serious theoretical wave study define frequency in term of phase function. In general, for any wave motion, there must be a smooth phase function, θ, so that we can define wave number, k, and frequency as

$$k = \frac{\partial \theta}{\partial x}, \text{ and } \omega = -\frac{\partial \theta}{\partial t} \qquad (2)$$

Therefore, by cross differentiation, we have

$$\frac{\partial k}{\partial t} + \frac{\partial \omega}{\partial x} = 0 \qquad (3)$$

All wave motions have to obey this fundamental kinematic conservation law. For Eq. 3 to hold, it is obvious that both the wave number and the frequency have to have instantaneous values and also be differentiable. Based on this criteria, the constant wave number and frequency defined through Fourier analysis would also have problem. Certainly the Fourier frequency and wave number satisfy the kinematic conservation, but that would be a trivial condition of zero plus zero equal to zero. Only with the true instantaneous frequency can we describe the richness of variation in frequency of the nonlinear and nonstationary waves, where the intra-wave frequency modulation is the rule rather than the exception.

Since instantaneous frequency depends on a phase function [12], therefore, the necessary condition for a general time series to have physically meaningful phase function and instantaneous frequency is to reduce the general time series as a collection of intrinsic mode function (IMF) through Empirical Mode Decomposition (EMD).

The EMD is implemented through the following steps: For any data, we first identify all the local extrema, and then connect all the local maxima by a cubic spline curve as the upper envelope. Then, we repeat the procedure for the local minima to produce the lower envelope. The upper and lower envelopes ld cover all the data between them. Their mean is designated as m1,1, and the difference between the data and m1,1 is the first proto-IMF (PIMF) component, h1,1:

$$x(t) - m_{1,1} = h_{1,1} \tag{4}$$

The operations are summarized in Figure 1A.

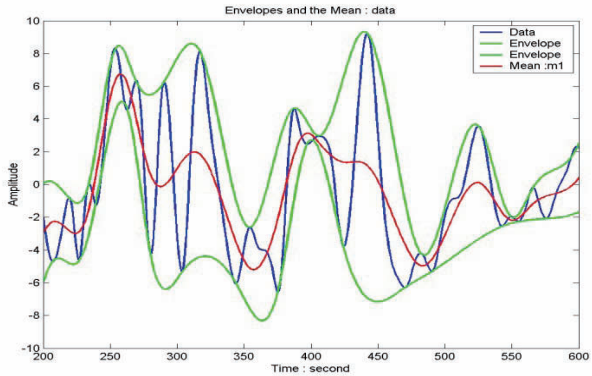

Figure 1A The envelopes and local mean constructed by spline. All the extrema of the data (in blue) are divided into two groups: the maxima and minima. The upper (lower) envelope is a natural cubic spline line through all the maxima (minima) (in green). The mean of the two envelopes is the local mean (in red), which is to be used as the new horizontal reference axis.

Technically, the mean, m1,1, is the medium, for it is the mean of maximum and minimum. As shown by [10] , medium is a better reference value than the average. By construction, this PIMF, h1,1, should satisfy the definition of an IMF, but the change of its reference frame from rectangular coordinate to a curvilinear one can cause anomalies, where multi-extrema between successive zero-crossings could still existed, mostly due to some inflection points having become local extrema as shown in Figure 1B.

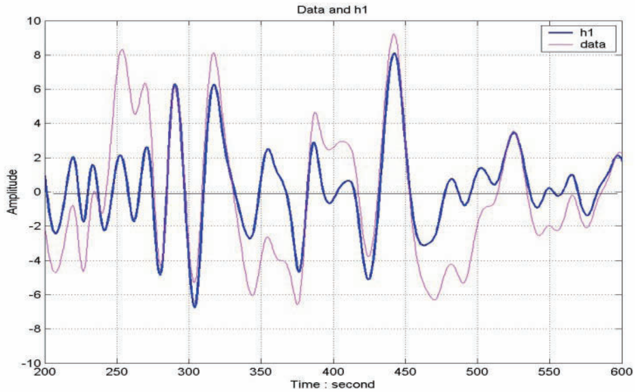

Figure 1B The data in this new reference coordinate is given in blue, with the original data given in light red line. By construction, this new data should have all the maxima positive and minima negative. Most of the oscillations fit this requirement, but there might be some exception as near 500 second point, where an inflection point becomes an extremum. Repeating the same operation could force all the oscillations eventually fit the requirement.

To eliminate such anomalies, the sifting process has to be repeated as many times as necessary to get rid of the riding waves. In the subsequent sifting process steps, h1,1 is treated as the data. With the iteration of the steps, we have

$$\begin{aligned} & h_{1,1}(t) - m_{1,2}(t) = h_{1,2}(t); \\ & \quad \vdots \\ & h_{1,k-1}(t) - m_{1,k}(t) = h_{1,k}(t); \\ & \quad \Rightarrow h_{1,k}(t) = c_1(t), \end{aligned} \tag{5}$$

After each repetition, we will check the results against a 'stoppage criterion.' Various criteria have been proposed by [3] and [11-14 repetion], for example. Through extensive study of white noise,[11-12] have found that the filtering property of EMD is near dyadic when the iteration is repeated 10 times. Thus the current implementation of EMD is based on this stoppage criterion. Whenever the stoppage criterion is satisfied, the PIMF is designated as an IMF, c1(t). The "stoppage criterion" actually determines the number of sifting steps to produce an IMF; it is thus of critical importance in a successful implementation of the EMD method. Furthermore, the spline function used is also of critical importance,

$$
\begin{aligned}
& x(t) - m_{1,1}(t) = h_{1,1}(t); \\
& h_{1,2}(t) = h_{1,1}(t) - m_{1,2}(t) = x(t) - (m_{1,1} + m_{1,2}); \\
& \quad \vdots \\
& h_{1,k}(t) = h_{1,k-1}(t) - m_{1,k}(t) = x(t) - (m_{1,1} + m_{1,2} + \cdots + m_{1,k}); \\
& \quad \Rightarrow c_1(t) = x(t) - (m_{1,1} + m_{1,2} + \cdots + m_{1,k}).
\end{aligned}
\tag{6}
$$

for Thus c1(t) is the result of the data minus a sum of spline functions. From Equation (6), we can see that if we subtract the first IMF, c1(t), from the data, the residual is the sum of spline functions. Mathematically, we have

$$x(t) - c_1(t) = r_1(t) \tag{7}$$

Therefore, the residual, r1(t), contains all the rest of information in the data other than the first IMF, c1(t). We can, therefore, repeat the above operation using r1(t) as the next set of data, and re-iterate the process, we should have

$$
\begin{aligned}
& r_1(t) - c_2(t) = r_2(t); \\
& r_2(t) - c_3(t) = r_3(t); \\
& \quad \vdots \\
& r_{n-1}(t) - c_n(t) = r_n(t); \\
& \Rightarrow x(t) - \sum_{j=1}^{n} c_j(t) = r_n(t), \text{or } x(t) = \sum_{j=1}^{N=n+1} c_j(t).
\end{aligned}
\tag{8}
$$

By summing up Eqs. (7) and (8), we finally obtain the last equation in (8), which means that the data could be decomposed into a sum of IMFs and a residue, rn(t), which can be either a constant, a monotonic mean trend or a curve having only one extrema; it could also be counted as a component. With this operation, it is easily shown that

(9)

Thus all the IMFs are the combination of the spline functions. Therefore, the EMD is critically dependent on the spline function selected. Natural cubic spline was selected for its smoothness and continuity up to second derivatives. It should be pointed out that the decomposition obtained here in terms of IMFs satisfies all the criteria of a basis a posteriori and empirically: completeness, convergence, orthogonality and uniqueness as discussed in [3]. Some brief explanations and elaboration are warranted here. The completeness is given by equation (8). The convergence is only empirically verified: envelopes are smoother than the carrier; therefore, the temporal scales will increase with the decomposition process. Uniqueness is subject to the spline used and the stoppage criteria adopted. The orthogonality is based on the Reynolds decomposition. As the decomposition is nonlinear, the orthogonality condition could only be true approximately, for strictly speaking orthogonality could only be satisfied by linear decomposition.

Recent studies by [15] and [16] have established that the EMD is a dyadic filter, and it is equivalent to an adaptive wavelet. Being adaptive, we have avoided the pitfalls of using an a priori-defined basis, and also avoided the spurious harmonics that would have resulted had the a priori basis is adopted.

The IMFs generated by the EMD algorithm are usually physically meaningful, if there is no scale mixing (defined as mixed characteristic scales in a single IMF component). To avoid the scale mixing, [16] had proposed an Ensemble EMD (EEMD), which is essentially the same EMD procedure, except that the procedure will be repeated n times each with a different white noise added to the data. The procedures are:

a. add a white noise series to the targeted data;
b. decompose the data with added white noise into IMFs;
c. repeat step 1 and step 2 again and again, but with different white noise series each time; and
d. obtain the (ensemble) means of corresponding IMFs of the decompositions as the final result.

Mathematically, we treat each trial data yi(t) as the sum of the original data, x(t), and a white noise, ni(t),

$$y_i(t) = x(t) + n_i(t). \tag{10}$$

After the ensemble of trials, the final result will be the ensemble mean. The true IMF is defined by

$$c_j(t) = \lim_{N \to \infty} \frac{1}{N} \sum_{k=1}^{N} \{c_{j,k}(t) + \alpha n_k(t)\}, \tag{11}$$

where α is a constant indicating the magnitude of the added noise. The vital concept advanced in the EEMD is based on the following observations:

a. a.A large number collection of white noise signals will cancel each other out in a time domain ensemble mean; therefore, only the signal can survive and persist in the final noise added signal ensemble mean.
b. Finite, not infinitesimal, amplitude white noise is necessary to force the ensemble to exhaust all possible solutions; the finite magnitude noise will make the different scale signals to reside in the corresponding IMF dictated by the dyadic filter banks, and render the resulting ensemble mean more meaningful.
c. The true and physical meaningful answer of the EMD is not the one without noise; it should be the ensemble mean of infinite number of trials consisted of the noise added signal.

This new method proposed in EEMD has utilized all these important statistical characteristics of noise. Based on the study of white noise, [11] has also proposed a test for the statistical significance of each IMF, which would determine which IMF component is not noise like. But the critical conclusion of the EEMD is that the final IMFs obtained is not the one with zero noise, but should be the ensemble mean of a large number of trials each with different perturbation of finite amplitude of noise.

The Ensemble EMD represents a major improvement over the original EMD. EEMD has fully utilized the statistical characteristics of noise assisted data analysis. The study by [6] has established that the level of added noise is not of critical importance, as long as they are of finite amplitude to enable a fair ensemble of all the possibilities. Therefore, the EEMD can be used without any subjective intervention; thus, it provides a truly adaptive data analysis method. By eliminating the problem of mode mixing, it also produces a set of IMFs that bears the full physical meaning for the signal, and a time–frequency distribution without transition gaps. EMD, with the Ensemble approach, has become more regular due to the fixed dyadic window dedicated by the added noise. It has become a more robust and mature tool for nonlinear and nonstationary time series analysis. One example could illustrate the power of the EEMD. Let us use the sound of "Hello" as given in Figure 2A, the EMD and EEMD results are given in Figure 2B and 2C respectively. Clearly, the each IMF from EEMD is clean and continuous all consisted of the same scale. They all represent physically meaningful components.

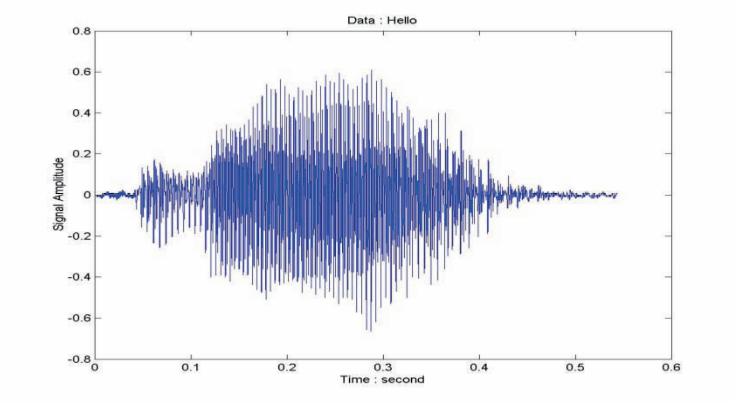

Figure 2A The data of the sound, Hello recorded at a sampling rate of 22,050 Hz.

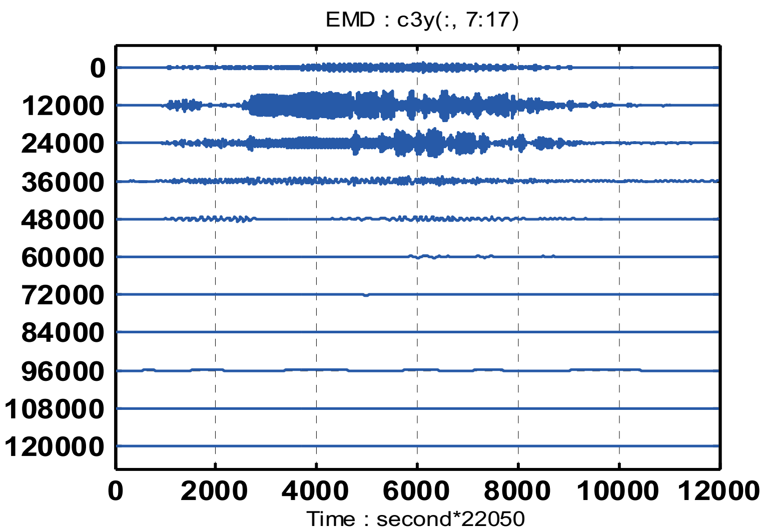

Figure 2B The IMF component derived from the data using regular EMD method. Note the fragmented signal, known as mode mixing indicated by sections of different temporal scale oscillation residing in one single mode, or a continuous component got separated into different IMF components. This fragmentation is caused by intermittency in the data.

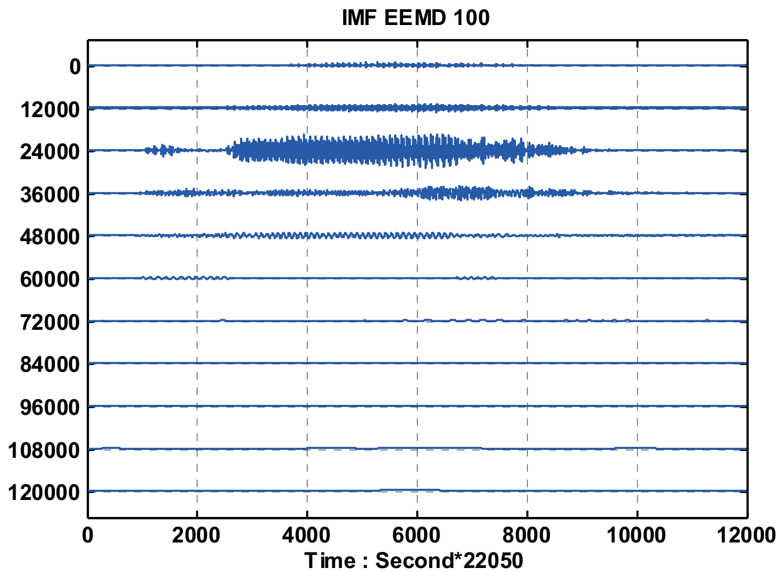

Figure 2C The IMF component derived from the data using regular Ensemble EMD method. Note the fragmentation of the IMF component disappeared. Each IMF is consisted of oscillation of similar temporal scale, a necessary for the IMF to have physical significance.

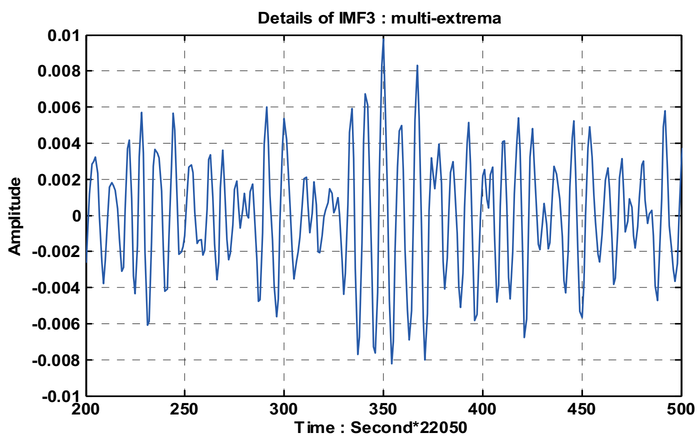

Figure 2D As the sum of IMFs might not be an IMF, one possible consequence is the result of EEMD might not be an IMF. The detailed examination of the EEMD result indeed showed some defects of multi-extrema between zero-crossings. These defects could be ameliorated by rectification.

One minor shortcoming for EEMD is that the resulting component might violate the strict definition of IMF and having more extrema between successive zero crossings as shown in Figure 2D. This flaw could be eliminate, or at least ameliorate, through a rectification step.

3. Hilbert Spectral Representation

Once the data is decomposed into IMF components, the true instantaneous frequency can be computed in a number of ways as given by [10] and [17]. Each IMF component can be written as

$$x(t) = \Re\left(\sum_{j=1}^{N} a(t) e^{i\theta(t)}\right) = \Re\left(\sum_{j=1}^{N} a(t) e^{i\int_{\tau} \omega(\tau) d\tau}\right), \tag{12}$$

where θ is the phase function and ω is the instantaneous frequency. Then, the data could be represented in a time-frequency-energy presentation designated as the Hilbert Spectrum [17] H(ωj, ti),

$$H(\omega_j, t_i) = \frac{1}{\Delta\omega \cdot \Delta t} a_{i,j}^2, \tag{13}$$

for all bins within ωj=ω0+jΔω and ti=t0+iΔt. Here the smallest Δt is the sampling rate, but there is no restriction for Δω. In other words, the frequency resolution could be arbitrarily zoomed in any range. The marginal spectrum h(ωj) is

$$h(\omega_j) = \sum_{i=1}^{n} H(\omega_j, t_i)\Delta t = \frac{1}{\Delta\omega \cdot \Delta t} \sum_{i=1}^{n} a_{i,j}^2 \cdot \Delta t. \tag{14}$$

There is no advantage in using the marginal spectrum, for the time integration would obliterate the time variation. For an nonlinear and nonstationary processes, we would loss an important marker for the temporal variation. As a comparison among all the other 'time-frequency' representations as in Wavelet, Wigner–Ville and spectrogram, the voice signal analysis results are given in Figure 2E.

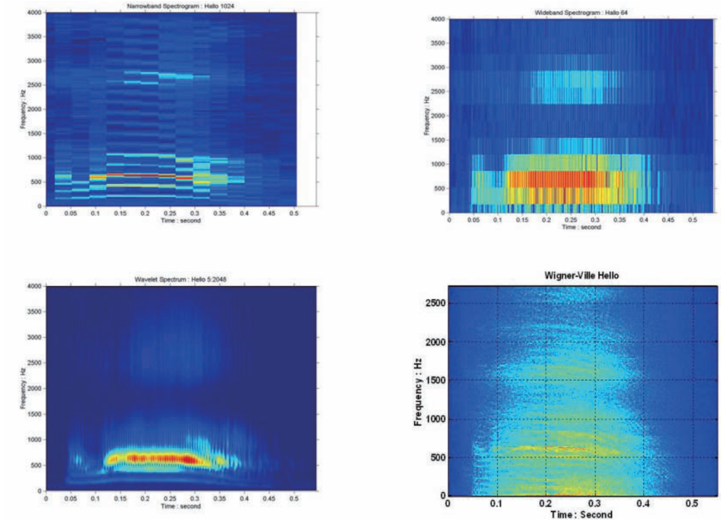

Figure 2E Different traditional time-Frequency representations of the voice signal, "Hello". Upper left: the narrow-band spectrogram computed with a window size of 1024 data points. As a result, the spectrogram has super frequency resolution but the temporal resolution is severely smeared.
Upper right: the wide-band spectrogram computed with a window size of 64 data points. As a result, the spectrogram has very poor frequency resolution but the temporal resolution is much sharper. The incapability to obtain both temporal and frequency precision simultaneously is governed by the uncertainty principle: $\Delta\omega \times \Delta r \geqq 1/2$ Lower left: The Continuous Morlet Wavelet analysis. The dilation and give the wavelet uniform resolution, but the resolution is also uniformly poor due to limited wave in each wavelet function. As wavelet is also an integral transform, the result also suffered from the limitation of uncertainty principle.
Lower right: the Wigner–Ville distribution. In principle, this is the contour of individual Fourier spectrum computed from central auto-correlation at any given time. Therefore, it suffers all the limitation of the Fourier analysis.

The effect of uncertainty principle is clearly seen in the top row of Spectrogram results. These results are drastically different from the Hilbert spectral representations given in Figure 2F, which represent the results both from regular EMD and EEMD respectively. While EEMD result has revealed a lot of details, but the mode mixing indeed had cause the time–frequency representation to be fragmented. The Hilbert spectrum from the EEMD result, however, gives a continuous and physically more satisfactory answer with the steady vocal cord vibration at around 100Hz and the nonlinear vocal chamber reverberation up to 1,000Hz.

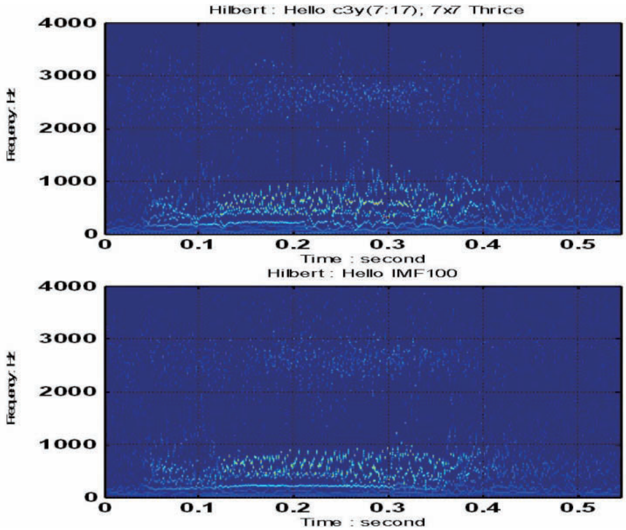

Figure 2F The Hilbert Spectrum of the voice signal, "Hello." Upper panel: The Hilbert spectrum computed from the IMF produced thro ugh EMD. Though this presentation gives super time-frequency resolution without the limitation of uncertainty principle, the mode mixing caused the fragmentation of the time-frequency line. Note the intra-wave frequency modulation causes the frequency to fluctuate over a finite range near the mean value.Lower panel: The Hilbert spectrum computed from the IMF produced through Ensemble EMD. The EEMD eliminated the mode mixing and resolved the problem of time-frequency fragmentation. The super time–frequency resolution is obvious.

The crucial differences between the HHT and traditional methods can be summarized in Table 1 as given in [14]. The versatility of the adaptive approach is clearly shown: without the limitation of the uncertainty principle, HHT could give frequency values at any time to any degree of precision limited only by the data quality.

	Fourier	Wavelet	HHT
Basis	a priori	a priori	Adaptive
Frequency	Integral Transform: Global	Integral Transform: Regional	Differentiation: Local
Presentation	Energy–Frequency	Time–energy –frequency	Time–frequency–energy
Nonlinear	No. Harmonics	No. Harmonics	Yes. Intra-wave frequency modulation
Nonstationary	No.	Yes.	Yes. Inter-wave frequency modulation
Uncertainty	Yes.	Yes.	No resolution limit.
Harmonics	Yes.	Yes.	No.

4. Applications in Cerebral Blood Flow Regulation

Cerebral autoregulatory mechanisms are engaged to compensate for metabolic demands and perfusion pressure variations under physiologic and pathologic conditions [18,19]. Dynamic autoregulation reflects the ability of the cerebral microvasculature to control perfusion by adjusting the small-vessel resistances in response to beat-to-beat blood pressure (BP) fluctuations by involving myogenic and neurogenic regulation. Reliable and noninvasive assessment of cerebral autoregulation (CA) is a major challenge in medical diagnostics. Transcranial Doppler ultrasound (TCD) enables assessment of dynamic CA during interventions with sudden systemic BP changes induced by the Valsalva maneuver (VM), head-up tilt and sit-to-stand test in various medical conditions. [19,21-25] Conventional approaches typically model cerebral regulation using mathematical models of a linear and time-invariant system to simulate the dynamics of BP as an input to the system, and cerebral blood flow as output. A transfer function is typically used to explore the relationship between BP and cerebral blood flow velocity (BFV) by calculating gain and phase shift between the BP and BFV power spectra[19,21-25). Many studies have shown that transfer function can identify alterations in BP–BFV relationship under pathologic conditions such as stroke, hypertension, and traumatic brain injuries that are associated with impaired autoregulation [21,23,24,26-31]. This Fourier transform based approach, however, assumed that signals are composed of superimposed sinusoidal oscillations of constant amplitude and period at a pre-determined frequency range. This assumption puts an unavoidable limitation on the reliability and application of the method, because BP and BFV signals recorded in clinical settings are often nonstationary and are modulated by nonlinearly interacting processes at multiple time-scales corresponding to the beat-to-beat systolic pressure, respiration, spontaneous BP fluctuations, and those induced by interventions. To overcome problems in CA evaluations related to nonstationarity and nonlinearity, a novel computational method called multimodal pressure–flow (MMPF) analysis was recently developed to study the BP-BFV relationship during the Valsalva maneuver (VM).[30] _ENREF_2 The MMPF method enables evaluation of autoregulatory dynamics based on instantaneous phase analysis of BP and BFV oscillations induced by the intervention (a sudden reduction of BP and BFV followed by an increase in both signals).

The main concept of the MMPF method is to quantify nonlinear BP-BFV relationship by concentrating on intrinsic components of BP and BFV signals that have simplified temporal structures but still can reflect nonlinear interactions between two physiologic variables. The MMPF method includes four major steps:

a. decomposition of each signal (BP and BFV) into multiple empirical modes;
b. selection of empirical modes for (dominant) oscillations in BP and corresponding oscillations in BFV;
c. calculation of instantaneous phases of extracted BP and BFV oscillations;
d. calculation of biomarker(s) of CA based on BP–BFV phase relationship.

The MMPF applies an empirical mode decomposition (EMD) algorithm to decompose complex BP and BFV signals into multiple empirical modes. Each mode represents a frequency-amplitude modulation in a narrow frequency band that can be related to a specific physiologic process. For example, this technique can easily identify BP and BFV oscillations induced by the VM (0.1–0.03 Hz, i.e., period ~10 to 30 sec). Using this method, a characteristic phase lag between BFV and BP fluctuations corresponding to VM was found in healthy subjects, and this phase lag was reduced in patients with hypertension and stroke. [32] . These findings suggested that BFV–BP phase lag could serve as an index of CA. However, intervention procedures, such as the VM, introduce large intracranial pressure fluctuations and also require patients' active participation. As a result, such procedures are not applicable under various clinical conditions, such as in acute care settings.

It has been hypothesized that CA can be evaluated from spontaneous BP–BFV fluctuations during resting conditions [33,34]. This hypothesis has been motivated by the facts that

a. CA is a continuous dynamic process so that it should always engage to regulate cerebral blood flow;
b. BP and BFV display spontaneous fluctuations at different time scales [26,27,33-35] even during resting conditions.

Since spontaneous BP and BFV fluctuations can be entrained by respiration or other external perturbation over a wide frequency range [0.05–0.4 Hz][36-37] and the dominant frequency of spontaneous BP fluctuations varies among individuals over time and under different test conditions, reliable measures of the nonlinear BFV–BP relationship without pre-assuming oscillation frequencies and waveform shapes are needed. These requirements are well satisfied by the MMPF algorithm which extracts intrinsic BP and BFV oscillations embedded in the original signals and quantifies instantaneous phase relationship between them. If the MMPF is sensitive and can provide reliable estimation of autoregulation using spontaneous BP and BFV fluctuations, it is expected that, similar to BP and BFV oscillations introduced by the VM, spontaneous BFV and BP oscillations during resting conditions should also exhibit specific phase shifts.

To test whether the MMPF can evaluate the dynamics of CA from spontaneous BP–BFV fluctuations during supine rest, our recent study compared the BP-BFV phase shifts obtained from BP and BFV oscillations introduced by the VM and from spontaneous BP–BFV oscillations during supine baseline [38]. Data of 12 control, 10 hypertensive and 10 stroke subjects during VM and baseline resting condition were analyzed using the improved MMPF method.

Spontaneous oscillations (period: mean±SD, 15.7±9.2 seconds) in the same frequency range as the VM oscillations (17.7±7.9 seconds, pair t-test p=0.37) were chosen. BP–BFV phase shifts during spontaneous oscillations (ranging from ~−60 to 120 degrees) were highly correlated to those obtained from VM oscillations (left side middle cerebral arteries R=0.92, p<0.0001; right side R=0.80, p<0.0001) (Figure 3). Consistently, the paired-t test showed that the average BP–BFV phase shifts during baseline were statistically the same as the values during the VM (p>0.47). These results indicate that the MMPF method can enable reliable assessment of CA dynamics and its impairment under pathologic conditions using spontaneous BP–BFV fluctuations.

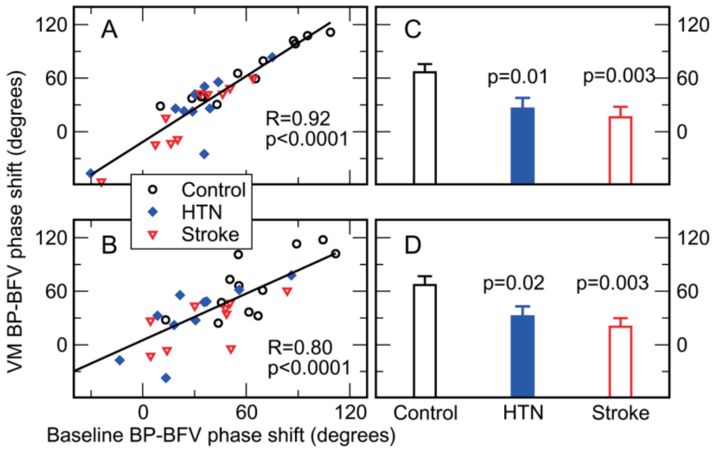

Figure 3 Comparison of the BP–BFV phase shift during two different conditions and between control, hypertensive (HTN), and stroke groups.
A–B: For each subject in this study, BP–BFV phase shifts for left (A) and right (B) side middle cerebral arteries (MCA) were measured during the Valsalva maneuver (VM) and during supine baseline conditions. The straight line is the linear regression fit of the data. The phase shifts during VM and baseline showed a strong correlation (left: R=0.92, p<0.0001; right: R=0.8, p<0.0001).
C–D: BP–BFV phase shifts during VM were smaller in hypertensive and stroke groups than in control group in both left and right MCAs (HTN: left p=0.01, right p=0.02; Stroke: left p=0.003, right p=0.003). Adapted from [39].

Moreover, in our recent study [38], the MMPF method was applied to study the relationship between spontaneous BP–BFV oscillations at the respiratory frequency (~0.1–0.4Hz) in healthy (control) and diabetic subjects. The results showed that in healthy subjects, there were also specific phase shifts between spontaneous

BP and BFV oscillations over this frequency range (0.1–0.4Hz) and that the phase shifts were significantly reduced in patients with type 2 diabetes, indicating altered dynamics of BP–BFV relationship, and thus impairment of vasoregulation in diabetic subjects (Figure 4).

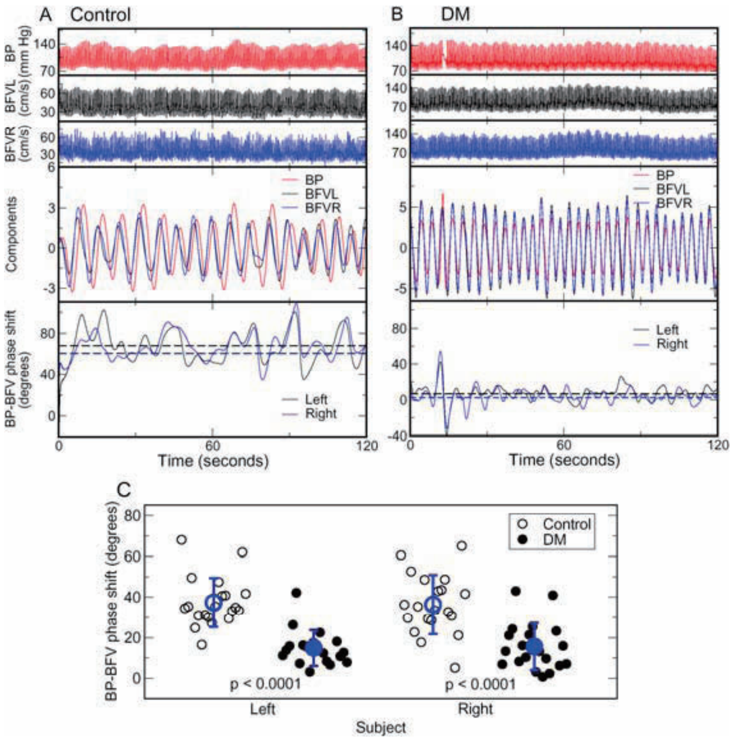

Figure 4 Spontaneous oscillations of blood pressure (BP) and cerebral blood flow velocity (BFV) in panel A: a 72-year-old healthy control woman and panel B: a 52-year-old man with type 2 diabetes during supine baseline. Panel A was adapted from [38]. BP, left and right BFVs (Subpanels 1 to 3 in A and B) were decomposed into different modes using ensemble empirical mode decomposition algorithm, each mode corresponding to fluctuations at different time scale. The components corresponding to respirations at frequency ranging from ~0.1 to 0.4Hz (the forth subpanels in panel A and panel B) were extracted and used for the assessment of BP–BFV relationship. Instantaneous phases of BP and BFV oscillations (solid lines in the bottom panels of panel A and panel B) were obtained using the Hilbert transform. There were large time/phase delays in BP oscillations compared to the BFV oscillations. For each subject, the average BFV–BP phase shift (horizontal dashed lines in bottom subpanels of panel A and panel B) was obtained as the average of instantaneous BFV–BPV phase shifts during the entire 5-min supine baseline. Panel C:

Phase shifts between spontaneous oscillations of BP and BFV were much smaller in diabetes group than in healthy control group ($p<0.0001$). The group averages of control and diabetes are shown in blue symbols with error bars as the standard deviations. There was no significant difference in phase shifts between left and right blood flow velocities in both control and diabetes groups.

5. Conclusions

Ever since the recent advances in information technology, there is a flood of new way to measure and collect data of all sorts. As the technology becoming more sophisticated, the more data both in quantity and quality would increase. We are overwhelmed by the volume of the data, yet at the same time we are also underserved by the information we could extract from the data. The key here is the data analysis methodology under strict artificial limitations. The only way to break through this bottleneck is to use adaptive data analysis. HHT is an adaptive data analysis, which enable us to define instantaneous frequency, the true and physically meaningful way to represent frequency. With the frequency definition, we can also quantify the degree and order of nonlinearity, and also determine the trend. Ever since it was introduced, it has found wide applications. The algorithms associated with HHT are finely tuned. They are robust and highly effective. Yet there still is no firm mathematical foundation for the method. New development from the nonlinear optimization approach might fill this gap soon. Meanwhile, we can use the method in a similar way we used HHT as in many applied mathematics tools, such as Fourier transform, before the full mathematical foundation is firmly established. For example , the proposed multimodal pressure–flow (MMPF) analysis overcomes many limitations of Fourier Transfer Function Analysis (TFA) by examining the phase shift of intrinsic BFV–BP oscillations at different time scales. The MMPF, thus provides more dynamic information in a more accurate manner. The current findings strongly suggest that these nonlinear approaches without the assumption of stationarity are more suitable for the assessment of complex physiological interactions. In conclusion, our experience indicates that HHT could help us to clarify and provide insight to the underlying physical processes.

6.Acknowledgments

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Mobile Technologies and the Exposome: Continuous Assessment of Environmental Exposures Critical to Health

Kevin Patrick[1], Bill Griswold[2], Greg Norman[3], Fred Raab[4], Jacqueline Kerr[5], Barry Demchak[6], Ingolf Krueger[7], Sanjoy Dasgupta[8], Nima Nikzad[9], Celal Ziftci[10], Nakul Verma[11], Piero Zappi[12], Elizabeth Bales[13], Nichole Quick[14]

(e-Mail: kpatrick@ucsd.edu)

Abstract — Francis Collins, MD, PhD, Director of the US National Institutes of Health, states that: "genes are like bullets in a gun, but the environment pulls the trigger." The exposome is a construct that represents all the environmental exposures of an individual in a lifetime and how these exposures relate to disease onset and, in turn, disease prevention and wellness. Exposures begin before birth and act continuously over the life-course and include insults from environmental and occupational sources, stress, diet, and lifestyle factors such as use of drugs and alcohol, and physical activity. They also include positive influences such as family, social networks, cultural influences and healthy environments. Traditional methods of considering environmental causes of disease usually focus on a single element (e.g., asbestos and mesothelioma) or risk factor (e.g., alcohol and esophageal cancer; tobacco and lung cancer). Of course, the exposome is much more complex, multilayered and multidimensional than this but we have been limited in our ability to measure it because we have not had sufficient technical infrastructure to do so. However, the rapid proliferation of mobile sensing, networking and computing technologies now supports the collection, analysis and use of ever-increasing amounts of data about the exposome and about factors that influence the type, amount and intensity of exposure: the microbiome, biological and physiological factors, health behaviors, social networks and the environment. These data will allow us to better understand the multi-layered and interconnected systems important to human health. Moreover, the technologies that support measurement of the exposome can also support data-driven and systems-based interventions for population health that will almost certainly eclipse individual-level interventions

in terms of reach, impact, cost-effectiveness, quality, acceptability and outcome. This paper outlines selected examples of research underway at UCSD/Calit2 on these technologies.

Keywords — exposome, environment, health behavior, GIS, GPS

1. Background

In the late 1990s, reviews of interventions to promote healthy behaviors indicated very little success [1] . These interventions focused on the individual and did not consider the contexts in which health behaviors occur, e.g., where someone lives, what food they have access to, or how far they have to drive to work. The obesity epidemic further confirmed the failure of existing public health approaches to reduce consumption of unhealthy high-fat foods and to increase physical activity levels [2]. National data now indicate that less than 5% of adults engage in sufficient physical activity to maintain cardiovascular health [3]. An alternative to the individual approach to behavior change emerged in 2000; namely the Ecological Model of Behavior Change [4]. This model posits that health behaviors occur in multiple locations and have multiple influences from the proximal, e.g. individual motivations, to distal, e.g., national policies that support active transportation. Since 2000, a flurry of research on built environment and neighborhood influences on health has been conducted, partly under the auspices of the Active Living Research program [5]. Further, national and international agencies (e.g., CDC, WHO, IOM) have recommended a multilevel ecological approach to help solve the obesity crisis [6]. Studies have shown several cardiovascular disease risk factors (e.g., physical activity, diet, obesity, asthma, blood pressure, depression), outcomes and even mortality are related to neighborhood design.

At the same time as research on the environment was developing, advances in genetics occurred. The NIH therefore brought the two themes together in the Gene, Environment Initiative in 2007 and funded researchers to improve measurement of behavioral health, exposure biology and environmental health in order to support Gene-Environment research. While the built environment research field has highlighted the importance of place in health, studies have focused principally on residential environments around the home.

Yet we know that many behaviors, healthy (e.g., eating fresh vegetables and exercising) and unhealthy (e.g., excessive driving, sitting, consuming alcohol) occur away from home and are not dependent on the availability of resources around the home. Despite the reemergence of place as a determinant of health, the existing studies have found disappointingly small effect sizes and in some cases inconsistent findings [7]. One study demonstrated that this focus on residential neighborhood for behaviors that occurred outside of the neighborhood was suppressing the true impact of the totality of environmental exposures on health (e.g., at work, to-from work, and elsewhere [8].; and may underestimate true health disparities in access to resources. Theoreticians have also called for a more dynamic and fluid approach to defining healthful environments [9]. The use of GPS data, combined with other person-worn sensors (e.g., accelerometers) that can identify where and when activities and exposures occur is greatly improving the potential of built environment research to understand and solve public health issues [10].

2. The Exposome

"At its most complete, the exposome encompasses life-course environmental exposures (including lifestyle factors) from the prenatal period onwards"[11].

The construct of the exposome is gaining currency as a complement to the genome in understanding the totality of influences on human health. Environmental exposures include air pollution, tobacco smoke, industrial waste, contaminants in drinking water, noise, heat stress and electromagnetic fields. These, combined with behavioral mediators such as physical activity, sedentary behavior and diet contribute to disease onset via pathways that involve inflammatory response, oxidative stress, hormonal dysregulation and altered immune response [12-15]. Taken together and at the population level, the components of the exposome contribute up to 80%–85% of the causes of cardiovascular disease, cancer, diabetes, stroke and other leading causes of death in Western societies [16]. Traditional methods of understanding environmental causes of disease usually focus on a single element (e.g., asbestos and mesothelioma) or risk factor (e.g., tobacco and lung cancer). The exposome is much more complex, multilayered and multidimensional than this but we have been limited in our ability to comprehend it because we have not been able to define the necessary methods for doing everything from measuring the exposome to the data analysis challenges when so many factors come in to play. Several projects being conducted by UCSD/Calit2 researchers are addressing this issue.

PALMS: Personal Activity Location Measurement System

Featured last year in Nature's analysis of the top 7 exposure-based science approaches [17] is the Personal Activity Location Measurement System (PALMS) a system for aggregating data on exposure to built/social environments with physical activity data. PALMS outfits participants with a GPS data logger and physical activity monitor that constructs a detailed picture of a participant's day: travel patterns, locations, time sequences; and time, duration and locations/levels of physical activity. Developed with funding from the NIH Gene-Environment Initiative (U01 CA130771; PI: K. Patrick), PALMS filters, synchronizes and merges data streams from GPS data loggers and accelerometers to determine where a person is active, using algorithms and calculations to detect transportation modes and distinguish indoor and outdoor locations. PALMS supports multiple researchers as they examine their data and if so desired, share it with others[18]. Since it went live in 2010, PALMS has captured data on 1500+ participants for times ranging from 2-14 days, with populations ranging from pre-school children to elders, much of this within San Diego County.

Two validation studies of PALMS are underway. The first was a study to validate algorithms that are specific to GPS & accelerometer data collection. This involved creating an annotated 'truth' dataset for testing existing and new PALMS algorithms. A total of 714 protocol-driven travel trips were made by two trained researchers. Vehicle, bus and bicycle trips varied in length from 800 to 1500 meters with an average duration between 5.5–7 minutes depending on the mode of transportation. Walking trips were approximately 800 meters in length with an average duration of 12.6 minutes. The annotated dataset contains data from 2 GPS devices (GlobalSat DG100 & Qstarz BT-1000) at 3 different epochs (5, 15, and 30 seconds) in multiple settings to explore the factors that best predict behavior (i.e., transportation mode: bus, car, walk, bicycle). Each researcher carried 8 GPS devices simultaneously and performed specific behaviors in controlled settings. They recorded the trip start and end-times, pause points, travel mode, and test conditions. Test conditions included urban canyons versus open view areas, warm or cold GPS start, and movement from indoors to outdoors. In addition to the GPS devices, researchers wore an Actigraph GT3X accelerometer set at 30-second epochs and a heart rate monitor. Algorithm classification for a trip mode was considered correct if the type of transportation was correctly classified for 85% of the trip epochs. Initial analyses of sensitivity and specificity for the 30-second epoch warm-start data indicated there were no significant differences by device model. Across conditions sensitivity ranged from 0.46–0.61 and specificity 0.44–0.53. Under the best conditions (i.e., warm start, pause between trips, open space location) sensitivity ranged from 0.73–1.0 and specificity ranged from 0.12–0.25 for both device models. Further analysis of the currently algorithms for GPS travel mode classification are ongoing. Novel machine learned algorithms under development that will be imported into PALMS are demonstrating over 80% accuracy.

A second validation study for PALMS is a field test in an ongoing R01 study of a place-based physical activity intervention among church going Latinas in San Diego County called Fe en Accion (Dr. Elva Arredondo PI; NCI/NIH). This field-based validation study is designed to ensure that PALMS is feasible to use—by both research staff and research participants—in "real world" conditions, and that it provides valid information about what it is intended to measure: the geospatial and temporal characteristics of physical activity. Usability testing of PALMS will include two rounds of assessments of research staff and participants at baseline and 12 months. We will objectively assess performance features of the system (e.g., processing time and failure rates) and participant compliance (e.g., number of hours of valid data). We will collect self-reported measures of participant burden and both self-reported and objective (when appropriate) measures of staff burden and satisfaction with the system, its support materials and functionality. We will also assess the construct validity of PALMS to identify time spent in physical activity in specific locations (e.g., parks and local neighborhoods) compared with existing self-reported survey measures using a Multi-trait-multi-method approach, at baseline and 12 months. The value of using GPS to measure time spent in specific activity locations will be demonstrated to predict moderate

and vigorous physical activity in comparison with self-report and GIS based neighborhood estimates of access to parks and neighborhoods. Finally, a small sub-study is being conducted using the SenseCam device, a wearable camera that continuously captures information on location as
well as activities.
(http://research.microsoft.com/en-us/um/cambridge/projects/sensecam)

3.CitiSense

Another project is CitiSense (NSF/CPS-0932403; PI: W. Griswold) a participatory air quality sensing system that bridges the gap between personal sensing and regional measurement to provide micro-level detail at a regional scale. The CitiSense system is comprised of three main parts: a wearable air pollution sensor, mobile phone application, and web interface. The sensor and phone are mobile and can be carried with an individual throughout their day and specifically during their commute. The sensor and phone provide instantaneous access to the current air conditions and are meant for "in the moment" observations. The third aspect of the CitiSense system is a web interface accessible from a desktop or laptop computer. The website provides historical data and trends which users can explore to reflect on their overall exposure to pollutants. CitiSense was recently evaluated in a user study of [16] commuters in San Diego and measurements of several components of air quality varied significantly from those provided by official regional air pollution monitoring stations. Application of geostatistical techniques to CitiSense data supports inferences of a regional map of air pollutants with greater detail than official regional summaries [19].

Other research we are presently conducting in our lab is investigating the use of the SenseCam to better understand the exposome on selected populations, including elders living in continuing care retirement communities and bicycle commuters. Finally, our CYCORE project is exploring how to better capture exposomic data from individuals in the context of cancer research [20]. This research is formative at present but shows promising results at improving how we understand the totality of human experience and the full range of influences on human health.

4.Conclusion

We are in a remarkable and transformative era in which the many influences of health can be understood: across space, across time and in relationship to one another. Enabling this is the increasing ubiquity of sensing technologies, both mobile and fixed. Smartphones combined with wearable sensors and linked into cloud-based services provide the capability for the simultaneous measurement of human movement at any scale desired. This enables rich characterization of environmental exposures that are critical to gene/environment interactions and our understanding of who is susceptible to what sorts of exposures, when, and why. The ability to apply analytical approaches such as machine learning and other novel statistical modeling to data derived from these sensors will advance the field of "big data" science in as yet unforeseeable directions

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Wireless Technology for Health Behavior Change Measurement & Intervention

Gregory J. Norman[1], Kevin Patrick[2], Simon J. Marshall[3]

Department of Family & Preventive Medicine
Center for Wireless & Population Health Systems
California Institute for Telecommunications & Information Technology
University of California, San Diego
9500 Gilman DR, MC-0811, La Jolla, CA 92093-0811 USA

(e-Mail: gnorman@ucsd.edu, kpatrick@ucsd.edu, sjmarshall@ucsd.edu)

Abstract — There is a need for new and effective ways to change people's physical activity and dietary patterns to impact obesity. Mobile and social technologies that are integrated into daily living can set the stage to assess and give feedback on health behaviors. This presentation will highlight three applications of wireless technology for health behavior change. First, on board sensors in smart mobile phones combined with machine learning can be used to determine physical activity patterns. Second, text messaging can deliver tailored messages for weight loss. Third, Facebook and mobile apps can target weight loss in an ongoing user-centered program. mHealth technology strategies present opportunities to think differently about how to influence health behaviors at the individual, social, and environmental levels.

Keywords — mobile phones, health, obesity, physical activity, diet, social networks

1. Introduction

In the U.S., 68% of adults age 20 and over are overweight or obese [1] and by 2030, 50% are projected to be obese [2]. Obesity contributes to six of the ten leading causes of death in America, including heart disease, type 2 diabetes, certain cancers, and high blood pressure [3].

It is well known that for most people obesity is caused by a positive energy imbalance [4], which occurs primarily due to lack of physical activity and over consumption of an energy dense diet [5], [6]. Excessive energy intake and sedentary behavior partially explain the recent emergence of obesity as a leading public health problem.

Research has shown that even a modest (5-10%) weight reduction in obese individuals with hypertension, dyslipidemia, and type 2 diabetes results in health benefits, and is considered the most effective non-pharmacologic method of improving health status [7]. It has been known for over 30 years that a 10% reduction in weight in men corresponds to an approximate 20% reduction in coronary disease incidence, whereas a 10% increase in weight is associated with a 30% increase in cardiovascular morbidity [8].

Fortunately, obesity is highly preventable and treatable with modifiable lifestyle changes [9], [10]. Research indicates that weight loss is best achieved through a combination of improved diet and physical activity behaviors [11]. Therefore, to reduce the burden of illness and disability caused by obesity, it is critical to design effective interventions that help individuals improve these behaviors.

In this article we first present a brief health behaviors related to obesity, including physical activity, sedentary behavior, and dietary behaviors. We then introduce the concept of mHealth technologies as new tools for measuring and intervening health behaviors. In sections II to IV, we highlight three applications of wireless technology for health behavior change. First, on board sensors in smart mobile phones combined with machine learning can be used to determine physical activity and sedentary behavior patterns. Second, SMS text messaging can be used to deliver tailored messages for weight loss. Third, Facebook and mobile apps can be used to target weight loss in a user-centered intervention for overweight young adults.

.Health behaviors

Physical Activity (PA) reduces the risk of developing several leading chronic diseases including obesity, coronary heart disease, and type 2 diabetes. There is also mounting evidence that PA is associated with better psychosocial health and wellbeing. Compared with inactive people, physically active individuals report higher scores for positive self-concept, self-esteem, positive moods, sleep quality, and overall quality of life. PA has also shown to be an efficacious adjunctive treatment for depression [12]. The scientific evidence supporting the health benefits of regular PA are so unequivocal that the US government issued the first federal guidelines about PA in 2008, which called for all American adults to accumulate at least 150 minutes per week of moderate intensity PA (MVPA), with single bouts required to last at least 10 continuous minutes to be of benefit. MVPA equates to brisk walking or taking at least 100 steps per minute [13].

Sedentary behavior (SB) is now emerging as a concept distinct from PA and as received widespread research interest because we spend more than half the waking day sitting and its determinants and health consequences may be independent of MVPA [14]. For these reasons, experts now recommend that SB and MVPA be treated as potentially independent influences on health. Sedentary behavior refers to a class of behaviors characterized by low levels of energy expenditure, typically between 1-1.5 metabolic equivalent units (METS) [15]. This includes behaviors such as lying down, working at a desk, and watching television.

For women and men, sitting time and TV viewing has shown to be detrimentally associated with waist circumference, BMI, systolic blood pressure, fasting triglycerides, HDL cholesterol, and fasting insulin [16]. In adult women, research showed that, independent of exercise levels, sedentary behaviors, especially TV watching, were associated with significantly elevated risk of obesity and type 2 diabetes and that light to moderate intensity PA was associated with substantially lower risk [17][18].

Although exercise and other structured MVPA contributes meaningfully to physical activity thermogenesis, most individuals spend less than 5% of their waking hours engaged in this type of activity when it is measured objectively [19]. The vast majority of the between-subject variance in physical activity thermogenesis can be explained by low and very low intensity movement such as posture (lying, sitting, and standing), incidental movement (e.g., fidgeting, talking, and typing), and light intensity ambulation (e.g., walking, doing chores, etc.). The combined sum of energy expended during these 'sub-threshold' activities has been referred to as Non-Exercise Activity Thermogenesis (NEAT) [20]. Compared to lean individuals, obese individuals spend an extra 2.5 hours per day in a sitting position--a postural 'habit' that remains even after weight loss. Similarly, when lean individuals were experimentally induced to gain weight, their sitting time did not change. Replacing 2.5 hours per day of sitting with standing and light intensity ambulation could result in an additional 350 kcal per day being expended [21].

Poor dietary behaviors are a known risk factor for the development of obesity, as well as for diabetes, CHD, cancer and stroke. Research supports that a diet rich in fruits and vegetables and low in fat is important in preventing these chronic diseases, and is recommended by the USDA, USDHHS, Surgeon General, NRC, NHLBI, NCI, ACS, and AHA. Although national surveys indicate a decline in the average proportion of calories from total and saturated fat over the past several decades, the CDC estimated in 2000 that only 38% of individuals 2 years and older met the recommendation for total fat intake and 41% of these individuals met the recommendation for saturated fat intake. In addition, data from the 2005 Behavioral Risk Factor Surveillance System (BRFSS) showed that only 32.6% of the U.S. adults consumed fruit two or more times per day, and only 27.2% ate vegetables three or more times per day. Simple dietary restriction has not been associated with successful weight control and may result in a nutritionally inadequate diet. Thus, rather than focusing only on limiting total energy intake, it is important to promote a diet that is nutrient dense: high in vegetables, fruits, grains, and other fiber-rich plant foods, yet low in fat, at a given level of energy intake.

mHealth

Intervention programs to date have had limited success for weight loss and weight loss maintenance. Some success has been shown with weight loss intervention programs delivered via the Web and email [22], [23]. A review of randomized controlled trials of computer-tailored education on physical activity and dietary behaviors reported significant results on nutrition behaviors in 20 of 26 studies, while only 3 of 11 PA studies had a significant effect [24]. Another review of 47 current "second generation" eHealth interventions (i.e. using only interactive technologies such as email or the Internet), found that 51% of study outcomes favored the intervention group compared to controls, highlighting the need for further evaluation to identify successful components of these interventions [25]. The reach of the Internet makes it an appealing possibility in interventions targeting a population wide problem such as obesity. However, results are typically modest and primarily limited to populations of white adults. Web-intensive programs are hampered by several issues such as program use limited to desktop devices that may not meet the needs of those without regular access to a desktop machine due to work or home circumstances or income levels that hinder accessibility. Also, adherence is a common concern, as usage tends to drop significantly over time with online programs. While there is consensus on the promise of web technologies for behavior change, further research is needed on mobile technologies and their use to improve health outcomes [26]. Mobile technologies, in particular mobile phones, are beginning to show promise in health behavior interventions but there is very little reported about their use for obesity-related behaviors.

mHealth is broadly defined as the delivery of health related services through mobile communication technology. It includes the use of wireless technologies to combine sensors and other technologies for health measurement and intervention. mHealth can be viewed as an integration of wireless technologies, data analytics process the data streams received from sensors, and the persuasive design principles feedback the processed information through the wireless technologies. All of which create interactive feedback loops for health behavior change. mHealth lets us "think differently" about what is possible for population-based health behavior change. We can develop systems that are able to be 'on the go', 'just in time', 'passive monitors', and 'gentle reminders.' Critical open questions regarding mHealth are whether it can improve health behavior measurement through unobtrusive data collection and activity recognition; and can mHealth improve intervention for health behavior change through mobile systems with message feedback, location awareness, social network and sharing components? Three technologies that are emerging as serving important functions in mHealth and persuasive design are body sensors, online social networks, and Global Positions, and persuasive design features. The wireless technologies gather data; the analytics systems (GPS).

In the last 20 years, activity inference using body sensors has come a long way. In mHealth body sensor collected data are beginning to take the place of health and behavior data collected through surveys and periodic doctor visits. The cost and size of senor hardware is shrinking and the early 2000s were marked with advancements in instrumenting the person with wearable sensors. These wearable sensors are now making their way into cell phones in the form of GPS, accelerometers, proximity sensors and cameras. The mobile phone is, of course the ideal platform to serve as a data collection hub because it is nearly always on and always with us. We can now measure moment-by-moment data information from a person and use that information to provide intervention feedback systems.

Instead of (or in addition to) measuring a person's perceived social support with questionnaires, we can look at online social networks to understand how people are influenced by important others. As a measurement tool, we can examine social ties and the influence of important others on one's behavior. As part of a health intervention program, we can engage peoples' social network to help with behavior change.

Context awareness and Environmental data collected through Geographic Information Systems (GIS) and GPS provide information about our surroundings. On the measurement side, we can determine the environmental exposures that can be facilitators or barriers to being active in one's neighborhood. On the intervention side, we can develop 'context aware' interventions where a system can make suggestions and recommendations based on an individual's location to help him reach his activity and nutrition goals.

2. Measuring physical activity and sedentary patterns with smart mobile phones

Measurement of PA and SB is a critical but non-trivial task for developing effective behavior change interventions. Self-reported data are subject to bias and errors. Objective methods that use accelerometer motion sensors are gaining increasing attention. Using mobile phones and their onboard sensors to measure physical activity and sedentary behavior is also now being realized. Smartphones are an ideal platform for monitoring activity patterns because they are carried by people throughout the day and smartphones have powerful computational capabilities, and allow development of customized applications that integrate monitoring and intervention. Researchers have used accelerometers on Nokia N95 phones [27], [28] and Android phones [29] to detect common activities such walking, stair climbing, jogging, and sitting.

We recently conducted a study to create a valid activity classification tool that uses sensors (e.g., accelerometer and gyroscope) onboard today's smartphones [30]. Data from these sensors were processed using machine learning to classify activity types. Using minimally extracted features from the smart phone sensors general categories of activity (walking, jogging, stair climbing and sitting) were classified with several machine learning algorithms. This step gave an indication of the possibilities and limitations of using a smart phone as an activity data collector.

We used the iPod Touch (Apple Inc.) as the hardware platform for data collection (Figure 1). It has essentially the same accelerometer and gyroscope sensors as the iPhone (Apple Inc.), one of the most widely used smartphones on the market. The 4th generation iPod Touch we employed used STMicroelectronic's LIS331DLH accelerometer and L3G4200D gyroscope.

We studied 13 activity types in total, four of which were paced by research staff in a laboratory setting on a treadmill, and the rest were self-paced by participants to simulate a free-living condition. Sixteen adults (8 males, 8 females; age = 41.19, BMI = 28.82 kg/m2) completed the activities. In the laboratory 3-minute bouts on the treadmill included walking at a slow pace (1.5 mph), a normal pace (3.0 mph), a brisk pace (4.0 mph), and jogging (5.5 mph). Participants then recorded time sitting and bouts of walking up and down stairs at a brisk and normal pace. This was followed by completing 400m self-paced walking bouts at slow, normal, and brisk paces as well as one 400m jog on an outdoor track. The iPod Touch was carried on the participant in the front shorts pocket or on the arm.

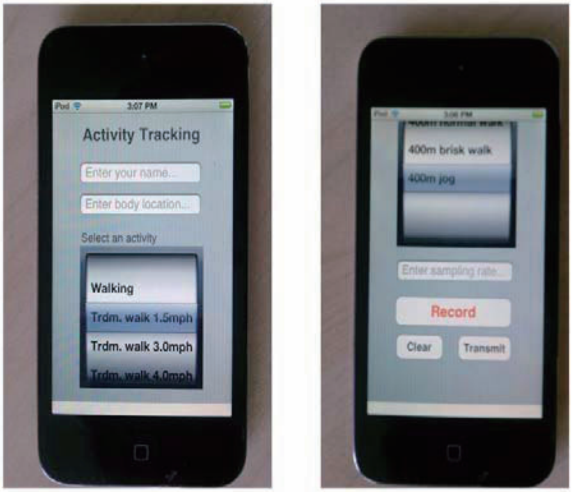

Figure 1 iPod Touch (Apple Inc.) with activity tracking app.

Mean and variance of the vector magnitude of the 3-axis acceleration and gyroscope values served as the extracted features for classification. Different size sliding windows of data segments were tested and a 2-second window was found to be optimal. We compared the performance of a number of classifiers, including: C4.5 (J48) Decision Tree, Multilayer Perception (MLP), Naive Bayes (NB), logistic, k-Nearest-Neighbor (kNN or IBk). 10-fold cross validation was used for all experiments. Among these basic classifiers, kNN generally produced the best accuracy results with an average weighted accuracy of 90.2%. High accuracies with kNN were achieved for walking at different paces (90.1%-94.1%), jogging (91.7%), and sitting (100%). Stair walking proved to be the most challenging activity with recognition accuracies ranging from 52.3% to 79.4%.

Among all the misclassified sample segments, a significant number were caused by the difficulty of differentiating walking at different speeds, and differentiating walking on stairs from walking on a level ground. Using both rotation rate (from the gyroscope) and acceleration features (from the accelerometer) with kNN resulted in higher accuracies for all activity classes compared to using only acceleration features, with improvement ranging from 3.1% to 13.4%.

This study is among the first to validate smartphone sensors including accelerometer and gyroscope for activity recognition. The results suggest clear benefits of using gyroscope as an additional data source for classifying activities. Including other signal data from the phone such as GPS may further improve the system but only for specifically identifying outdoor activities, and with the potential cost of reducing battery life of the smart phone. Other sensors such as heart rate monitoring might also further improve identifying intensity of activities (e.g., brisk walking compared to jogging). However, the trade-off of the extra burden of wearing an additional sensor would limit the public health impact of our system.

This study is the first step in our effort to develop a measurement tool that can integrate with technologies for to intervene on PA and SB. Combining time and frequency features of both acceleration and gyroscope measurements from sensors onboard smartphones, common activity patters were classified with high accuracy.

3. Tailored text messaging programs for weight loss

The use of Short-Messaging Service (SMS), or text messaging, for promoting health behavior change is rapidly growing [31] [32] as mobile phones have many capabilities that can be used for health promotion [33]. It is an inexpensive and instantaneous form of two-way communication that transmits brief written messages (up to 160 characters) via a mobile phone. Ninety-eight percent of cell phones worldwide have SMS capabilities with 187.7 billion monthly text messages sent in the U.S.

SMS technology can collect and deliver time- and context-sensitive information in succinct messages that can be read discreetly. These messages are asynchronous—that is, they can be accessed any time or place that is convenient for the user. The messages will also be stored on the phone even if the phone has been turned off, and messages will be delivered when the phone is turned back on. SMS technology can reach rural areas or places with limited cellular service because it requires a lower bandwidth compared to phone calls made with mobile phones. These SMS features can be useful for a wide variety of health behaviors and conditions, such as simple appointment reminders or complicated tasks like weight loss counseling [33], [34].

One of the reasons why SMS is effective at promoting health behavior changes is that many SMS features relate to important constructs from behavior change theories such as cues to action, reinforcement, goal setting, goal reminders and feedback. In addition, research has shown that SMS programs impact behavior change constructs such as social support [35], self-monitoring [36], [37], perceived control [38], anxiety [39], and self-efficacy [35].

SMS has shown to be effective at improving health related behaviors such as diabetes management [40] and smoking cessation [41]. A few studies have focused on weight loss as the primary aim, with diet and physical activity messages sent to participants. In a study conducted by Joo and Kim [42], a weight reduction program that included access to a public health center and pedometers, printed materials, an initial nutritional assessment by a registered dietician, and SMS, helped participants lose 1.6 kg of weight in 12 weeks. Haapala and colleagues [43] found that their SMS program, which did not include any supplemental intervention strategies, decreased participant weight by 4.5 kg in 12 months. Gerber and colleagues [44] also conducted an SMS-only weight management program that focused on perceptions of use and found that women receiving text messages about weight loss had positive attitudes towards the incoming messages.

Our first text message intervention, named mDIET (Mobile Diet Intervention through Electronic Technology) was developed to improve diet and physical activity for weight loss in obese men and women [34]. mDIET was a 16 week program that featured daily text messages. Three to five messages were sent each day at time chosen by the user. Many messages were personalized and tailored to the individual. Personalized messages could include the users name, children or pets name, social support person, or name of favorite grocery store. Messages were tailored based weight loss and weight management strategies derived from responses on the O'Neil Eating Behavior Inventory. In addition, non-tailored messages that served as reminders, prompts, or weekly topic information were also sent.

The text message intervention engine consisted of a database of user information and over 3,000 messages. A Java application applied the intervention logic rules that automated the system that was connected to a mail gateway to send and receive the SMS messages. The weight loss program included 16 weekly topics (e.g., self-monitoring, meal planning, and portion control). These topics were also provided to users in a printed binder and monthly calls lasting about 10 minutes were conducted by a health coach to review progress, address strategies and problem solve. The goal of the program was to create a 500 kcal/day deficit through calorie consumption reduction and increased energy expenditure by reaching and maintaining a 12, 000 steps/day goal.

The mDIET program was evaluated in a two-group randomized control trial. Sixty-three adults (81% women, mean age 46 years) were randomized to the mDIET program or a usual care control group. The mDIET program resulted in 2.88 kg weight reduction in 4 months compared to the control group. Participant feedback on the program was positive with 96% saying they would recommend mDIET to friends and family members. Some participants commented that the program, “keeps me focused”, “was a steady reminder, keeping health on my mind”, and “served as an excellent reminder to watch what I ate.” This initial study demonstrated that the mDIET program was feasible to implement and efficacious for modest weight loss. Based on these promising findings we are currently evaluating the mDIET program in a 1-year intervention trial with 300 randomized overweight and obese adults.

4. Facebook and mobile apps for a user-centered weight loss program

The SMART (Social/Mobile Approach to Reduce WeighT) study is a current NIH funded study that is focused on weight loss of 18-35 year olds. Web, mobile phone, and Facebook’s online social network are components through which the intervention provides tools and information to facilitate weight loss. The study target population is college students recruited at three universities in the San Diego, California region. A total of 400 eligible individuals were enrolled and randomized to and active treatment or control group study arms.

The goal of the study was to design a ‘user-centered’ intervention that operated through Facebook with mobile apps as tools for diet and physical activity behavior change. Rather than creating an online social network for study participants, SMART was designed to harness the participant’s existing social network on Facebook. Figure 1 displays a simplified conceptual network structure where at the center of the network is the SMART study page with participants randomized to the intervention represented by the red colored nodes. Each participant has her own network of friends, which is represented by the green colored nodes as one connected friend to each participant. The yellow colored nodes are friends of participants’ friends, who are indirectly related to the participants. Based on studies by Christakis and Fowler [45][46], through the concept of contagion participants in the SMART study can influence friends’ health and be influenced by friends and friends of friends. It was hypothesized that positive health contagion would be a mechanism by which the SMART intervention influenced participants to lose weight.

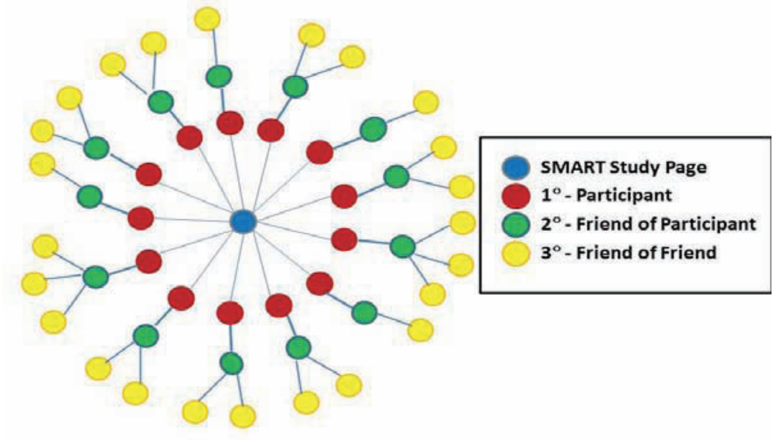

Figure 2 Conceptual social network structure of SMART study participants.

The SMART program is a two year intervention. Most weight loss programs are short-term in duration lasting between 12 to 24 weeks. A challenge the SMART study faces is keeping participants engaged in the program for two years. The proposed solution was to allow the intervention to change over time by introducing new mobile apps and content. While this approach to changing a treatment program at the same time as it is being evaluated is uncommon in randomized controlled trial research, and might even be considered methodologically problematic, it parallels real-world Internet use and product development. The concept of an evolving intervention that has an initial structure but grows organically over time was seen as a necessary and novel approach to the ongoing program.

While the SMART intervention is designed to change overtime, we also needed to have aspects of the study remain constant so that all participants received a high fidelity program with certain common elements. To achieve this we grounded the intervention in a set of core behavior change strategies. These strategies were determined by a systematic review of behavior change interventions conducted by Abraham and Michie [47]. This review resulted in a list of 19 strategies drawn from social science theories of behavior change such as Social Cognitive Theory, Operant Learning, and Self-Regulation Theory. Abraham and Michie determined that the five behavior change strategies most often found in efficacious interventions were self-monitoring, Intention formation, goal setting, goal review, and feedback on performance. These five strategies became the underlying core behavior change components that would be the focus throughout the intervention program for all participants. That is, regardless of what mobile apps and other components were changing in the program, participants would always have access to tools and information related to these five strategies.

The SMART intervention program is called, 'ThreeTwoMe' based on the contagion concept of influence in social networks. The program includes a website, facebook page, mobile apps, emails, bathroom scale, and a pedometer. The program begins with an initial 30 minute session with a health coach. The health coach assesses the participants' intentions and motivations along with current physical activity and diet behaviors. The health coach helps the participant to set initial weight loss and behavior change goals. The session also includes reviewing use of the mobile apps and any technical issues the participant may be having with the system. The ThreeTwoMe.com website is where all the intervention content is located. Sixteen weekly themes are presented to participants sequentially as they go through the program. Themes include topics such as counting calories, portion control, eating out, and social eating. Theme content is stored in a knowledge library on the website and other program components refer participants back to specific themes. The website includes a 'document library' with tips, charts, and other tools that participants can print-out as needed. A blog is maintained on the website by the study nutrition coordinator. Blog entries are on current relevant topics that center around events such as holidays and the academic schedule. Blog topics have included, 'A stress-less approach to finals week' and 'Staying active through the summer.'

The Facebook page is linked to the webpage and provides the online social network component of the program. Participants can find posted polls, challenges, messages, fun facts, quizzes and relevant campaigns on the Facebook page. Participants can encourage their friends to view the page and participants can comment and 'like' posts on the ThreeTwoMe Facebook 'wall.' Wall posts also appear in participants' own Facebook newsfeed, allowing them to see updates and interact with the program from their own Facebook account. Campaigns launched on the Facebook page have included, 'The 10,000 step challenge' and 'Surviving the holidays.'

The mobile apps are a critical feature of the program and provide the tools needed for behavior change. The mobile apps are developed as web-browser-based using J-Query in order to look and function like native apps on the phone's operating system (e.g., iOS or Android). This eliminates the need to program apps for different operating systems. This design also allows participants to use the apps on a PC or tablet computer, which is important since individuals are not required to have a smart phone to participate in the study. All the apps have a social network component that ties the app to Facebook. The protocol for the study is to monitor study participants' usage of the apps and based on usage, determine when an app needs to be updated or replaced. Additional apps that include core behavior change strategies will also be introduced over the course of the intervention.

Currently, three apps are available to users with other apps in development. The 'Be Healthy' app provides daily healthy tips for users to act upon and share their experience with others. A daily health tip can be activity related, "Take the stairs today" or nutrition related, "Skip the sports drink." Users can post and see others' comments about the tip and the program stores completed tips as 'accomplishments' that users can refer back to. 'Goal Getter' is an app for setting goals and sharing your goals with Facebook friends. Friends can then leave hidden messages of encouragement to help motivate the user toward completing the goal. The app stores the type of goal, the duration of the goal, and the frequency of the goal. For example, a user's goal might be to walk 10,000 steps a day for 4 days during the week. 'Trend Setter' is an app for self-monitoring health behaviors and viewing patterns of behavior over time. Participants can choose to track different nutrition and physical activity 'trends' and the selected trends serve as reminders of goals and strategies that the person is working on.

5. Conclusions

We presented three current directions in the use of mobile technologies to influence behavior change and impact obesity. Smartphones as activity sensors, SMS messages, and Facebook with mobile apps demonstrate that the mobile phone is a viable platform for health behavior change measurement and intervention. A key feature of these mHealth applications is that they can deliver interactive intervention content through 'pulling' information from sensors or the user and 'pushing' needed information back to the user. With an interactive system, content can be sent back to the user when and where it is needed and accessed when convenient.

The analytics within a system can be designed to adapt interventions to the individual or to groups.

The goal of behavior change through mHealth is to create systems that integrate with the user's daily life and are unobtrusive, convenient and simple to use. These systems are designed to make relatively 'small' changes in behaviors and weight loss that accumulate over time compared to more intensive clinical types of programs. For example, the SMS and SMART systems are hypothesized to result in slower (e.g., about 1 pound weight loss/ week) but lasting weight loss by changing everyday habits. This is in contrast to a 'large changes' approach where more rapid weight loss is expected from bigger shifts in energy expenditure and calorie restriction, which are changes that are likely not sustainable for long period of time by most people.

In addition to the mHealth systems we presented here, there are other technologies to measure, track, and give feedback on physical activity (e.g., wireless pedometers, Fitbit, Nike+, SenseWear armband) and other lifestyle behaviors (e.g., wireless body weight scales, Bluetooth blood pressure monitors, digital calorie counters). Different combinations of these technologies are available in some commercially available systems and services. These integrated systems allow users to interact with their data, interact with other users and receive expert knowledge.

Ideally, scientific study and accumulated evidence should drive the application of mHealth technology. These technology channels can be used to create persuasive intervention programs by closely following the tenets of behavior change theory. That is, we hypothesize that a new technology is useful when it allows us to design interventions that closely follow postulates of a theory for how to change behavior. For example, Social Cognitive theory posits that accomplishing realistic performance goals will increase one's self-efficacy for a given behavior. Mobile technologies can assist in goal setting, providing goal reminders, and providing performance feedback to help individuals successfully complete their goals. While new and exciting technologies will continue to offer a variety of communication and persuasion mechanisms, we caution against using technology just because it is new and exciting. Numerous technologies will continue to emerge with much hype for how they will change our lives, but we believe that careful research on mHealth technologies will result engaging and scalable systems that have the potential to make a significant public health impact on chronic disease prevention and management.

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Home-based Sleep Monitoring System Based on Cardio-pulmonary Coupling Analysis

Albert C Yang, M.D.[1,2,3,] Chung-Kang Peng, Ph.D.[3,4]

1. Department of Psychiatry, Taipei Veterans General Hospital, Taiwan
2. School of Medicine, National Yang-Ming University, Taiwan
3. Center for Dynamical Biomarkers and Translational Medicine, National Central University, Chungli, Taiwan
4. Margret and H. A. Rey Institute for Nonlinear Dynamics in Medicine, Beth Israel Deaconess Medical Center/Harvard Medical School, Boston, Massachusetts, USA

(e-Mail:accyang@gmail.com)

Abstract — Assessment of sleep quality is essential in evaluating the severity of insomnia and subsequent treatment response. Currently, sleep quality assessment is primarily based on self-report sleep questionnaires and the polysomnography (PSG) study. The disadvantage of the former (e.g. Pittsburg Sleep Quality Index) is its indirect measure of sleep quality based on subject's recall of sleep status. Although PSG can further identify objective sleep stages during the sleep, it requires an expensive and encumbering setting which may not be readily applied to large-scale screening or used in repeat clinical evaluations. Therefore, enhanced quantitative assessments of sleep quality, especially if measurable at home and in a simple and inexpensive manner such as the electrocardiographic (ECG) signal, could have substantial clinical utility. We recently applied a new analysis termed cardiopulmonary coupling (CPC) analysis which utilizes surface ECG signals to evaluate sleep quality in patients with major depression. This home-based sleep monitoring system can is more applicable in clinical practice as a simple and effective tool for assessing sleep quality.

Keywords — cardiopulmonary coupling analysis, home-based sleep monitoring system

I. Introduction

Contemporary approaches to assess sleep quality rely mostly on qualitative sleep questionnaires and objective sleep examinations based on polysomnography (PSG) study [1]. However, conventional sleep staging in PSG study is based on arbitrary criteria of identifying morphological markers in electroencephalographic (EEG) signals[2], and were found to have poor correlations with subjective sleep measures [3,4] . Previous study also shows that benzodiazepines may reduce "deep" sleep (i.e., decreased Delta power in EEG signals) but still improve sleep continuity and subjective sleep quality[5]. Moreover, the settings of PSG that requires expensive and encumbering resources may not meet the timely demand of sleep examination from daily clinical practice. These limitations may reduce the value of the PSG study as an effective measure to evaluate sleep quality in clinical practice. Enhanced quantitative assessments of sleep quality, especially if measurable in a simple and inexpensive manner, could have substantial clinical utility.

A complementary approach to quantify sleep quality is suggested based on a particular EEG morphology named Cyclic Alternating Patterns (CAP) [6-11]. CAP is a condition of phasic EEG activity associated with microarousal during sleep and therefore is suggested to be a marker for sleep instability[7-8]. Previous study has shown that CAP-EEG is altered in insomnia patient and can be used for evaluation of treatment efficacy[12]. Recently, research group at Beth Israel Deaconess Medical Center / Harvard Medical School (Thomas and colleagues) further demonstrated that the presence of CAP in EEG is associated with alternating physiological dynamics of heart rate and respiration, thus open a window to utilize the electrocardiographic (ECG) signal alone as an alternative mean to quantify CAP/non-CAP states during sleep[13]. This newly developed analysis is called cardiopulmonary coupling (CPC) analysis and has been previously reported to detect sleep apnea based solely on the ECG signal[13].

We have demonstrated the utility of this CPC analysis to evaluate sleep stability in patients with major depression[14]. Our results suggests that 1) depressed patient had significantly decreased stable sleep and increased unstable sleep and REM/wake state comparing to normal controls, and 2) the objective indices obtained from CPC method are well correlated with subjective measure of sleep quality using ratings scales.

2. Cardiopulmonary Coupling Analysis

Figure 1 outlines the technical details of the CPC algorithm. We first identify the normal-to-normal (NN) interbeat interval as well as ECG-derived respiration (EDR) time series from ECG raw signals. We then further analyze the coherence of these two signals using Fourier method. The concept of identifying stable or unstable sleep can be summarized as following: 1) during physiologically stable (non-CAP) sleep, our coupling measurement detects sinus arrhythmia at the relatively high frequency of 0.1 to 0.4 Hz, reflecting the respiratory rate of 6 to 24 breaths per minute, and 2) During physiologically unstable (CAP) sleep, recurrent arousals induced by abnormal respiration cycles consistently generate abnormal coupling of R-R and EDR signals in the low frequency spectrum (0.01 to 0.1 Hz range), reflecting the typical respiratory event cycle time of 10 to 100 seconds. This low frequency coupling represents periods of physiologically unstable sleep behavior. Therefore, it is now possible with this new ECG-based cardiopulmonary coupling measure to detect CAP and non-CAP states and thus periods of unstable and stable behaviors, respectively.

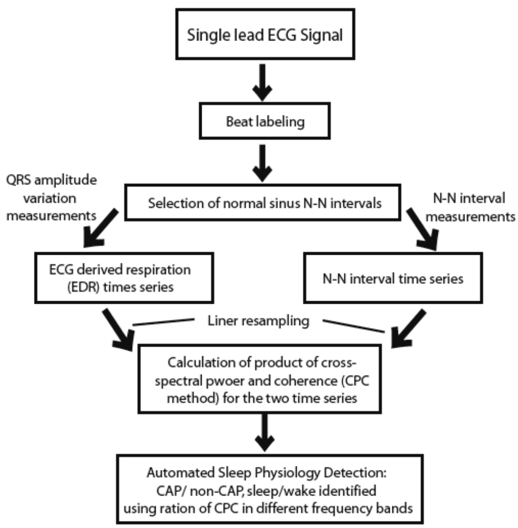

Figure 1. Sequential steps in the derivation of cardiopulmonary coupling measures. ECG refers to electrocardiogram; CAP, cyclic alternating pattern.

3. Home-Based Sleep Monitoring System

In addition to original scope of CPC method to detect sleep apnea, we have demonstrated the utility of CPC analysis to evaluating sleep quality in patient with major depression using the home-based sleep monitoring system[14]. The schematic of home-based sleep monitoring is illustrated below.

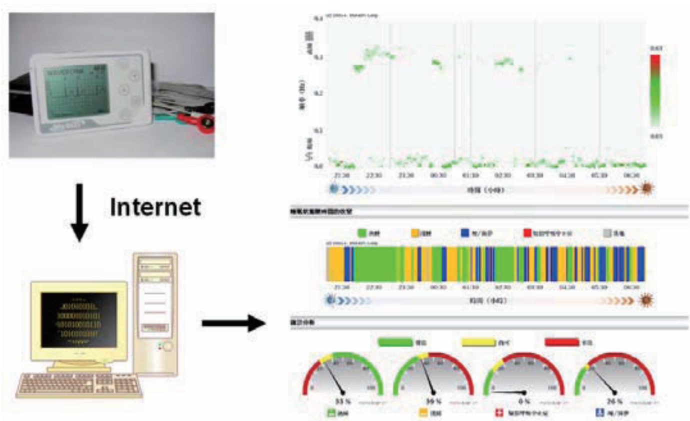

Figure 2 Schematic illustration of home-based sleep monitoring system

The home-based sleep monitoring system using CPC analysis complements traditional approaches used to assess sleep stability/quality because it objectively incorporates features of physiological dynamics not accounted for by EEG-based techniques [15,16]. Our applications to major depressive disorders show that the system can detect decreased stable sleep and increased unstable sleep and REM/wakeful states in depressed individuals that are consistent with well-known features of altered EEG sleep structures in major depression, namely an increase in sleep state fragmentation, a reduction in slow wave sleep, and an increase in REM pressure [17-20]. Moreover, these results indicate that insomnia in depression may be not only a "brain" symptom but also a systemic phenomenon that represents inter-linked physiological processes, including autonomic, respiratory and electrocortical functions [21].

Importantly, the CPC indices were associated with subjective sleep quality and the severity of depression, particularly the stable sleep and REM/wakeful components. These findings may enhance the utility of this ECG-based method for evaluating insomnia in depressed patients. Figure 3 shows an online report of a primary insomnia patient (without depression).

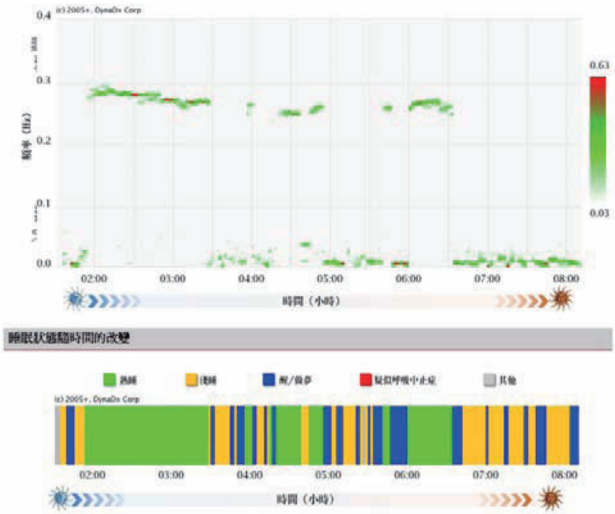

Figure 3 Tentative sleep report shows a pattern of increased shallow sleep and frequent arousal in the middle of sleep based on the analysis of ECG signals obtained from a patient with primary insomnia.

This home-based sleep monitoring system can be potentially to track treatment effects of insomnia using hypnotics. Benzodiazepine hypnotics can reduce EEG-CAP states [22-24] and, thus, presumably reduce the physiological unstable sleep state. The use of hypnotics may, therefore, produce "masking" effects that could make depressed patients appear to have more stable sleep than they might have without medication. We have found that despite the restoration of the amount of stable sleep, medicated patients still showed a longer latency to stable sleep than healthy control subjects.

Finally, the home-based sleep monitoring system using CPC analysis provides a unique viewpoint on sleep stability in the context of cardiovascular physiology. This readily repeatable ECG-based method could provide a simple and objective way to evaluate insomnia in depression, and possibly track treatment effects.

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Brain Signal Controlled Nursing System

Po-Lei Lee[1,2] and Kuo-Kai Shyu[1]

1.Department of Electrical Engineering, National Central University, Taiwan.
2.Center for Dynamical Biomarkers and Translational Medicine, National Central University, Jhongli, Taiwan.

(e-Mail: pllee@ee.ncu.edu.tw)

Abstract — This study presents a steady-state visual evoked potential (SSVEP) - controlled nursing system. SSVEPs, induced by phase-tagged flashes in eight light emitting diodes (LEDs), were used to control eight different functions of a hospital bed. EEG signals were measured by one EEG electrode placed at Oz position, referring to the international EEG 10-20 system. Since SSVEPs are time-locked and phase-locked to the onsets of SSVEP flashes, EEG signals were bandpass-filtered and segmented into epochs, and then averaged across a number of epochs to sharpen the recorded SSVEPs. Phase lags between the measured SSVEPs and a reference SSVEP were measured, and targets were recognized based on these phase lags. The current design used eight LEDs to flicker at 31.25 Hz with 45° phase margin between any two adjacent SSVEP flickers. The SSVEP responses were filtered within 29.25-33.25 Hz and then averaged over 60 epochs. Owing to the utilization of high-frequency flickers, the induced SSVEPs were away from low-frequency noises, 60 Hz electricity noise, and eye movement artifacts. As a consequence, we achieved a simple architecture that did not require eye movement monitoring or other artifact detection and removal. The high-frequency design also achieved a flicker fusion effect for better visualization. Seven subjects were recruited in this study to sequentially input a command sequence. The accuracy and information transfer rate (ITR) (mean ± std.) over the seven subjects were 93.14 ± 5.73 % and 28.29 ± 12.19 bits/min, respectively. The proposed system could provide a reliable channel for severely disabled patients to control external devices.

Keywords — Brain-computer interface (BCI), steady-state visual evoked potential (SSVEP), electroencephalography (EEG), phase-tagged flickering sequence.

I. Introduction

Patients suffering from severe motor disabilities, such as amyotrophic lateral scleroses (ALS), severe cerebral palsy, head trauma, multiple sclerosis, and muscular dystrophies, are incapable of communicating with external environments [1]. Several research groups have dedicated themselves to developing novel techniques, which allow users to control external devices or express their intentions independent of peripheral neuromuscular functions. Among those proposed solutions, one promising technique, called brain computer interface (BCI), was developed to help patients communicate with external environments by means of recording specific brain signals induced from elaborately designed tasks, and then translating the measured brain signals into communication or control signals. Over the past few decades, several BCI systems have been designed based on various kinds of brain signals, such as sensorimotor Mu rhythm, slow cortical potential, P300, motor-related potential (MRP), visual evoked potential (VEP), etc. [2-5].

Among those BCIs, the VEP has drawn great attention, due to its easily measurable nature, high communication efficiency, and high reliability. At least four different VEP-based BCI systems have been developed. Sutter developed a brain response interface (BRI) by measuring fast multifocal visual evoked potentials (FMFVEPs) induced from a pseudo-random sequence [6]. The measured brain signals were correlated with a stereotypical designed 'response template' to detect the gaze target by checking the latency of maximum correlation. [7-9] utilized mutually independent flickering sequences to induce onset and offset flash visual evoked potentials (FVEPs). Onset and offset FVEPs in central visual field were enhanced by means of a time-locked average process. [10] implemented attention-regulated SSVEP-based BCI which permits a users' SSVEP amplitudes to be regulated by their attention levels [10-12] used multi-frequency flickers to induce user's steady-state visual evoked potentials (SSVEPs) and the gazed-target was detected by checking the spectral peaks on the estimated spectrum. Nevertheless, the aforementioned systems utilized multiple frequencies or random flickers as visual stimuli. The stimulation frequencies in those systems were low and the induced VEPs typically existed in low frequency ranges (<20Hz). As a consequence, the induced VEPs in these systems may be easily contaminated with VEP-unrelated noises, such as eye-blinking artifacts, Mu rhythm, cardiac noise, respiratory movement-induced noise, occipital alpha rhythm, etc. [13-14], and the low-frequency display can occasionally cause participants to feel uncomfortable.

In our system, we propose an SSVEP-based BCI system. All SSVEP flickers are driven by phase-tagged flickering sequences at a chosen frequency. Users' gazed-targets can be discerned by detecting the phase lags in the measured SSVEPs. Our current design utilizes eight light-emitting diodes (LEDs), flashing at 31.25 Hz, to control eight distinct cursor functions. Our system achieves phase detection in high-frequency SSVEP, which not only avoids the induced SSVEPs being interfered by low-frequency noise but also induces flicker fusion effect and attains better visualization [13,15].

2. Materials and Methods

Subjects and Tasks

Seven volunteers (Six males and one female), ages from 24 to 32 years, were recruited to sit on a comfortable armchair in a dimly illuminated room. Each subject had corrected Snellen visual acuity of 6/6 or better, with no history of clinical visual disease. All subjects gave informed consent, and the study was approved by the Ethics Committee of the Institutional Review Board, Taipei Veterans General Hospital, Taiwan. Every subject was requested to participate in an application study to control eight cursor functions, including four direction functions (⇧: cursor up, ⇨: cursor right, ⇩: cursor down, ⇦: cursor lef) and four button functions (ON: system on, OFF: system off, BR: right button, BL: left button) (see Fig. 1). All participants were requested to produce a sequence of eight cursor commands, which was designed arbitrarily as 'ON⇦BL⇧⇩BR⇨OFF' three times. The signal processing was computed by a personal computer (CPU 3.0 GHz/1GB RAM) and cursor commands were inputted one-by-one with the provision of phonetic biofeedback for each valid output to inform subjects which cursor function was just executed. Error key outputs, which were produced validly but did not follow the desired sequence order, were also recorded but subjects were instructed to neglect those phonetic feedbacks.

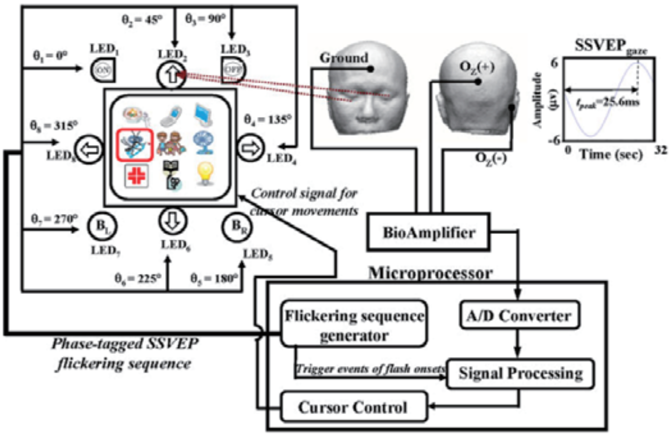

Figure 1. The schematic diagram of the proposed SSVEP-actuated BCI system.

EEG recordings

This study used only one bipolar EEG channel, one electrode (Oz(+)) placed at Oz position and the other (Oz(-)) placed at the right mastoid, with respect to a ground electrode placed at frontal position (Fpz) (bandpass, 0.5-50 Hz; MacLab, BioAmp, ADInstruments, Castle Hill, Australia) (see Fig. 1). All EEG electrode placements were based on the international EEG 10-20 system [16-18]. EEG recordings were digitized (NI-PCI 6071E, National Instrument) at 8 kHz.

Visual Stimuli

Eight white LED devices (Part number: LYBSB93W1303R012BP, LedTech Electronics Co., Taiwan; rise time < 50 ìs; wavelength ranging from 400 to 700 nm), covered with thin white paper diffusers, were used to produce unpatterned visual stimuli. The luminance of each visual stimulus was calibrated using a luminance meter (LS-110; Konica Minolta Photo Imaging Inc., USA) and set at 150 candelas (cd) /m2. The eight LED flickers were placed surrounding a computer monitor and numbered from 1 to 8 in clockwise order (see Fig. 1). Flicker LED1 to LED8 were used to control the cursor functions of ON, ⇧, OFF, ⇨, BR, ⇩, BL, and ⇦, respectively (see Fig. 1). Each LED was driven by a flickering square wave consisting of ON-OFF alternative states, generated from a microprocessor, oscillating at 31.25Hz (32 ms duration for each ON-OFF cycle) with a designated phase delay. The phase delay assigned for the ith LED flicker (LEDi) was set as

$$\theta_i = (i-1)\times 45^{\circ} \quad , i = 1,\ldots,8$$

so that the phase angles were equally distributed over a full phase cycle (360°) with a ±22.5° phase margin. Since the flickering frequency is known as 31.25Hz, the phase delay can be controlled by setting a time delay on the square wave generation:

$$t_i = \frac{\theta_i}{360^{\circ}} \times T \qquad (1)$$

where θ_i is the phase delay assigned to the flickering sequence of the ith LED flicker, t_i is the requisite time delay for achieving θ_i, $T = 1/f$ is the cycle duration, and f is the flickering frequency set at 31.25 Hz in this study. The phase delay (θ_i) was used for gazed-target identification in the application study.

Figure 2 demonstrates the generation of eight phase-tagged flickering sequences, from flicker LED1 to LED8. A 45° phase increment was set for generating the eight flickering sequences, resulting in a ±22.5° phase margin for any adjacent two flickering sequences. The phase delays for flicker LED1 to LED8 were 0°, 45°, 90°, 135°, 180°, 225°, 270°, and 315°, respectively, corresponding to time delays of 0 ms, 4 ms, 8 ms, 12 ms, 16 ms, 20 ms, 24 ms, and 28 ms using Eq. (1). The flash onsets (OFF-to-ON) in the flickering sequences of flicker LED1 were used as trigger events for the following epoch-average process.

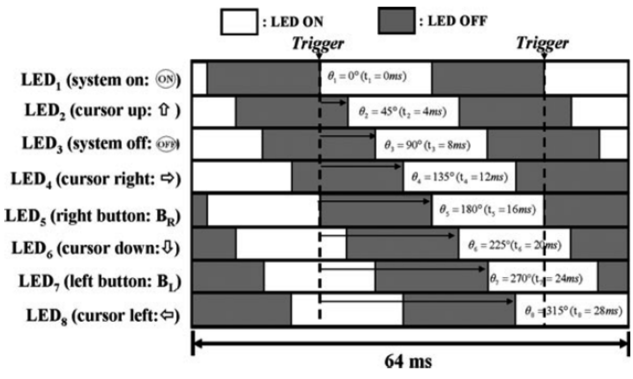

Figure 2. The generation of eight phase-tagged flickering sequences. Each LED was driven by a flickering sequence consisting of ON-OFF alternative states, generated from a microprocessor, oscillating at 31.25Hz (32 ms duration for each ON-OFF cycle) and endowed with a designated phase delay. The phase delay assigned for the ith LED (flicker LEDi) was set as θi = (i-1)×45°, i = 1,…,8, so that the phase angles were equally distributed

over a full phase cycle (360°), to achieve a ±22.5° phase margin. The phase delay in the ith square wave can be controlled by setting a time delay ti as ti= θi /360×T.

Signal processing of SSVEP

The Oz EEG signals were bandpass-filtered between 29.25 and 33.25Hz (zero-phase, 6th-order, IIR Butterworth filter) to obtain noise-suppressed SSVEP responses. The SSVEP responses were then segmented into epochs, from 0 ms to 32ms, based on the timings of flash onsets in the flickering sequence of flicker LED1, which was the flickering sequence tagged with 0° phase delay. Epochs were stored in an epoch register, in the computer memory. Owing to the time-locked and phase-locked characteristics of SSVEP [19], noise which was neither time-locked nor phase-locked to flash onsets was further suppressed by applying an epoch-average process. It is important to note that LED1 was used to estimate the subject-specific phase lag in performing the application task. The latency of the maximum amplitude peak in SSVEPref was detected, denoted by tref, and used as reference latency for the subsequent phase lag detections. In the application task, epoch-average process was performed every 0.1 second to average across the latest N (N=60) epochs in the epoch register to obtain SSVEPgaze. The choice of 0.1 second was based on the shortest time for optimal data transmission between AD card and the LabView program in our current setup, and the rationale for choosing 60 epochs was justified based on the result of control task.

Gazed-target identification based on the detection of phase lag between $SSVEP_{gaze}$ and $SSVEP_{ref}$

The present study accomplished recognition of user's gazed-target by detecting the phase lag between $SSVEP_{gaze}$ and the $SSVEP_{ref}$. Since $SSVEP_{gaze}$ and the $SSVEP_{ref}$ are two averaged SSVEPs induced by flickers with the same flickering frequencies, this study achieved phase lag by measuring the time shift between these two SSVEPs. The following describes the procedure for gazed-target identification in the proposed system. First, an epoch-average process is applied to average across the latest N (N=60) epochs in the epoch register to obtain a $SSVEP_{gaze}$ every 0.1 second. Second, the latency of maximum amplitude peak in $SSVEP_{gaze}$ is detected and designated as t_{peak}. Third, time lag (t_d) between the t_{peak} and t_{ref} is calculated, i.e., $t_d = t_{peak} - t_{ref}$. Fourth, since the flickering frequency f and duration cycle T

are known, the phase $\theta_{detected}$ between the $SSVEP_{gaze}$ and $SSVEP_{ref}$ is

$$\theta_{detected} = \frac{t_d}{T} \times 360^\circ \qquad (2)$$

The $\theta_{detected}$ is further readjusted within 0° and 360° to obtain phase lag (θ_d) by

$$\theta_d = \theta_{detected} - 360^\circ \times r \qquad (3)$$

where r is an appropriate chosen positive integer to confine the phase lag θ_d within 0° and 360°.

Fifth, the phase distances between the θ_d and the expected phase delays ($\theta_i = (i - 1) \quad 45^\circ,\ i = 1, \ldots, 8$) were then calculated, i.e.,.

$$D_i = \sqrt{(\theta_d - \theta_i)^2}$$

The i^{th} LED (flicker LED_i) with minimum angle distance D_i is recognized as the gazed-target. The current setup in both our application tasks detected the gazed-target every 0.1 second and confirmed it as a valid output of cursor command after 15 consecutively successful detections. The incorrect outputs were also recorded for further performance analysis.

The accuracy ($N_{correct}/N_{total}$), command transfer interval (CTI) and information transfer rate (ITR) are computed in all the seven subjects. The command transfer interval (CTI) is defined as total experimental time (T_{total}) divided by the number of total output commands and letters (N_{total}), i.e., T_{total}/N_{total}. The information transfer rate (ITR) is computed as:

$$\frac{Bits}{command} = \log_2 K + P\log_2 P + (1-P)\log_2[(1-P)/(K-1)] \qquad (4)$$

$$ITR = \frac{Bits}{command} \cdot \frac{60}{CTI} \qquad (5)$$

where K is the total number of LED flickers (K = 8) and P is the accuracy.

3. Results

Figure 3 shows one example for on-line signal processing of extracting SSVEPgaze when subject I was gazing at flicker LED2. The first panel shows the ON-OFF states of the flickering sequence of flicker LED1 which was assigned with zero-degree phase delay. The raw Oz EEG signal shown in the third panel was bandpass-filtered within 29.25 - 33.25 Hz to obtain the SSVEP response (see the fourth panel). The flash onsets of flicker LED1 flickering sequence, marked by dashed vertical lines, were used as trigger events to segment the SSVEP response into epochs, based on trigger events (every 0.1 second). An epoch-average process was applied to the latest 60 epochs (epoch index shown in the second panel) based on trigger events to obtain SSVEPgaze. The enlarged plot at the bottom shows one SSVEPgaze with tpeak detected at 25.6 ms.

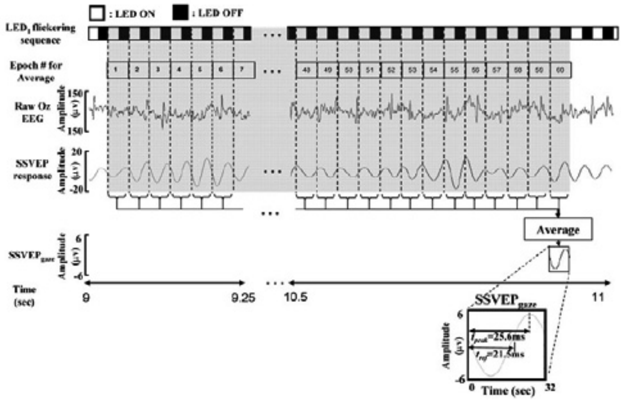

Figure 3. Signal processing for extracting SSVEPgaze when subject I was staring at flicker LED2. The first panel shows ON-OFF states of the flickering sequence of flicker LED1, assigned with zero-degree phase delay. Its flash onsets, marked by dashed vertical lines, were used as trigger events for the epoch-average process. The recorded Oz EEG signal shown in the third panel was bandpass-filtered within 29.25 - 33.25 Hz to obtain the SSVEP response (see the fourth panel). The SSVEP response was then segmented into epochs, from 0 to 32ms, based on trigger events. The epoch-average process was applied to the latest 60 (N=60) epochs (epoch index shown in the second panel) based on trigger events to obtain SSVEPgaze. The enlarged plot at the bottom shows one SSVEPgaze with tpeak detected at 25.6 ms.

Figure 4. illustrates one example of the raster plot of SSVEPgazes induced

from subject I when trying to produce the cursor command sequence 'ON ⇦BL⇧⇩BR⇨OFF' in the application study. Each SSVEPgaze was obtained by an average of the latest 60 consecutive epochs relative to the time point of gazed-target detection. The phase lag, èd, in each SSVEPgaze was detected, and SSVEPgazes were expressed in degrees of phase lags between 0° and 360° based on their phase lags (èd). The SSVEPgazes obtained from 3 to 41 seconds were vertically aligned with their amplitudes presented in color scale. The first two seconds were skipped due to the insufficient epoch number (N<60) for epoch-average calculation. The gazed-target was detected every 0.1 second and each valid output of the cursor command required recognizing the same target 15 successive times. The valid cursor commands are labeled at the top of Fig. 4, and those SSVEPgazes used for producing valid cursor commands are marked by green solid ellipses. Table 1 shows the command sequences generated by all seven subjects in application study with errors underlined. In both the application studies, all the seven participants completed the pre-defined command sequences with minor errors. In the application task, the mean accuracy and standard deviation was 93.14 ± 5.73%, and that for CTI, and ITR were 6.03 ± 2.20 sec/command and 28.29 ± 12.19 bits/min, respectively.

4. Discussion

This study presents a SSVEP-based BCI using phase-tagged flickering sequences. The proposed system allows all SSVEP flickers to be flashed at the same frequency with distinct assigned phases. The EEG signals are bandpass-filtered, followed by a time-locked epoch-average process to segregate the induced SSVEPs from SSVEP-unrelated noises. The straightforward SSVEP extraction procedure enables extracting high-frequency SSVEPs in a short time with high SNR. The following describes the distinct features of the proposed BCI system.

First, our system utilizes only one flickering frequency for visual stimulation and avoids the amplitude-frequency problem, which has been reported in other SSVEP-based BCI systems using multi-frequency SSVEP flickers [20-21]. The SSVEP has an amplitude that varies with frequency, with a few frequencies that seem to be preferred by the visual system to produce bigger responses [20,22-24]. Herrmann explained that this amplitude-frequency characteristic may be owing to axonal connections between the neurons of an oscillating ensemble [20], contributed by the temporal characteristics of spike propagation between different neurons. Wang [24] checked the amplitudes of SSVEPs induced by visual stimuli at different frequencies [24], and concluded that human SSVEP has three preferred frequency ranges, centered at low- (15Hz), middle- (31Hz) and high-frequency (41Hz) ranges. The SSVEP induced by stimulation frequencies beyond these three frequency ranges may result in weak SNR and decreased accuracy. This implies that SSVEP-based BCI systems using multi-frequency flickers need a calibration process to calibrate the amplitude-frequency problem across different frequencies and among different individuals. In contrast, our system uses only one stimulation frequency, requiring no amplitude-frequency calibration, which greatly increases the usability of the proposed system.

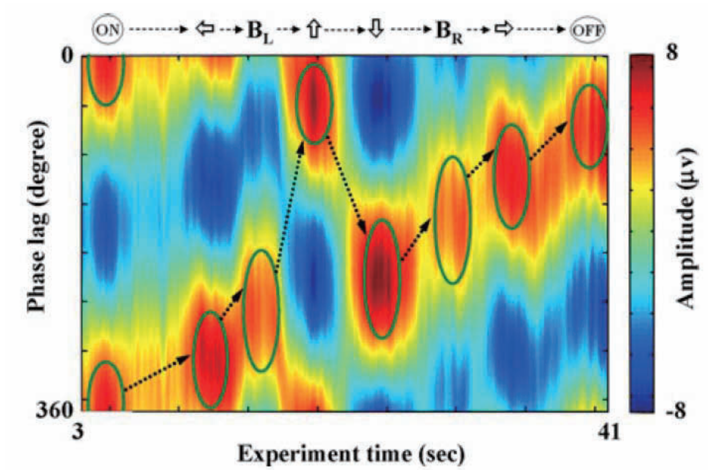

Figure 4. The raster plot of induced SSVEPgazes when trying to produce a command sequence in the application study. The SSVEPgazes obtained from subject I were recorded when he was trying to produce a cursor command sequence ‘ON⇦BL⇧⇩BR⇨OFF’ (ON: system on, OFF: system off, ⇦: cursor left, ⇧: cursor up, ⇩: cursor down, ⇨: cursor right, BR : right button, BL : left button). Latencies in all SSVEPgazes were expressed in the phase angle and readjusted between 0° and 360° based on their phase lags (θd). The SSVEPgazes obtained from 3 to 41 seconds are vertically aligned with their amplitudes being presented in color scale. The first two seconds were skipped due to the insufficient epoch number (N<60) for epoch-average processing. The gazed-target was detected every 0.1 second and each valid output of cursor command required recognizing the same target for 15 successive times. The valid cursor commands are labeled at the top, and those SSVEPgazes used for producing valid cursor commands are marked by green solid ellipses.

Subject	Input results (wrong underlined)	T_{total} (sec)	Accuracy ($N_{correct}/N_{total}$)	CTI (sec/Command)	ITR (bits/min)
I	ON ⇦ BL ⇧ ⇩ BR ⇨ OFF ON ⇦ BL ⇧ ⇩ BR ⇨ OFF ON ⇦ BL ⇧ ⇩ $\underline{\Downarrow}$ BR ⇨ OFF	92	96% (24/25)	3.68	43.13
II	ON ⇦ BL ⇧ ⇩ BR ⇨ OFF ON ⇦ BL ⇧ ⇩ BR ⇨ OFF ON ⇦ BL ⇧ ⇩ BR ⇨ OFF	110	100% (24/24)	4.58	39.30
III	ON ⇦ BL ⇧ ⇩ BR ⇨ OFF ON ⇦ BL ⇧ ⇩ BR ⇨ OFF ON ⇦ BL ⇧ ⇩ BR $\underline{B_R}$ ⇨ OFF	119	96% (24/25)	4.76	33.34
IV	ON ⇦ BL ⇧ ⇩ BR ⇨ $\underline{\Rightarrow}$ $\underline{\Rightarrow}$ OFF ON ⇦ BL ⇧ ⇩ BR ⇨ $\underline{\Rightarrow}$ $\underline{\Rightarrow}$ OFF ON ⇦ BL ⇧ ⇩ BR ⇨ $\underline{\Rightarrow}$ OFF	197	82.8% (24/29)	6.79	16.39
V	ON ⇦ $\underline{\Leftarrow}$ BL ⇧ ⇩ $\underline{\Downarrow}$ BR ⇨ OFF ON ⇦ BL ⇧ ⇩ BR ⇨ OFF ON ⇦ BL ⇧ ⇩ BR ⇨ $\underline{\Rightarrow}$ OFF	241	88.9% (24/27)	8.93	14.68
VI	ON ⇦ BL ⇧ ⇩ BR ⇨ OFF ON ⇦ BL ⇧ ⇩ BR ⇨ OFF ON ⇦ BL ⇧ ⇩ BR ⇨ $\underline{\Rightarrow}$ OFF	113	96% (24/25)	4.52	35.11
VII	ON ⇦ BL ⇧ ⇩ BR ⇨ OFF ON ⇦ BL ⇧ ⇩ BR ⇨ OFF ON ⇦ BL $\underline{B_L}$ $\underline{B_L}$ ⇧ ⇩ BR ⇨ OFF	233	92.3% (24/26)	8.96	16.02
Average		157.86 ± 63.56	93.14 ± 5.73%	6.03 ± 2.20	28.29 ± 12.19

Table 2. Results of producing command sequences from seven subjects. (a) The results of producing the command sequence {'On ' , 'Left' , 'Left button (BL)' , 'Up' , 'Down' , 'Right button (BR)' , 'Right' , 'OFF'} in application task. (b) The results of producing command sequences in application task, which was three repeated times of the application task (24 cursor commands in total). Cursor commands were inputted one-by-one, and outputs of wrong cursor commands (underlined) were instructed to be ignored.

Second, this study presents a new flickering sequence to implement SSVEP-based BCI. This research detects phase, rather than the frequency, as the feature for recognizing gazed-targets. Since all LEDs are flashed at the same frequency, this work applies a narrow-band bandpass filtering followed by an epoch-average process for noise removal. Noise, which is neither time-locked nor phase-locked to visual stimuli, e.g., sensorimotor Mu rhythm, occipital alpha rhythm, electrocardiac activity (ECG), elecctromyographic activity (EMG), and electro-ocular artifacts (<20 Hz), [13] can therefore be suppressed. Compared to other SSVEP-based BCIs using multiple frequencies for driving SSVEP flickers, SSVEP responses should be analyzed in several frequency bands which could inevitably invite unexpected noises into the recorded SSVEP responses. Those systems recognize gazed-targets by detecting spectral peaks on an estimated frequency spectrum. Nevertheless, accurate detection of spectral peak typically requires a long data interval for spectrum computation to provide sufficient frequency resolution. Consequently, a compromise between the spectral resolution and the requisite data interval for spectrum computation may sometimes limit the capability of available ITR. In contrast, our system utilizes a simpler architecture for signal processing that achieves high accuracy (>83 %) and high ITR (>24 bits/min) with little or no training. Our system detects phase lag by finding the time difference between the waveform peaks of SSVEPgaze and SSVEPref, which differs from the correlation-based technique used in FMFVEP-based system[6]. Furthermore, the FMFVEP-based system presumes an identical response of VEP across all trials and uses it as a template for the correlation process. Such an assumption might be too stringent, since the latencies, peak amplitude, waveforms, etc., of human VEPs can vary from trial-to-trial, and using such a stereotypical template for correlation may result in incorrect detection when using a short data length [4, 7,8,26].

Third, the phase information in the induced SSVEP is a stable index for BCI control. The phase detection approach enables dividing a full cycle (360°) into several phase regions and assigning each phase region with a corresponding cursor function. Very few studies have investigated phase information in SSVEP. Strasburger [27] used a grating stimuli with different spatial frequencies to study the consistency of phase angles in SSVEPs [27], and concluded the SSVEP phase as a remarkably stable index even when the SSVEP amplitude is very low. Ding et al. [23] studied the effects of attention modulations on SSVEPs and found that both the phase-locking index (PHI) and the power of SSVEPs were enhanced, especially in theta and alpha bands, when the subjects were concentrating on the gazed flicker [23],[28] interpreted this attention-regulation phenomenon as a 'spotlight' effect [28], which enhances the cortical representation of stimulus presented in attended regions. The attention-regulation effect has also been demonstrated in a number of EEG studies[29 -31], and neuro-physiological studies [32-35].

Fourth, our system employs high-frequency flickers for visual stimulations and enables all LEDs flashing at the same frequency. Since studies have reported a messy display achieved by SSVEP flickers as a key factor leading to user fatigue [36], SSVEP flickers with a high-frequency design can cause flicker fusion effect to attain a more comfortable visualization [37]. A high-frequency visual stimulation (>30Hz) has the advantage of avoiding the induced SSVEP from being interfered with low-frequency environmental noise and some brain rhythms as well. Compared to other SSVEP-based BCI using multiple frequencies for visual stimulation, flickering frequencies around alpha and beta bands should be excluded and high-frequency flickers (>20 Hz) were seldom used due to lack of an effective procedure for high-frequency SSVEP extractions [12]. This study carefully selected the flickering frequency at 31.25 Hz, reported as the stimulation frequency for inducing the largest SSVEP amplitudes within the middle frequency range.56 The chosen frequency is far enough away from the ranges of alpha and beta rhythms, EOG artifacts, and electricity noise (50 or 60 Hz) noise to allow robust phase detection [14,38].

5. Conclusions

This work proposes an SSVEP-based BCI using phase-tagged flickering sequence to produce cursor commands for communication purposes. Subjects shift their gazes at different LED flickers and phase information of the induced SSVEP is extracted for recognizing the gazed-targets. The salient features of the proposed system are: (1) SSVEP is a very stable and reliable neuro-electric signal to be detected; (2) phase-tagged flickering sequences are adopted and only one flickering frequency is used; (3) SSVEP-unrelated noise can be removed by simply applying bandpass filtering and an epoch-average process; (4) high-frequency flickers are used so that the induced SSVEPs can avoid interferences from low-frequency noises; (5) the high-frequency design achieves a more comfortable visualization. Our current system enables encoding eight distinct phases on a flickering frequency. The proposed system can be further extended by reducing the phase margin or utilizing more flickering frequencies to increase the number of available commands. The proposed system provides an efficient and reliable channel for the neuromuscular disabled to communicate with external environments.

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Using Wireless Technology to Promote Exercise and Fitness

Simon J. Marshall[1], Greg Norman[2]

1,2.Department of Family & Preventive Medicine
Center for Wireless & Population Health Systems
California Institute for Telecommunications & Information Technology
UCSD Moores Cancer Center
University of California, San Diego

(e-Mail:sjmarshall@ucsd.edu)

Abstract — Obesity and low levels of physical activity present a global public health challenge. Recent advances in wireless technology has led to the proliferation of small portable devices designed to help individuals track their activity habits and become more active. This presentation will highlight four key issues important for designing wireless technology to promote exercise and fitness. First, for wireless devices to be effective at changing exercise and fitness habits, team science is needed to bring together experts from multiple disciplines, including engineering, computer science, exercise science, and behavioral science. Second, an understanding of physical activity and fitness concepts is important to ensure that appropriate behaviors and biologic mechanisms are being targeted. Third, designing technology to promote exercise and fitness habits requires an understanding and application of evidence-based behavior change strategies. Finally, examples of commercially available technologies with embedded behavior change strategies are provided.

Keywords — health, physical activity, energy expenditure, team science, behavior change strategies, self-regulation, body monitors.

1. Introduction

Recent advances in wireless technology have led to a proliferation of new devices and equipment designed to increase levels of physical activity, exercise, and fitness of the general public. This has in part been fueled by an increasing recognition in the health and fitness industry that 'fitness technology' needs to move beyond a singular appeal to the 'athlete' and more towards the general public if it is to contribute to reducing the global pandemic of obesity and one of its major causes: low levels of physical activity. One billion people around the world are now considered overweight or obese[1] and the three main sectors of the fitness industry--home-based exercise equipment, fitness centers, and weight loss solutions--have responded largely with product-focused solutions.

There have been a number of recent trends that have affected the fitness industry's response to technology-based products and services. First, there has been a shift in the demographic characteristics of people who use and purchase fitness products and services. For example, in the 1970s and 1980's, the largest demographic user group was 18-34 yr olds, but in the new millennium, this broadened to children, teenagers, and adults over 50 years of age [2]. This shift has meant that more fitness products and services are now developed with different demographic groups in mind. For example, game design principles (e.g., immediate feedback, rewards, levels of mastery) are common among technologies that target children and adolescents, whereas health maintenance and monitoring tools (e.g., tools to monitor blood sugar and blood pressure) are popular among older adults, and so on. Second, during periods of economic recession there is an increase in the number of people walking and running for exercise because it is free and requires very little equipment. This has led to an increase in the number 'self-tracking' tools and services available, such as devices that provide feedback about geolocation (e.g., GPS data), or physiologic and metabolic indicators of exertion (e.g., heart rate and energy expenditure).

2. Solutions in search of problems

Recent advancements in technology (e.g., faster data transmission protocols, chip miniaturization, improved data storage and power management, etc) coupled with the growing fitness market has led to the development and marketing of many new fitness products and services. Indeed, as the pace of scientific research accelerates so too does the bombardment of fitness devices and gadgets that promise rapid fat loss, toned muscular physiques and lifelong behavior change. Many have very little chance of actually improving health and/or are accompanied by claims unsubstantiated by scientific evidence. Many have been widely discredited in the scientific literature, although public outcry often follows in response to civil lawsuits of false advertising rather than a body of scientific evidence that the device works no better than sham intervention.

3. Wireless technology for behavior change requires transdisciplinary science

For new wireless technologies to be effective at improving exercise and fitness, their conceptualization, design, testing, and evaluation requires input from individuals from diverse scientific disciplines. For example, if a wearable sensor is to provide accurate feedback about physiologic surrogates of energy expenditure, a mechanical engineer might be needed to design the physical elements of the sensor system (such as an accelerometer); a computer scientist and software engineer might be needed to design the cyberinfrastructure capable of collecting, filtering, storing and analyzing data; an exercise scientist might be needed to validate the physiologic mechanism of action; and a behavioral scientist might be needed to ensure that the application has sufficient behavior change strategies embedded within it to increase the likelihood that the person will use it. When a device is proven to be ineffective (e.g., it doesn't work, it violates a known physiologic or biological principle, or people don't use it or buy it) it's often because the development team have ignored a crucial element in this chain. When teams of scientists from different disciplines converge to develop new methods in order to solve common problems (such as how to develop a wireless sensor to measure and increase energy expenditure of obese adults) it is often referred to as transdisciplinary science or 'team science.' Team science creates innovations and advances that are often not possible within a unidisciplinary team working in isolation, such as a group of engineers designing a sensor to promote behavior change [3].

4. A primer in exercise and fitness concepts.

A first step in designing new wireless technologies that promote exercise and fitness is a conceptual understanding of what exercise actually is and how it differs from physical fitness. Figure 1 presents the relationships between the different concepts involved in exercise and fitness. From Figure 1, it is evident that physical activity is a behavior, of which exercise and sports are specialized subcomponents. In contrast, fitness is an attribute that is a result of engaging in PA, exercise or sport. The five health-related fitness components have all shown to be health protective [4] and are therefore important targets of physical activity programs and technologies.

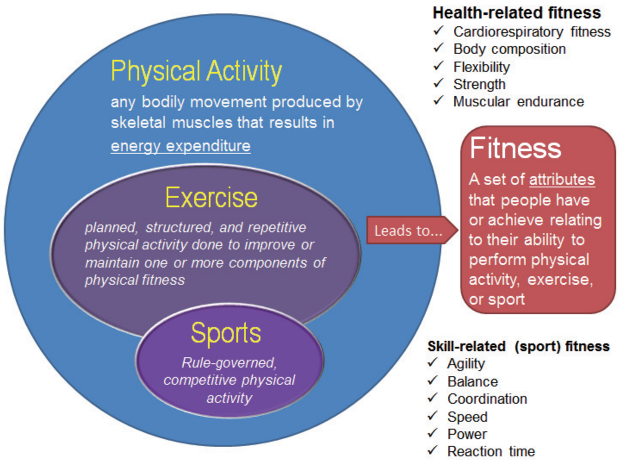

Figure 1. The relationship between the different concepts of physical activity, exercise, sports, and fitness.

All physical activity can be measured along five domains [5]:

1. Intensity refers to the magnitude of the physiologic response to physical activity and is often quantified by the amount of metabolic work performed (e.g., kilocalories expended). Because it is difficult to measure metabolic work directly, intensity is often captured using physiologic surrogates (e.g., heart rate) or perceptual categories (e.g., very light, light, moderate, hard, very hard). Physical activity intensity may also be expressed in relative or absolute terms. Relative intensity is defined by a workload expressed as a percentage of an individual's maximum capacity (e.g., 60% of maximal heart rate), whereas absolute intensity refers to the workload expressed in units that are independent of an individual's capacity or tolerance (e.g., a heart rate of >155 beats/min).
2. Duration refers to the length of time (usually in minutes) the activity is performed.
3. Frequency refers to number of times the physical activity is performed within a specific time period (e.g., minutes per week, month, or year).
4. Type refers to the main physiologic systems used (e.g., aerobic, anaerobic) during the activity, though it can also refer to features of the behavior itself (e.g., walking, jumping, running).

5. Domain refers to the context or setting in which physical activity occurs (e.g., at work, during leisure time, for transportation) and can be useful for understanding the purpose or intent behind the activity.

5. The unifying framework of energy expenditure.

Another way to understand and link physical activity, exercise, and sports is through the unifying framework of energy expenditure [6]. The term total energy expenditure (TEE) refers to an individual's entire energy output, measured in kilocalories (kcal) or kilojoules (kJ). Total energy expenditure consists of basal metabolic rate (BMR) (the energy required to maintain basic physiologic processes at rest), diet-induced thermogenesis (the energy required to transport, digest, and absorb food), and physical activity thermogenesis (the energy required for bodily movement). For most people, physical activity composes only 15% to 30% of their TEE. This physical activity portion can be further divided into different intensity categories based on multiples of the metabolic rate when seated at rest (which approximates 3.5ml $O2$ per kg of body weight per minute). These multiples are referred to as metabolic equivalents (METs) [7]. For example, a 3.5 MET activity requires 3.5 times the energy expenditure of sitting at rest (i.e., 12.25ml $O2$ per kg of body weight per minute). Because there are an infinite number of MET values, we group activities into the intensity categories of Light (1.5-3.0 METs), Moderate (3.0-6.0 METs), and Vigorous (>6 METs) activity. An important message is that all forms of movement contribute to TEE. Participation in vigorous physical activity requires a higher rate of energy expenditure but occurs over shorter periods of time. Light activity, in contrast, has a lower rate of energy expenditure but can be done for longer periods of time. A concept that helps to clarify some of the ambiguity in conceptualizing physical activity is non-exercise activity thermogenesis (NEAT) [8]. NEAT includes the energy expenditure associated with posture allocation (e.g., sitting, standing, and lying), fidgeting, and routine daily movements such as walking, performing house chores, and playing. Thus, NEAT can also be thought of as the energy expenditure associated with sedentary behavior and light activity. Because NEAT is likely to be the largest component of activity thermogenesis—we spend the majority of our life in this state—it reminds us that energy expended during activities of daily living can be extremely important for maintaining caloric balance.

6. Measuring physical activity accurately with wireless sensors.

Accelerometers.

Accelerometers have become the accepted standard for most field-based studies of physical activity [9]. These devices work by measuring the acceleration of body segments or limbs during movement. Small piezoelectric or resistive elements contained within the device translate forces or changes in resistance to electrical signals, which are then filtered and stored as movement counts. While more research has been conducted with the ActiGraph monitor (ActiGraph LLC, Fort Walton Beach, FL), a number of other instruments provide similar information (e.g., Biotrainer, Actical, R3D). A well-known limitation of waist-worn activity accelerometers is the inability to detect physical activities that involve upper body movement, and the inability to capture the increased energy cost of walking up a grade or carrying a load [10]. A number of equations have been developed to characterize the relationship between accelerometer counts and movement, but accurate estimations of individual energy expenditure remain elusive. Equations based on locomotor activities tend to underestimate the energy cost of free-living or lifestyle activities, but equations based on a diverse set of locomotor and lifestyle tasks tend to overestimate the energy cost of locomotor activities [11]. More recently, a two-stage regression model has been proposed [12] to improve the prediction accuracy of EE from accelerometer data, and validation evidence suggests that is works quite well in children and adults [13, 14]. However, as a general rule, accelerometers provide useful estimates for group comparisons but not for individual estimates of energy expenditure.

Heart rate monitors.

Heart rate provides an indicator of activity that reflects the true physiological stress on the body. While this circumvents the calibration issue just described for the accelerometers, it introduces a different form of error due to inherent individual differences in heart rate response to activity. More highly fit individuals have a lower heart rate response to activity than less fit individuals, so the absolute differences in heart rate cannot be used to capture differences in the activity levels. Corrections based on resting heart rate or individual calibration [15] can overcome this limitation but add complications to data collection that may limit utility for field-based research.

Multichannel activity monitors.

Recent developments in technology have led to the development of combination sensors that integrate data from heart rate monitors and accelerometers. Studies with the new Actiheart monitor (Mini Mitter, Bend, OR) show that this combination device may provide more accurate estimates than either measure used alone [16]. New pattern recognition monitors such as the Sensewear Pro II armband monitor (BodyMedia, Inc., Pittsburgh, PA) may also help to overcome limitations with current accelerometer technology. These devices use multiple sensors to detect the predominant activity being performed and then apply activity-specific algorithms for estimations of energy expenditure.

7. Evidence-based behavior change strategies to increase levels of physical activity

For wireless technologies to change human behavior, principles of behavioral science are needed. Behavioral science applied to physical activity behavior change refers to the systematic application of evidence-based principles designed to explain, predict and control physical activity patterns [17]. Evidence based principles are derived through observational and experimental methods. If the underlying mechanisms of behavior change are well understood, we can embed strategies in the technology that leverage these mechanisms to modify behavior.

Unfortunately, most textbooks and research papers only describe individual theories on which behavior changes techniques are based. The problem with this is that single theories identify only a subset of strategies that might be effective. A recent taxonomy[18] and subsequent meta-regression [19] of behavior change techniques sought to describe and quantify the efficacy of a broad range of strategies from multiple theories. The resulting taxonomy comprised of 26 theory-linked behavior change strategies that were reliably identified across a range of behavior change interventions. In this context, a 'behavior change strategy' refers to a reliable component of an intervention that alters causal processes that regulate behavior. In a sense, it is an 'active ingredient' of an intervention that is also supported by theory. A subsequent refinement expanded this taxonomy to 40 empirically supported techniques [20]. Results of the meta-regression supported the superior efficacy of five self-regulation strategies in particular, derived predominantly from Control Theory of human behavior [21]. The five most efficacious strategies are presented in table 2, together with examples of how these might be applied to physical activity behavior change.

Strategy	Description	Example of application to wireless technology for increasing physical activity behavior
1. Prompt self-monitoring of behavior	The person is asked to keep a record of the specified behavior(s) (e.g., in a diary)	Device has a self-tracking tool to monitor and record the number miles walked by an individual trying to lose weight.
2. Provide feedback about performance	Providing data about recorded behavior or evaluating performance in relation to a set standard or others' performance, i.e., the person received feedback on their behavior.	Device aggregates the number of miles walked by the individual each day, and presents this information in a chart at the end of each day. Feedback is also given to the participant regarding how their mean weekly walking distance compares to other people of the same age and gender.
3. Prompt intention formation	Encouraging the person to decide to act or set a general goal, for example, to make a behavioral resolution.	Device prompts the individual to commit to a goal of walking an extra half mile per day. Device requires response from the individual that they are willing to try.
4. Prompt specific goal setting	Involves detailed planning of what the person will do, including a definition of the behavior specifying frequency, intensity, or duration and specification of at least one context, that is, where, when, how, or with whom	Device has a goal setting function that asks the individual to enter information about when, how, and where they plan to walk the extra half mile each day.
5. Prompt review of behavioral goals	Review and/or reconsideration of previously set goals or intentions	At the end the week, the device presents a graphical summary of the total miles walked and whether or not the individual was successful in meeting their walking goal. If not, a new goal is set that is 10% lower than the unmet goal.

Table 2. Five strongly supported behavior change strategies for increasing physical activity and improving dietary behavior.

These data suggest that when designing new technology to change physical activity or exercise behavior, attempts should be made to incorporate these strategies into the user interface. In addition, the advantage of using wireless technology over more traditional behavior change methods, such as in-person coaching, is that each of these strategies can be embedded in a system that optimizes when and how they are applied. Indeed, it might be possible to improve self-monitoring (strategy #1) and feedback (strategy # 2) by providing it in real-time to the user, and in manner that minimizes the cognitive load required by the user to process and interpret the information being conveyed. For example, feedback can be designed to target pre-attentive processes by using visual cues such as color, patterns, and animation, instead of text or numeric scaling.

8. Examples of wireless technology that use evidence-based behavior change strategies.

The NIKE+ FuelBand (www.nike.com/fuelband) uses an accelerometer mounted in a lightweight, water proof silicon wrist bracelet that the user wears throughout the day. The FuelBand uses wrist-based acceleration data to predict caloric expenditure and steps taken (self-monitoring). Depending on the number of steps you take, FuelPoints are awarded to indicate progress (feedback) which are aggregated and compared to user-determined targets (goal setting) as marker of success. The wrist band also has Bluetooth capacity so it can be paired with a smart phone to log and record step data and FuelPoints. The wristband can also be connected directly to a computer to charge and upload data for storage and graphical display. A limitation of this device is that is uses wrist movements to estimate steps and energy expenditure, which is known to be less accurate than waist-based prediction models[22].

The Motorola MOTOACTV (www.motoactv.com) is a small, wrist worn device with a 1.6-inch touchscreen that helps the user track distance travelled, heart rate (it is ANT+ enabled and so can be used with a heart rate strap), and estimated caloric expenditure during different activities (self monitoring). When synched to a web interface (it is also Bluetooth and WiFi enabled) the MOTOACTV also has companion apps that allow you to receive Facebook or Twitter updates, and shows notifications for calls and texts. The MOTOACTV is also one of the few products to have an mp3 music player and built in GPS device to allow activity tracking data (e.g., distance, caloric expenditure) to be visualized on a map or summarized for different songs (feedback) that were being listened to at the time. Although the device comes with different attachment clips, it is intended primarily to be worn on the wrist and so has questionable validity for predicting energy expenditure.

The FitBit Ultra (www.fitbit.com) uses a triaxial accelerometry mounted in small belt clip worn on the waist to sense user movement. The FitBit measures steps taken, distance walked, calories burned, floors climbed, and activity duration and intensity (i.e., self-monitoring). It uses an OLED to display summary data on the device itself (feedback). When worn on a wrist band, it also measures sleep quality, but these functions have not been validated by scientific research. A wireless base station receives data from the device and when the device is mounted onto the base station, it is used to charge the battery. When the FitBit is connected to a computer the base station will upload data to the FitBit. From the website, a number of features are also available, including a review of physical activity, the ability to set and review goals, keeping food and activity logs, and interacting with other FitBit users. Use of the FitBit website is free.

Across these device examples, it is evident that a common use of existing tools is for self-tracking of ambulatory activity. The most commonly used behavior change strategies are self-monitoring and feedback. Although these are evidence based, future devices should attempt to incorporate additional behavior change processes known to be important [20]. For example, wireless technology can be used to continuously, yet passively, monitor your physical activity and exercise behaviors then give you specific feedback, at the right time, and in the right way to be more persuasive Figure 2 presents a simple theory- and evidence-based design model for new wireless technology to increase exercise and fitness. As information about your physical activity behavior is sensed, onboard data processing algorithms could be used to clean, filter, and aggregate these data which would then be used to design a message to gauge the user's willingness to change their behavior (intention formation strategy). If the user agrees, then the device could recommend specific, measurable, and challenging goals to increase physical activity levels.

Success at meeting these goals could be evaluated by comparing subsequently tracked data against a criterion, which in turn would be used to refine future goals.

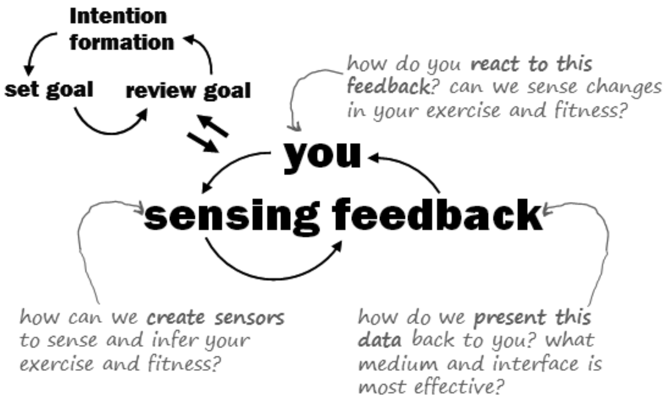

Figure 2. A simple theory- and evidence-based design model for new technology to increase exercise and fitness
(adapted with permission from Dr. Jon Froehlich, Dept of Computer Science and Engineering, University of Washington, USA).

9. Conclusions

This paper presents an overview of how wireless technology can be used to promote exercise and fitness. For technology to be effective in changing behavioral habits, principles of team science is needed to bring together experts from engineering, computer science, exercise science, and behavioral science. It is insufficient for teams comprised solely of engineers to develop, test and evaluate these technologies because (1) an understanding of physical activity and fitness concepts is important to ensure that appropriate behaviors and biologic mechanisms are being targeted, and (2) exercise behavior change requires an understanding and application of behavioral science. Wireless devices are currently available that have evidence-based behavior change embedded, but are mostly limited to self-tracking and feedback tools. A simple design model was presented to help guide the development of new devices that incorporate additional evidence-based strategies.

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Diffuse Optical Tomography Using Mammogram Structural Information for Breast Tumor Detection

Min-Chun Pan[1,2], Jhao-Ming Yu[2], Liang-Yu Chen[2],
Hung-Chih Chiang[2], Min-Cheng Pan[3], Sheng-Yih Sun[4],
Chia-Cheng Chou[4]

1Graduate Institute of Biomedical Engineering, National Central University, No.300, Jhongda Rd., Jhongli City, Taoyuan County 32001, Taiwan
2Department of Mechanical Engineering, National Central University, No.300, Jhongda Rd., Jhongli City, Taoyuan County 32001, Taiwan
3Department of Electronic Engineering, Tungnan University, New Taipei City 222, Taiwan
4Tao-Yuan General Hospital, Taoyuan City, Taoyuan County 33004, Taiwan

(e-Mail:pan_minc@cc.ncu.edu.tw)

Abstract — The study aims at developing an optical measurement module incorporated with an X-ray mammographic system to obtain diffuse optical images (DOI) for the detection of breast tumors. Two goals steer the study: (1) to enhance sensitivity and specificity of tumor detection through the use of functional DOI; and (2) to reduce radiation exposure by using only one mammogram, instead of two, as structure information to compute optical-coefficient images. A dual-direction (downward and upward) scanning device to project illuminated near infrared light with multiple-channel switching for both sources and detectors was designed and constructed to obtain double information. The designed and constructed NIR scanning module incorporates with GE Senographe 2000D to assist breast tumor detection.

Keywords — breast tumor detection, dual modality, diffuse optical tomography, mammogram

1. Introduction

The most common used non-invasive biomedical imaging modality of breast diagnosis, such as sonography and X-ray mammography, can acquire structural information of breast tissue. However, those imaging modalities are still trapped in overlapping structures, resulting in false diagnosis. Besides, X-ray mammography involves ionizing radiation. Diffuse optical tomography (DOT) is an emerging technique which can provide physiological or pathological information about the breast. On the other hand, DOT is inexpensive and non-ionizing [6]. By illuminating NIR laser light, we can measure optical variations responsive to tissue; e.g., power attenuation and phase difference, to reconstruct absorption- and scattering-property images of tissues. Furthermore, using light sources of different wavelengths is able to obtain functional images to evaluate oxyhemoglobin, deoxyhemoglobin, water, and lipid concentration in the breast. For the combination of DOT and other imaging modalities to detect breast tumor, Massachusetts General Hospital derived optical contrast from breast structure and compression through X-ray mammography [1], [2]). In the study, a dual direction projection scanning module, optoelectronic measurement system and image reconstruction scheme were implemented and incorporated with a commercial mammographic system. Combining with mammograms and using their anatomic information we reconstructed optical-property images for breast tumor detection through a bilateral NIR scanning scheme.

2. Instrumentation

Dual direction projection scanning device:

The NIR scanning module is eventually assembled and incorporated with a commercial X-ray mammographic system. To be accommodating with the frame of the system, the module with source and detection fibers operates to compress breast tissue between two parallel plates for enhancing SNR during a measuring process. Based on the previous studies, different NIR scanning schemes including the slab type were investigated and compared [6]. In the design using slab-type scanning [2], however, the quality of reconstructed images was restricted by the available data obtained from single direction projection. In this study, a dual-direction projection device was designed with two pairs of one dimensional scanning array of 7 by 7 source-and-detector combination mounted with the upper and lower compression plates, respectively. As shown in Fig. 1, S and D denote a source array and a detection array, respectively. Through this, double NIR data can be acquired to obtain better optical-property image quality.

As shown in Fig. 2, dual-direction projection scanning module consists of four major parts including (1) source part, (2) mechanical part, (3) detector part, and (4) signal processing part. In the module, two translation stages move source-detection fiber sets to illuminate NIR light and collect out-emitted data, and one translation stage moves a photomultiplier tube (PMT) to translate photo power into electrical signals. Figure 3 illustrates the scanning device, source-detection pairs, and breast-like phantom with two inclusions mimicking tumors. Two sets of X-Y table (on the top and bottom plates) are mounted with white source fibers and black detection fibers. Light souces scan in the coronal direction to obtain NIR detection data for the image reconstruction of a sagital plane, and the sets of source fibers and detection fibers move in the sagital direction to acquire the detection data of different sagittal planes.

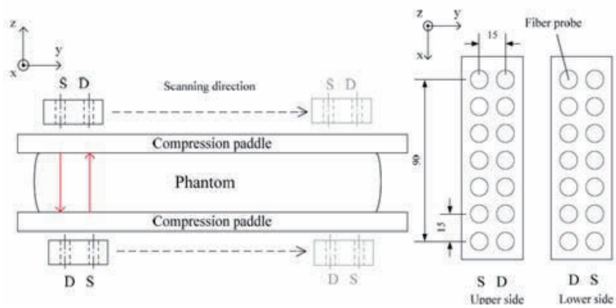


Figure 1. Dual-direction projection scanning scheme.

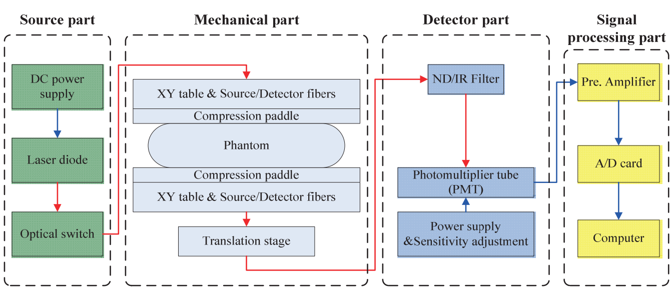


Figure 2 Four main parts and signal flow diagram of continuous-wave

NIR projection module.

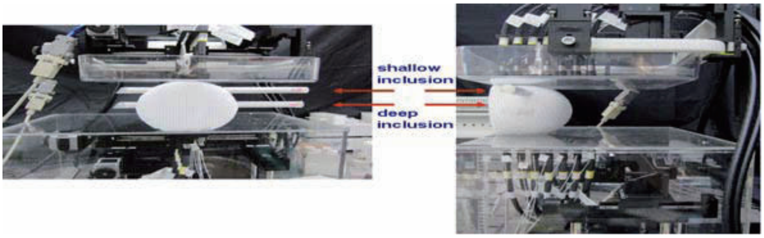


Figure 3. Illustration of the scanning device, source-detection pairs, and breast-like phantom with two inclusions. (left) The photograph of breast-like phantom in the (back) coronal view, and (right) the photograph of breast-like phantom in the sagittal view. Two sets of X-Y table (on the top and bottom plates) are mounted with white source fibers and black detection fibers. Light souces scan in the coronal direction, and the sets of source fibers and detection fibers move in the sagital direction.

Optoelectronic measurement system.

This NIR scanning module adopts continuous wave measurement. A DC power supply first provides the laser diode with a preset voltage that drives a constant NIR light power. Then, NIR light shines into each source fiber connected to source-detection fiber sets through an optical switch that can transmit NIR light to source fibers fast. Then, the out-emitted light from the phantom (or breast) at each detector port is collected by fourteen fibers mounted on two translation stages, thereby the light power on the top and the bottom surface are acquired. In the detector part (Fig. 2), the transmitted light passes though an adaptive neutral density filter design and an IR filter in order to attenuate light power that may saturate the PMT, and to filter out the light power of other wavelength. The PMT transforms light power into electrical current. In signal processing part, the output current is converted into voltage and amplified about 40dB by a preamplifier. At last, the voltage signal is recorded and digitized by a data acquisition system with an ADC.

3. Image Reconstruction Scheme

The image reconstruction algorithm of DOT based on the diffusion equation involves both the forward computation and the regularization of inverse reconstruction. The flowchart of the image reconstruction algorithm of optical coefficients is shown as Fig. 4. Diffusion equation (Eq. (1)) is used to describe light transporting in a highly scattering medium such as breast tissue (Paulsen et al., 1996).

$$, \quad \nabla \cdot D\nabla\Phi(r) - \left(\mu_a - \frac{i\omega}{c}\right)\Phi(r) = -S_o(r) \qquad (1)$$

where Φ is intensity, μa is the absorption coefficient in mm-1, c is speed of light in the medium and D is the diffusion coefficient in mm.

Forward computation.

The forward computation uses a finite element method (FEM) for solving diffusion equation to estimate the distribution of transmitted light on the basis of the light source and presumed parameters of the phantom. Type III or Robbins boundary conditions are used at all boundary nodes, where the exiting flux ($J \cdot \hat{n}$) (Eq. (2)) normal to the boundary is equal to some number a times the fluency rate (F) at the boundary (Arridge et al., 1993),

$$J \cdot \hat{n} = F = -D\nabla\Phi \cdot \hat{n} = \alpha\Phi \qquad (2)$$

,

where $\hat{n}$ is the unit vector normal to the boundary and α is a real positive number related to the internal reflection. Meantime, the Galerkin method is applied in FEM to Eq. (1) and the following discrete equation can be obtained.

$$\begin{bmatrix} A_{ij}^{bb} - \alpha B_{ij}^{bb} & A_{ij}^{bI} \\ A_{ij}^{Ib} & A_{ij}^{II} \end{bmatrix} \begin{Bmatrix} \Phi_j^b \\ \Phi_j^I \end{Bmatrix} = \begin{Bmatrix} C_i^b \\ C_i^I \end{Bmatrix} \qquad (3)$$

,

Inverse reconstruction

The image reconstruction procedure is a nonlinear, ill-posed, and ill-determined problem. In absence of an analytic inverse solution, the numerical way of achieving this inverse solution is to minimize the difference between measured intensity and forward computation intensity, i.e.

$$\min \chi^2 = \sum_{i=1}^{N}\left[\Phi_i^M - \Phi_i^C\right]^2 \tag{4}$$

where Φ_i^M and Φ_i^C are measured and computation intensity, separately. The Levenberg-Marquardt algorithm is adopted for iteratively updating the diffusion and absorption coefficients [2], i.e.

$$\begin{bmatrix} \Delta\mu_a \\ \Delta D \end{bmatrix} = \left([J]^T[J] + \lambda I\right)^{-1}[J]^T\left[\Phi^M - \Phi^C\right] \tag{5}$$

where [J] (Jacobian matrix) is an optical-property matrix that denotes $J(\frac{\partial\Phi_b}{\partial D}, \frac{\partial\Phi_b}{\partial\mu_a})$ and $\Delta\chi$ means (ΔD, $\Delta\mu_a$).

4. Case Design with Likely Area Definition

To justify the effectiveness of the reconstruction scheme a slab phantom (130×50 mm) with two circular inclusions (12 and 4 mm diameter, respectively), as shown in Fig. 5, was designed. The contrast of optical property for the inclusions is two times to the background. In order to compare reconstruction results, a homogeneous, lower and higher initial contrast guess for the likely area was performed. Figure 6 illustrates a procedure using the structural information of a mammogram that helps decide the NIR scanning plane, and then optical-coefficient images (absorption and scattering) can be reconstructed for tumor screeing or detection.

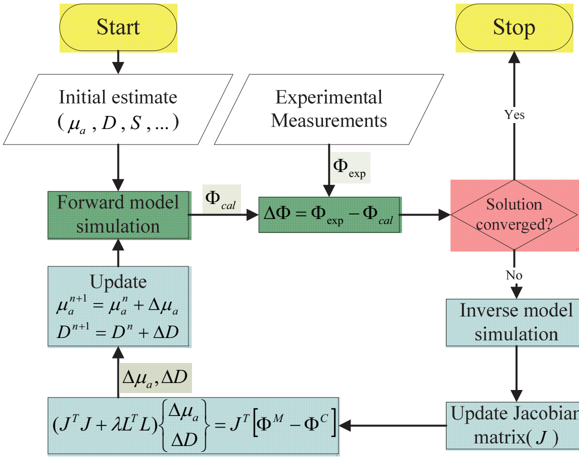


Figure 4. Flow chart of optical-coefficient image reconstruction algorithm.

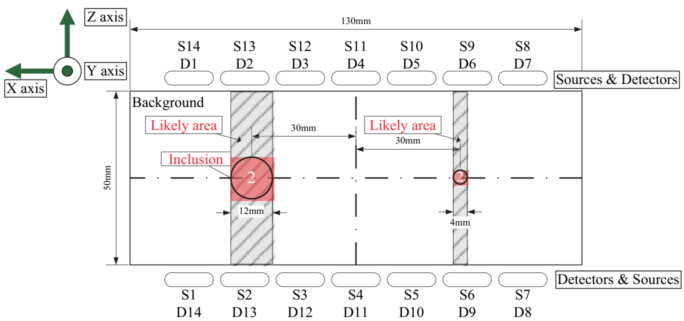


Figure 5. Case design with the likely area definition.

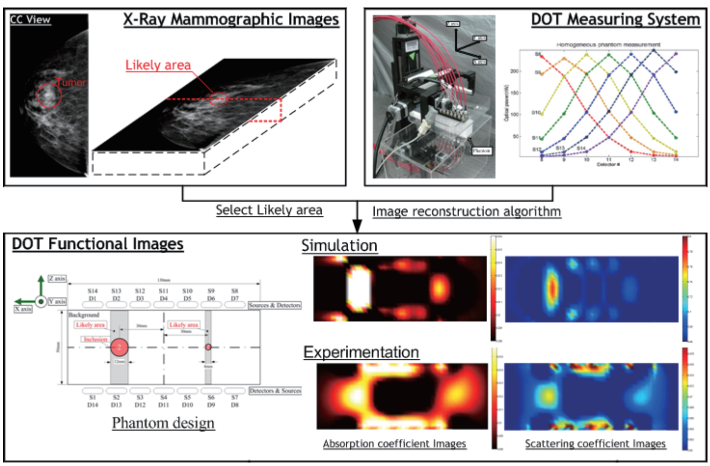
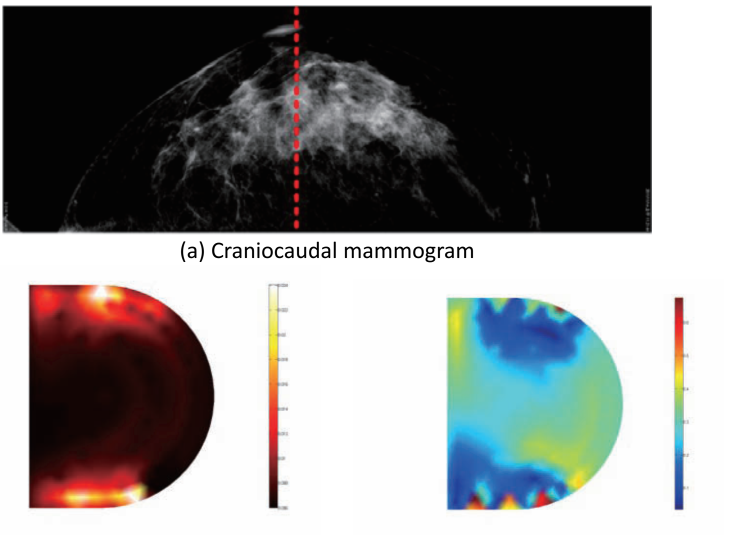


Figure 6. Mammogram-based diffuse optical imaging.

Breast examination

Figure 7 demonstrates optical images from the control subject, a 53-year-old women with normal mammograms, where Fig. 7 (a) displays the corresponding mammogram and Fig. 7 (b) and (c) show ìa and ìs’ images, respectively. The ìa optical image of the normal breast of the healthy control subjects are comparatively homogeneous and without increased absorption signals whereas ìs’ images show a slightly high contrast. As can be seen, no abnormalities appear in the scanned region. The homogeneous image shown here clearly suggests the overall low background of the optical measurement and reconstruction. The obtained images present the common characteristic feature i.e., the absorption images relates to functional information and the structures can be imaged from ìs’ images.

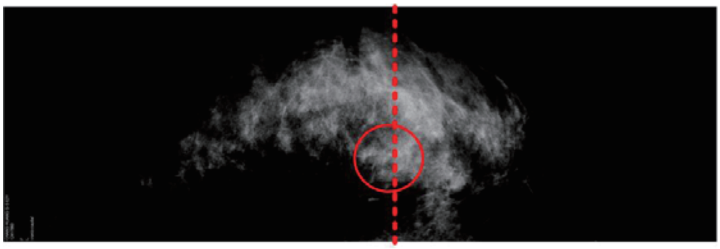


(a) Craniocaudal mammogram

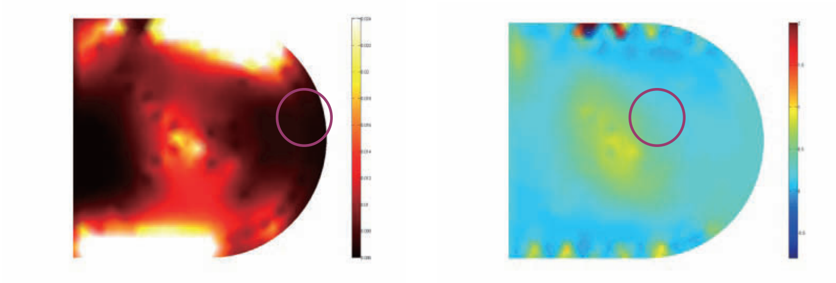
(b) absorption image (c) scattering image

Figure 7. The healthy right breast of a 53-year-old Taiwanese woman.

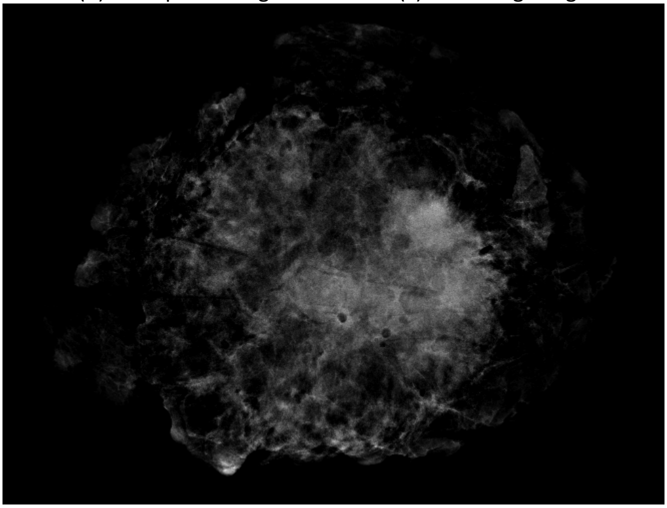
Figure 8 includes (a) a mammographic image and (b) optical absorption and (c) scattering images from a 64-year-old Taiwanese woman with a 6-cm suspicious mass in the left breast. Figure 8(b) shows the reconstructed ìa image as a craniocaudal slice, as can be seen, exhibits a marked absorption increase at the location corresponding to the tumor region that appears in the mammogram shown Fig. 8(a) and ìs’ image of Fig. 8(c) at the imaging plane displays a marked increase in scattering in the region of the tumor as well. These images present a characteristic feature of optical imaging, namely, the absence of clear borders for the anatomic structures imaged. A ratio of the tumor over the whole region was resolved by optical imaging of 16/100. She subsequently underwent surgical excision, and pathologic examination showed infiltrating ductal carcinoma with positive margins; the mammogram of the left breast obtained postoperatively is shown Fig. 8(d). Biopsy demonstrated a 25 mm×22 mm ×13 mm infiltrating ductal carcinoma.



(a) Craniocaudal mammogram



(b) absorption image (c) scattering image



(d) mammogram of the specimen

Figure 8. Infiltrating ductal carcinoma in the left breast of a 64-year-old Taiwanese woman**.**

5. Results and Discussion

Measured out-emitted NIR powers are charted as in Fig. 9 for 14 source points, i.e. 7 source channels for the upper and the lower compression plates, respectively. For each curve in the chart, that records the data as one NIR source shines into the phantom, 7 detection fibers mounted on the opposite plate collect out-emitted light power. From the two curves in one chart, the differences between the power measured from the homogeneous and the heterogeneous phantoms can be observed obviously, demonstrating that this dual-direction projection measurement system has capability of detecting power differences between a homogeneous phantom and a phantom with inclusions.

Like the phantom shown in Fig. 3, two phantoms with a shallow inclusion and a deep inclusion separately were designated to validate our mammogram-based DOT scheme. As the phantom with a shallow inclusion was test, the space for a deep inclusion was inserted by the same optical-property material as the background, and vice versa. Figure 10 shows the reconstructed images, where (a) and (c) are absorption-property images, and (b) and (d) are scattering-property ones; moreover, the image in (a) and (b) are for the shallow-inclusion phantom, and (c) and (d) for the deep-inclusion one. Both absorption- and scattering-property images can characterize the shallow or deep inclusions in the phantom. For the left images of Fig. 7(a), (b), (c) and (d), which are reconstructed through measured transmission data, it is noted that artifacts near the top and bottom surfaces may mislead the judgment of breast-tumor detection and diagnosis. To soothe this problem, using both transmission and reflective power out-emitted from the phantom can be considered. To justify the thought, the right image of each subfigure is reconstructed through using simulated reflective data besides transmission one. The reconstructed images seem rather 'clean' without the ambiguity of artifacts.

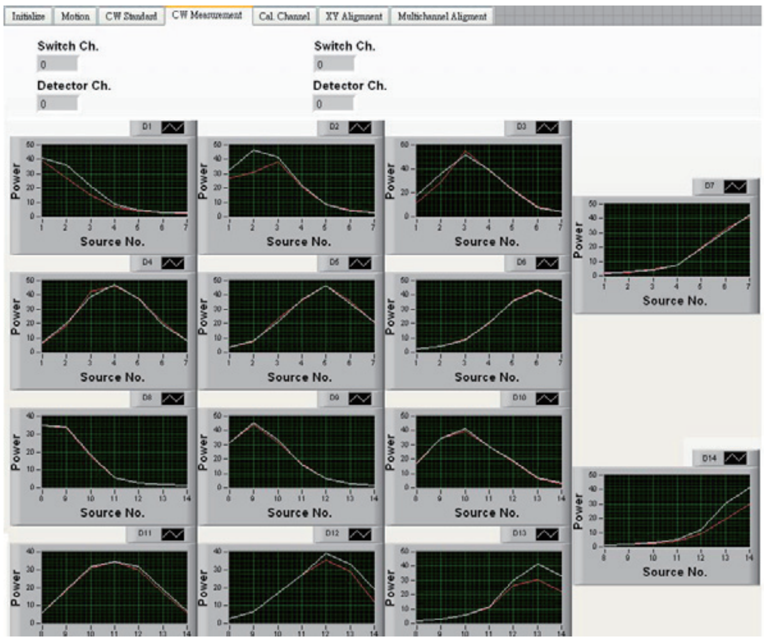


Figure 9 Measured out-emitted NIT intensity curves (14 source points and corresponding detection).

6. Concluding Remarks

This paper presents the development of a dual-direction projection scanning module incorporated with X-ray mammography for diffuse optical imaging. Figure 11 illustrates the prototyping device on a commercial mammographic system (GE Senographe 2000D). The prior anatomic information obtained from a mammogram with indicated suspicious regions was used as a reference to mesh the finite element model for forward and inverse computation. Reconstructed optical-coefficient images resulting from dual-direction projection data are superior to those from single-direction one. Besides, the slot design of scanning and optoelectronic measurement module is simple to be mounted on and withdrawn from a mammographic bench. This design also makes image registration easier.

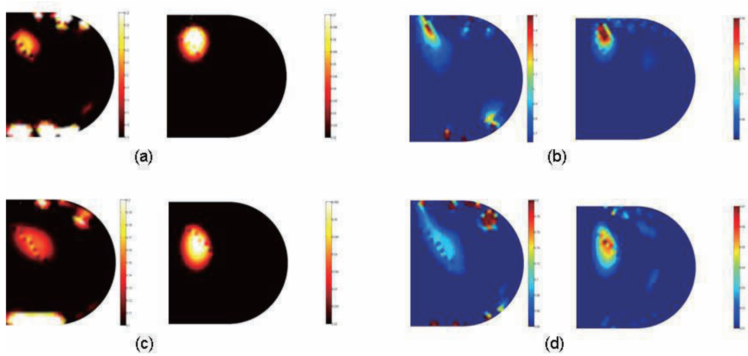


Figure 10. Reconstructed optical-property images using measured data. (a) Absorption and (b) scattering images of a phantom with a shallow inclusion, (c) absorption and (d) scattering images of a phantom with a deep inclusion. For (a), (b), (c) and (d), the left image is reconstructed through measured transmission data, the right image is reconstructed through both transmission and reflection data (simulation).

Figure. 11 DOT module combined with mammography.

Acknowledgements

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Assistive Systems for Disabled Persons and Patients with Parkinson's Disease

Mu-Chun Su, Jhih-Jie Jhang[1], Tun-Ya Yu[1], Pa-Chun Wang[2] ,
Yi-Zeng Hsieh[1], and Shih-Chieh Lin[1]

1.Department of Computer Science & Information Engineering,
National Central University, Taiwan, R.O.C.
2.Cathay General Hospital, Taiwan, R.O.C
.
(e-Mail:muchun@csie.ncu.edu.tw)

Abstract — In this article, we present two assistive systems- one for disabled persons and the other one for patients with Parkinson's disease. The first assistive system is an eyebrow switch for severely disabled persons. It allows disabled people to access computers and to communicate with other persons via raising their eyebrows. The second assistive system is developed for patients with Parkinson's disease. It is an augmented-reality-based assistive system which can provide Parkinson patients with both the auditory and visual cues to maintain and improve their mobility and gait speed.

Keywords — assistive systems, eyebrow switch, Parkinson's disease

I. Introduction

In recent decades, various new technology products are rapidly emerging. Without any doubt, computers are one of the most influential technology products. With the growing use of computers, the quality and the lifestyle of our lives and even the whole society are dramatically changing. Unfortunately, a disadvantage minority such as people who cannot manually access computers with dexterity cannot enjoy benefits provided by computers as able-bodies people on equal term since conventional computer interfaces (e.g., mouse and keyboard etc) are designed with the able-bodies in mind. Therefore, how to design alternative interfaces for people with disabilities to replace traditional computer input devices becomes a challenging and demanding task.

Recently, advances in hardware and software have led to assistive technology systems of every variety which allow people with disabilities to use their limited voluntary motions to access computers, communicate with family and friends, and control home appliances, etc. Some of these systems were based on the head movements (e.g., sensor-based systems [1-4], vision-based systems [5-6]). Recently, many eye-based systems were developed (e.g., eye-movement-based systems [7-12], eye-blink-based systems [13-15]). In addition, several brain-computer interfaces (BCIs) have also proposed for disabled people [16-17]. Each has its own advantages, considerations, and limitations.

For some people with severe disabilities, an extreme disability such as amyotrophic lateral sclerosis (ALS) deprives them of the use of their limbs and even facial muscles. Owing to this kind of extreme disability, eye-motion-based systems may provide an alternative option for people who only retain the ability to open/close their eyes. In our previous work, an "eye mouse" [11], an image-based eye-blink switch [14], and a mouth-based switch [18] have been proposed to allow people with disabilities to use their eye movements, eye blinks or mouth opening to access computers. In this article, we present a low-cost eyebrow switch. With this proposed switch incorporated with the communication aid presented in [11], [14], [18], ALS people are able to use their limited voluntary motions such as raising their eyebrows for communications, manipulating computers, and controlling home appliances.

The second part of this article is focused on the introduction of an assistive system for patients with Parkinson's disease (PD). PD is a degenerative disorder of the central nervous system. The most obvious symptoms are movement-related such as tremor, rigidity, slowness of movement, and postural instability [19]. Modern treatments are effective at managing the early motor symptoms of the disease, mainly through the use of levodopa and dopamine agonists [20]. There is some evidence that mobility problems can improve with rehabilitation. Regular physical exercise can be beneficial to maintain and improve mobility, flexibility, strength, gait speed, and quality of life [21]. This motivated us to propose an augmented-reality-based assistive system which can provide Parkinson patients with both the auditory and visual cues to maintain and improve their mobility and gait speed.

The remaining of this paper is organized as follows. The proposed two assistive systems will be described in Section II and III, respectively. Finally, Section 4 concludes the paper.

2. The Assistive System for the Disabled Persons

The Eyebrow Switch

The eyebrow switch is designed to be activated by raising one's eyebrow or wrinkling one's forehead. Some commercialized eyebrow switches are available on the market. Each kind of the existing eyebrow switches has its own advantages and disadvantages (e.g., high price). In this paper, we present a low-cost approach to implementing an eyebrow switch.

The proposed eyebrow switch is consisted of a metal frame with a bendable metal plate as shown in Fig. 1(a). While the frame and the plate are fixed at one end, there is a small gap between the metal frame and the bendable plate at the other end. The eyebrow switch is attached to the forehead of a user via a headgear as shown in Fig. 1(b). When adjusted appropriately, a little movement incurred by raising one's eyebrow or wrinkling one's forehead may force the bendable metal plate to touch the metal frame to activate the eyebrow switch. This effectiveness of the proposed eyebrow switch had been confirmed by a serious amyotrophic lateral sclerosis (ALS) patient.

(a) (b)

Figure 1. The eyebrow switch. (a) The structure of the switch consisted of a metal frame and a bendable metal plate. (b) The working environment where a user wears an eyebrow switch.

The Communication Aid

The communication aid has been partly introduced in some of our previous work [11], [14], [18]. It is an interface which dichotomizes daily living necessities into 7 groups was proposed for people with severe disabilities (e.g., Voiced Messages, Typing, Home Appliance Control, Help, A/V Entertainments, Web Surfing, Messages) as shown in Fig. 2. In addition to the seven selections, another two selections, Suspend and Exit, are another two available options.

The proposed eyebrow switch can be used to incorporate with the communication aid to allow people with severe disability to manipulate computers and communicate with their family members, friends, and health care providers. The communication aid sequentially scans through these nine selections on the row by row basis. The user raises and then soothes his/her eyebrows when his/her desired row is highlighted in red color. Then the aid will scan through each selection in that row and waits for the switch signal issued by the user. If there is no mouse clicking signal issued in two complete scans at the present layer then the aid will automatically jump back to the upper layer and start to scan the selections at the upper layer. An example is shown in Fig. 3. Once the user subsequently select the four selections, “Home Appliances”, “Fan”, and “Power”, the aid will automatically switch on the fan via a remote controller which is implemented by an infrared LED circuit incorporated with a RF transmitter/receiver.

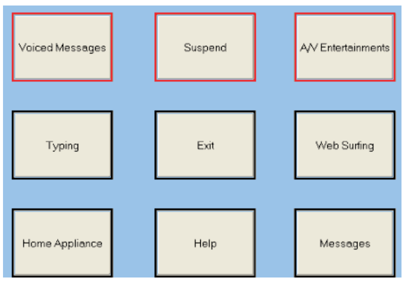

Figure 2. The first layer of the communication aid in the English version.

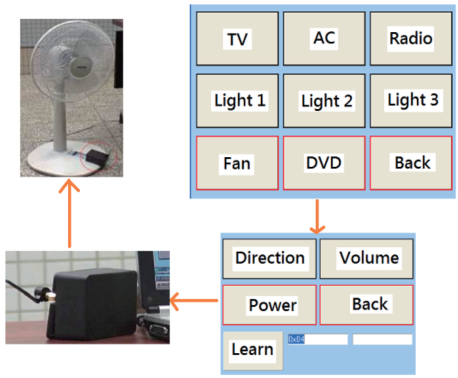

Figure3 . An example of its subsequent selections for controlling an electrical fan.

3. The Assistive System for the Patients with Parkinson's disease

PD is one of the most common nervous system disorders of the elderly, with most cases occurring after the age of 50. The most obvious symptoms of PD are movement-related such as shaking, slowness of movement, and difficulty with coordination. Lifestyle changes (e.g., good nutrition, regular exercise, physical therapy, assistive devices) may help patients to improve mobility symptoms. Particularly, regular physical exercise can be beneficial to maintain and improve mobility, flexibility, strength, gait speed, and quality of life [21]. Strategies to improve gait symptoms include utilizing assistive equipment, verbal cueing, exercises and altering environments [22].

As the disease progresses, PD patients will develop a distinctive shuffling gait with a stooped position and a diminished or absent arm swing. They are likely to take small steps and shuffle with their feet close together. With more advancing disease, patients will develop another distinctive freezing gait which makes patients feel as if their feet are stuck to the floor despite they attempt to force themselves to walk. When these gaits develop, they may be impairment of balance and are apt to fall. Therefore, falls become a major source of injury in PD patients. How to remedy the situation becomes a very demanding problem. While some persons may rely on a cane or a walker, some people may benefit from visual stimuli such as a pattern in tiles of the floor or a series of stripes on the floor [23]-[26]. The effect of placing parallel lines on the walking surface on

Parkinson gait was evaluated by Azulay et al. [27]. They identified the kind of visual cues (static or dynamic) required for the control of locomotion by testing two visual conditions: normal lighting and stroboscopic illumination. In addition, some research work pointed out that rhythmic auditory cue may help PD persons walk better [28]-[30].

The aforementioned discussions motivated us to propose an augmented-reality-based assistive system which can provide PD patients with both the auditory and visual cues to maintain and improve their mobility and gait. The system is consisted of four modules：1) the infrared sensor module: to detect the step amplitude or stride length and shuffling steps; 2) the projector module: to project a virtual visual cue on the ground; 3) the earphone module: to provide auditory signals; 4) the computer module: to provide the computing power, produce the visual pattern, output rhythmic auditory signals, and issue alarm signals when necessary. Fig. 4 shows a prototype of the proposed system.

The proposed system will issue alarm signals to PD patients whenever they develop shuffling or freezing gaits. A complete record during daily walking or exercising activities will be stored and upload to a computer server to provide physiotherapists with data to analyze and adjust corresponding rehabilitation exercises.

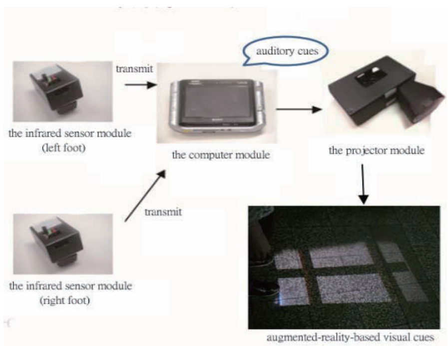

Figure 4. The prototype of the proposed augmented-reality-based assistive system for PD patients.

4. Conclusions

In this article, we present two assistive systems. The low-cost eyebrow switch was designed for persons with severe physical, neurological, or upper extremity disabilities or spinal cord injury to access computers and the augmented-reality-based assistive system was developed to provide PD patients with both visual and auditory cues to improve their gait problems. The effectiveness of the two systems still needs to be further validated in the future.

Acknowledgement

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Implementation of Cloud-Computing Healthcare based on Xenon uploading System and Hilbert Huang Transform

Yu-Cheng Lin[1], I-Te Hsieh[1],, Wei Ting Lin[1], Wei-Lieh Huang[1,2,3], Kuan-Liang Kuo[4], Guo-She Lee[5,6], Men-Tzung Lo[7,8], Cheryl C H Yang[1,5,9], Norden E. Huang[7,8],Terry B J Kuo[1,5,9]

1. Institute of Brain Science, National Yang-Ming University,Taipei, Taiwan
2. Department of Psychiatry,
National Taiwan University Hospital, Yun-Lin Branch, Yunlin, Taiwan
3. Department of Psychiatry, National Taiwan University Hospital, Taipei, Taiwan
4. Department of Family Medicine, Ren-Ai Branch, Taipei City Hospital, Taipei, Taiwan
5. Department of Education and Research,Taipei City Hospital, Taipei, Taiwan
6. Department of Otorhinolaryngology, Ren-Ai Branch,
Taipei City Hospital, Taipei, Taiwan
7. Research Center for Adaptive Data Analysis,
National Central University, Chungli, Taiwan
8. Center for Dynamical Biomarkers and Translational Medicine,
National Central University, Chungli, Taiwan
9. Sleep Research Center, National Yang-Ming University, Taipei, Taiwan

(e-Mail: tbjkuo@ym.edu.tw)

Abstract — With the advance of technology, cloud-computing healthcare is rapidly growing. Current methods for data acquisition and analysis, however, are not fully optimized. In the data acquisition, the wired transmission has been gradually phased out. The current wireless protocols are complicated, power consuming and hard to use. Therefore, they are not broadly applied in healthcare devices after years of promotion. With regard to data analysis, because of the non-linear and non-stationary nature of the physiological signals, traditional methods can not provide satisfactory analysis. To optimize data acquisition, we developed "Xenon" uploading system. It is seamlessly compatible with existing healthcare devices and automatically uploads data to the cloud server. To optimize data analysis, we constructed cloud-computing Hilbert Huang Transform (HHT) platform, which is suitable to analyze the non-linear and non-stationary physiological data. By an integration of the Xenon uploading system and cloud-computing HHT platform, the cloud-computing healthcare becomes more realistic. Users would have better opportunity enjoy a high

performance yet affordable automatic cloud-computing healthcare service.

Keywords — Ultra low power, Radio frequency,
Data communication, Data analysis

1.Introduction

With the advance of technology, more and more data processing systems appear on market. No matter they are personal computer based or cloud based, these systems are composed of the sensing, acquisition, storage, analysis, and output. Cloud-computing healthcare, a rapidly growing data processing system, has been applied in dairy care of blood pressure, heart rate and blood sugar. The acquired health data are uploaded and stored in the cloud server. After analysis, the results are delivered to the user via a general web browser. Nowadays, the data sensing, storage and output techniques for the cloud-computing healthcare are relatively mature. However, serious limitations still exist in the parts of data acquisition and data analysis.

Data acquisition for the cloud-computing healthcare can be broadly divided into the wired and wireless methods. With the aspect of a user, the wired method is not convenient, while the current wireless method was also inherited with several flaws including heavy power consumption, complicated operation, and high cost. The power consumption of current wireless technology (such as Bluetooth, ZigBee and WiFi) is more than 20 mA at 3 V so that the common coin-typed battery (CR2032) can not drive. Some technology needs complex settings, which is suitable for experts but not for general users. Furthermore, the data acquisition is always implemented in the personal computer and mobile phone, and both the developing and operating costs are high. Because of the limitations, the wireless technologies are still not popular in the healthcare application. This study intends to develop a optimized data uploading system for healthcare application, which utilize existing ultra-lower power (ULP) radio frequency (RF) silicon chip and optimized its function with a specially designed firmware. The role of the uploading system is to provide a seamless link between existing healthcare devices and cloud-computing platform. Specifically, it would automatically acquire data from existing healthcare device and upload the data to the cloud server without any intension.

With regard to data analysis, because of the non-linear and non-stationary nature of the physiological signals [1], traditional linear analysis methods can not provide a satisfactory analysis of physiological signals [2]. This study also intends to optimize the data analysis of the healthcare application with a latest technology. The Hilbert Huang Transform (HHT) which is designed for non-linear and non-stationary data, is expected to deal with the long-term physiological signals [2]. With the optimized data acquisition and data analysis, we want to enhance the efficiency of the cloud-computing healthcare in order to achieve an convenient and affordable healthcare service.

2.Material and method

Automatic data acquisition and uploading system

In order to seamlessly connet with existing healthcare devices and to provide a automatic uploading function, we developed a fully automatic data acquisition and uploading system, with a code name of "Xenon". This system was composed of two parts, an ultra-low power (ULP) radio frequency (RF) module (Xenon RF module) and its router (Xenon router) (Fig 1). The input of the system was the standard Universal Asynchronous Receiver / Transmitter (UART) and the output was the internet. The two parts were communicated with RF. The Xenon RF module was driven by a specially designed protocol (Xenon protocol) which realized an optimization of power consumption and data integrity. Although data rate was not the major concern of the Xenon protocol, a maximal sustained transfer rate of 10 Kbytes was provided for higher date rate application such as electrocardiogram or electroencephalogram. A transmission and acknowledge mechanism was adopted to avoid any data loss. The power consumption must be compatible with existing healthcare devices including those use the popular coin battery CR2032. Complied with all the above requirements, the Xenon proptocal coupled with a the silicon hardware realized a Xenon RF module. Currently a silicon hardware is a commercially available Xenon RF transceiver chip (nRF24LE1, Nordic), achieving a RF module with the weight of 0.95 g and the size of 2.7 x 1.3 cm2. Other specification is illustrated in the Table 1. The Xenon protocol, however, can be easily implemented in other silicon hardware.

The Xenon router was built with a Xenon RF module and a General Packet Radio Service (GPRS) module: the former provides connection to any healthcare device equipped with a Xenon module and the later makes the router connectable to the most popular network, the cellular phone network.

UART band rate		4800~19200
UART buffer		1024 B
RF Frequency		2.4 GHz
RF Power		1 mW
Max sustained data rate		10 KB/s
Operating voltage		1.9~3.6 V
Average current consumption for blood pressure monitor		10 μA
Standby	Current consumption	4 μA
	UART	On
	RF	Off
Transmitting	Current consumption	4 mA
	UART	On
	RF	On

Table I. Technical specification of Xenon radio frequency module
UART: Universal Asynchronous Receiver / Transmitter; RF: Radio Frequency

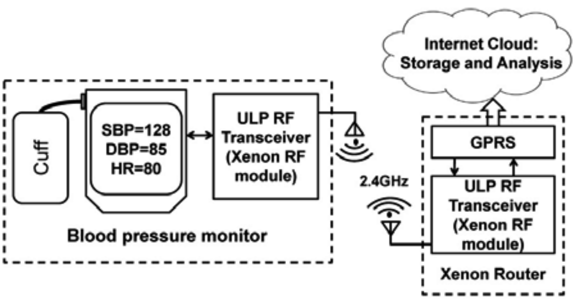

Figure 1. Block diagram of a cloud-computing blood pressure monitor equipped with the Xenon uploading system.
ULP: Ultra-Low Power; GPRS: General Packet Radio Service; RF: Radio Frequency
SBP: Systemic Blood Pressure; DBP: Diastolic Blood Pressure; HR: Heart Rate

Automatic data analysis system for physiological signals

With the application of the automatic data acquisition and uploading system, long-term recording of physiological signals became much easier than before. After great amount of data were accumulated, how to properly analyze the data became the next challenge. Long-term physiological signals contain various linear and non-linear components, which are generated from body and also from external environment, and it may be also stationary or non-stationary. In order to properly analyze these highly complex physiological signals, the HHT developed by Huang et al was adopted. In addition to the linear and stationary data, the HHT can also deal with the non-linear and non-stationary data which are difficult to analyze with traditional methods [2]. Empirical mode decomposition of HHT decomposes the raw data into a number of intrinsic mode functions and an adaptive trend. This method is expected to isolate confounding factors and measurement noises, therefore, the adaptive trend can correctly responded to a pathophysiologic mechanism. In order to adapt the HHT into the cloud-computing platform, an integration of the HHT source code, Matlab compiler, and mySQL database was done in this study. Physiological data stored in the cloud database automatically passed through the cloud-computing HHT platform. The analysis results were automatically delivered to the users with the help of a web browser in a personal computer or hand-held computing devices such as mobile phone or pad computer.

3. Results

In this study, we developed an optimized and fully automatic cloud-computing healthcare system. Almost all of the current healthcare devices can be connected to the system without difficulty by the Xenon RF module. The successfully connected devices include blood pressure monitor, body weight scale, blood glucose monitor, cholesterol monitor, uric acid monitor, peak expiratory flow meter, electrocardiography and actimeter. The physiological data were acquired by the Xenon RF module and were wirelessly and automatically relayed to the Xenon router. The data were then uploaded by the router and were stored in the cloud server, in which the data were automatically analyzed with the HHT technique. The analysis results were displayed to the user via the general web browser (Fig 2).

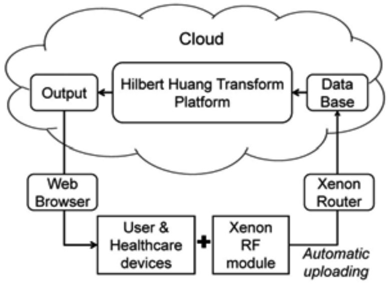

Figure 2. Automatic cloud computing healthcare system. RF: Radio

Frequency

The blood pressure monitoring was taken as the first example for the automatic cloud-computing healthcare system. The users were asked to measure their blood pressure once everyday. Thus the data were accumulated day by day in the cloud server (Fig 3A). After a specified period, e.g. 30 days, enough data were accumulated and each blood pressure time series was relayed to the HHT program in which empirical mode decomposition was carried out. Several intrinsic mode functions and an adaptive trend were generated in the cloud server (Fig 3B). Currently only the raw data and the adaptive trend were displayed on web page for users to browse (Fig 3A).

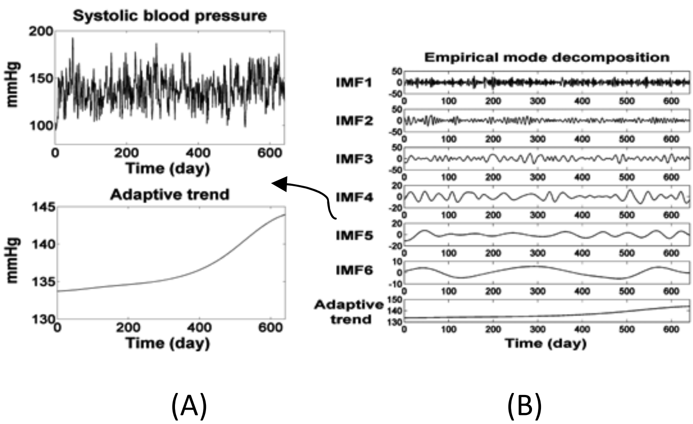

Figure 3. (A) Systolic blood pressure time series and its adaptive trend. (B) The empirical mode decomposition. The input is raw data and the output are intrinsic mode functions (IMF1-6) and adaptive trend.

4.Discussion and Conclusion

Traditional healthcare devices provide limited analytical power which can not be expanded. The purchase of new model is the only solution if a new function is required. However, the cloud-computing technology provides an alternative option. The originally limited instrument would be linked to a cloud-computing platform, then it would get unlimited function of data storage and data analysis. However, connecting a healthcare device to the internet is impractical previously because the available linking technologies such as wired ethernet and wireless WiFi, Bluetooth, and ZigBee are very difficult to implement and use. Not only the software needs to re-written from the ground, but also the hardware such as the power supply needs to be re-designed. The cost is relatively high. With regard to the users especially the elderly, to learn a new technique to upload his data to the cloud needs a lot of time and effort, which means a little change of success. In order to overcome these issues, we have developed the Xenon uploading system. With the Xenon RF module and Xenon router, the hardware and software of existing healthcare devices need only a very slight modification to be connected with the internet cloud. Users do not have to change their habits for using the healthcare devices. As a result, considerable developing and operating effort and cost were saved and the cloud-computing technology became much easier to access with the healthcare devices. After the connection between healthcare devices and internet cloud approaches optimization, the acquired and uploaded data would become numerous. The analysis of the long-term and massive physiological data would be the next challenge.

Most of the current analysis techniques are suitable for linear and stationary signals. However, the long-term physiological signals may have various non-linear and non-stationary components and may not be suitable to be analyzed by the traditional way. The development of HHT provides an opportunity to overcome these limitations. It has been successfully applied to analyze the global temperature data (Wu et al., 2007). Recently, the method is also used in analyzing physiological signals (Kuo et al., 2009; Li et al., 2008; Li et al., 2011; Oweis and Abdulhay, 2011). Traditionally most data analysis was carried out in a calculator or personal computer with complicated manual operating procedure. Sometimes professionals were needed to carry out a success analysis. This kind of operation takes a lot of resources and is not suitable for daily healthcare application. By the combination of cloud-computing technique and HHT, we realize a cloud-computing HHT platform that automatically performs HHT when the data are uploaded. Therefore every device with an data uploading capacity can become a powerful non-linear analyzer.

The Xenon uploading system is able to connect almost every existing healthcare device and automatically upload the health data to the internet cloud. The cloud-computing HHT platform can automatically analyze various types of physiological data. The results can be immediately delivered to the users by mobile devices such as pad computer or mobile phone. The integration of the Xenon uploading system and cloud-computing HHT platform makes the cloud-computing healthcare system more convenient and powerful, respectively. Users would have better opportunity to enjoy a high performance yet affordable cloud-computing healthcare service.

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Stroke Rehabilitation via a Haptics-Enhanced Virtual Reality System

Shih-Ching Yeh[1], Si-Huei Lee[2], Jia-Chi Wang[1], Yu-Tsung Chen[2],

1. Department of Computer Science and Information Engineering National Central University
2. Taipei Veterans General Hospital

(e-Mail:shihchiy@csie.ncu.edu.tw)

Abstract — Stroke is one of the major diseases causing brain injury, its sequela will, depending on persistent nervous injury, derive different types of limb and body exercise barriers, which will cause large challenge to the daily life of the patient and will seriously affect the quality of life of the patient. Along with the development and popularity of technology, scholars in the medical care and rehabilitation fields are trying to integrate all kinds of new technologies to perform the development of new rehabilitation training system.

In this study, for the rehabilitation of upper extremity, trainings are provided respectively for fore arm, for the endurance, stretching and flexibility of the wrist. Here game technology, force feedback technology and stereo image technology are associated to develop virtual reality body perceptive training task. In the rehabilitation process, multi-dimensional experimental results are acquired, for example, clinical test assessment, task performance, exercise track historical data and psychological emotional data. The research objectives are to verify the functionality of the system, to verify the effectiveness of the system on rehabilitation, to develop new assessment method and to investigate topics related to human machine interaction.

After initial pilot test is done on stroke patient, the experimental result has verified the functionalities of this rehabilitation training system in several aspects. Meanwhile, it can acquire reliable and valuable information successfully, for example, through the exercise analysis using exercise perceived subjectively, this system indeed can urge the patient to engage continuously rehabilitation therapeutic session that is based on this training system and enjoy it, besides, the authors are very confident on the possibly generated rehabilitation effect of these two training tasks.

Keywords — Stroke rehabilitation, haptics, virtual reality

1. Introduction

According to clinical data, it can be seen that within six months after the stroke, 88% of the acute stroke patient will have upper extremity hemiplegia, which includes the lack of strength in the arm muscle, incapability of stretching, heteronomous spasm, the loss of original acting scope of the wrist and palm, the loss of the capability to catch and take, sometimes, the loss of muscle strength or incapability of normal movement of the finger due to abnormal spasm might happen [1]. When the patient performs Activities of Daily Living, for example, the button-up of the clothes, the hanging of the clothes and dining, etc., all these actions will cause serious challenge to the patient, not only the living quality of the patient will be seriously impacted, the social cost accompanied due to the medical care need, for example, the human resource, material and medical resources needed for the medical care system, will also be pretty large.

Neurological exercise disorder originates the injury on the cortex exercise area of the brain, however, the cortex of the brain of human beings and the related nervous system are always in the plasticity state [2] and nervous re-organization processes [3], which in turn will affect and accelerate the learning (recovery) processes of the exercise function, and related researches also prove that systematic and group exercise rehabilitation model can indeed assist the enhancement of rehabilitation therapy, in addition, some researches also pointed out that for the learning of a new exercise technical model, the providing of the behavioral performance of the user to be used as expanded feedback mechanism is one of the important rings in the learning principles of enhancing the learning effectiveness. Similarly, exercise rehabilitation of brain injury can be seen as one type of exercise learning process, and the above principle can also be used to provide continuously the patient with rehabilitation performance as feedback [2][3], in another view, the feedback of vision and hearing is also one of the important factors to keep the exercise function [4].

However, for the action training method and therapeutic session design used in traditional physical therapy or occupational therapy, no matter in practice or economically, the above goals will all be difficult to be reached, and some inherent limitations do exist. In the mean time, the effect of rehabilitation therapeutic session will to certain extent be dependent on the level of engagement of the patient. Since the rehabilitation session is tedious, lots of external factors might reduce the participation or the motivation to complete the session from the patient, for example, when the therapeutic session content is too repeated or boring, or the traffic inconvenience factor, etc.

The constant advancement of 3D animation technology and internet technology not only provides technological enhancement, but also provides economic popularization, hence, lots of scholars performing medical rehabilitation related researches and the front line doctor or therapist in the world have tried to integrate the above technologies, and they try to use virtual reality, Augmented Reality and mixed virtual reality e as the theoretical basis, meanwhile, User Centered design concept is also put in, furthermore, user's perception on the system and usability and immersion of the system are also considered, and finally, the interactive model and strategy provided by the human machine interface are also used to perform the development of all kinds of new rehabilitation therapeutic sessions and rehabilitation technologies. Through the use of new technologies and new rehabilitation method as well as systematic digital management method, optimal rehabilitation efficiency and good rehabilitation quality can both be obtained, and the second injury in the rehabilitation process can then be reduced. Eventually, the effect of rehabilitation training can be enhanced, and the burden on the medical care personnel and the patient's family can be reduced, finally, a tool that allows the patient to do independent and autonomous rehabilitation can be developed. In the tool, game model is used to increase the user's aggressiveness and participation on rehabilitation training, moreover, a game of more fun is used to urge the patient to do rehabilitation, and the patient can, through this, obtain the feeling of entertainment and achievement from rehabilitation training. Not just this, the gaming process can also be recorded in digital data way to facilitate the tracking of the rehabilitation effect by the medical care personnel.

In addition, in order to assess the current status of the patient effectively so that medical personnel and the physical therapist can seize the current status of the patient more accurately and set up the rehabilitation goal. Moreover, in order to let the medical personnel be able to perform personalized therapeutic session design and provide the fittest rehabilitation therapeutic schedule and related rehabilitation strength design and to achieve the rehabilitation goal, effective physiological assessment tool is very important. Currently, there are lots of assessment tools designed for different parts of the bodies, for different functions and for different objectives, which include physical assessment and self assessment. Clinically, the frequently used physical assessment tools include Fugl-Meyer Assessment table, Wolf Motor Function. Test (WMFT) and TEMPA(Upper Extremity Performance Evaluation Test for The Elderly), and they will perform respective assessment on the exercise function of the upper extremity, the usage capability of the wrist and palm and whether daily actions can be finished smoothly or not. In self assessment aspect, EXCITE MAL Score Sheet, CONFIDENCE IN ARM AND HAND MOVEMENTS (CAHM) and Stroke Impact Scale (SIS) [5]-[9]. are frequently adopted to make self assessment on the usage injured part of the patient for confidence index and the actions needed for daily life after the carry-out of rehabilitation training, and the assessment includes whether the action needed for the life can be finished or not, the confidence index and the cause the action cannot be finished.

In the mean time, the behavioral performance values measured through digital system are very diversified in its type, and the data are also very rich in its quantity, hence, how to, from massive and diversified information, explore or delve out valuable clue and set up new medical assessment method, and how to act in accordance with the existed assessment method and to provide more accurate and faster assessment method for clinical medical diagnosis is going to be a direction with great potential.

During the rehabilitation process, in addition to the physiological state of the patient, the emotional factor of the patient is also very important. For the psychological emotional behavioral model of stroke patient, researchers including Maclean[10,11], Colombo[8] and Paolucci[9], have made studies regarding the correlation between the motive factor of stroke patient and rehabilitation effectiveness, hence, and the patient’s acceptance on new technology includes:

Factors such as whether the system is easy to be operated, whether the patient thinks this system is helpful or not, the level of pleasure provided by the system, whether strong focus is put on the system during the experimental process and whether it is easy to adapt to the environment set up by the system might all affect the patient’s participation and the willingness and motive in the rehabilitation therapeutic session.

In this study, trainings are to be provided for upper extremity rehabilitation items, for example, the endurance, stretching and flexibility of the fore arm and wrist; meanwhile, gaming technology, force feedback technology and stereo imaging technology are associated to develop virtual reality body perceptive training task. In the mean time, this research is going to perform clinical experiment, to recruit right handed patient with Fugl-Meyer Assessment score reaching the range of 40 to 50 to carry out a series of gaming type rehabilitation training therapeutic sessions that are based on virtual reality in association with physical-based equipment. There are a total of 12 therapeutic sessions, and each session lasts for two hours, and before and after the training, functional assessments will be performed, which include physical assessment and self assessment. In the training process, the exercise track and task performance of the patient is going to be completely measured and recorded, then after the finishing of the training, patient's technological acceptance on the new rehabilitation system is going to be measured. Based on the above measurement result, exercise analysis and statistical analysis will be performed so as to verify the functionality of the system, to verify the system's effectiveness on rehabilitation, to develop new assessment methods, and to investigate the topics related to human machine interactions.

2. LITERATURE REVIEW

In recent years, lots of research teams applied virtual reality in the rehabilitation of medical care [14-16], and after long term and repeated experiments, this technology has been proved to be effective in the rehabilitation training of the stroke patient. Virtual reality can display the realized training action in gaming way in the virtual environment, and in the gaming process, all kinds of rehabilitation actions can be implemented. Since all the objects interacted with the user are all virtual objects, not only the usage timing with the object can be controlled, the mutual accuracy with the user can be controlled, the feedback for achieving the task can be displayed, but also the safety of the rehabilitation training environment can be ensured. Moreover, real time gaming feedback let the user confirm his own rehabilitation progress, and it can also display the successful reaching of the goal and recognize the user's self capability and enhance the user's confidence. The application of virtual reality not only can let the user learn all kinds of learning skills, but also can train the recognition functions of the patients.

In this research, virtual reality with gaming characteristic is used as rehabilitation tool to give force feedback such as pushing force or dragging force to the hand. In the past, a team formed by scholar Lauri [17] has designed a set of system to give force to the hand through the wearing of pneumatic gloves. Here the glove is filled with air, and air pressure is used to give pushing force or dragging force so as to simulate the haptics or the weight of an object. In addition, through the optical mark installed on the body, the arm position is traced, and head-wearing type display is used to create the environment of virtual reality. The task of the game of the system is to operate in the virtual reality environment to let the palm move to the designated position, at different check points, tasks such as grasping, pinching or holding the object for a distance do not need to be achieved additionally, besides, the moving scope of the hand, the size of the force for seizing the object and whether supplemental force is added can be designed.

For this experiment, although certain positive result has been acquired in rehabilitation training, yet the equipment needed and the setting of the environment used is not so easy to general medical care personnel, moreover, it might brings up certain difficulty for the wearing of the gloves when considering the level of spasm of the hand of the patient, besides, the wearing of optical marks on the body of the patient for positioning might consume lots of time for pasting the optical marks onto correct positions. Besides, helmet type display might bring dizziness or psychological discomfort such as oppression to the patient due to long time of wearing. Therefore, we hope that simpler equipment and more comfortable operation environment can be used to achieve better training result. Not only it will become easier to use, but also it will make the rehabilitation process smoother and more efficient. In the mean time, the cost needed to purchase massive equipment and for maintenance can then be saved.

3.LITERATURE REVIEW

In this experiment, traditional upper extremity rehabilitation items have been referred to, and trainings have been provided for the endurance, stretching and flexibility of fore arm and wrist, and two training tasks are designed respectively with each task contains three types of force feedback models for selection. Moreover, the training content is performed with task simulation and design using the game engine Unity so as to urge the patient to implement the setup target action to complete the task; furthermore, virtual reality is constructed using the product 3D-Vision of Nvidia corporation, and the advantages are that this product is supported by the current mainstream stereo display and stereo projector display equipment, besides, 3D-Vision has price lower than other product and is easier to get, meanwhile, the equipment only needs USB to be connected to PC, then through simple setup, it can be applicable to any software supported by Nvidia corporation. Furthermore, the force feedback device Falcon as launched by Novint is selected. This device is single point haptics virtual equipment. Its mechanical arm is movable along six axes, and its updating frequency is 1000 Hz. In each update, Falcon will provide the coordinate of the mechanical arm currently in the space. In the mean time, during the exaggeration process of the game, the feedback vector and size can be provided simultaneously to the Falcon, and the haptics simulation or dynamic physical force feedback can then be achieved smoothly and stably, hence, through this machine, the interaction to the object in the virtual space can then be activated. In its utilization, USB is ready for plug and play. In the followings, two training tasks and force feedback models will be introduced respectively:

Wrist exercise

The task is designed as simulating a task of ”Flying and moving across the barrier”. The rehabilitation patient uses wrist exercise (inner rotation or outer rotation) to control the rolling of the airplane in virtual reality so as to move across a series of square and hollow frames, and these square and hollow frames possess respectively different rolling.

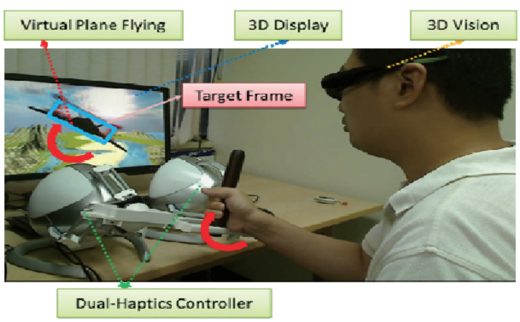

Figure 1. Game design and hardware equipment for wrist exercise

The system is designed in a way to use 3D game engine to construct an interactive virtual flying scene. Meanwhile, 3D stereo screen accompanied with polarized glasses are used to provide stereo depth of field; in the mean time, dual-haptics devices are used to construct flying controller, and through the characteristic of haptics simulator, the impact vibration can be simulated to be provided to the rehabilitation patient for force perception feedback. This system is also assisted with the measurement of brain wave to understand the correlation between the inner rotation or outer rotation exercise of the elbow and the brain wave under different torsion models.

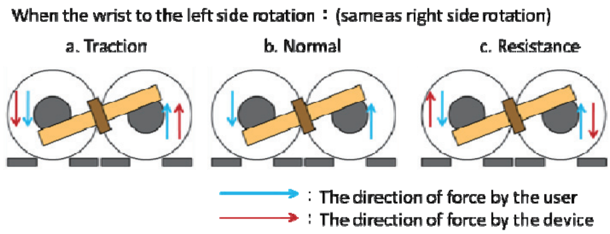

Figure 2. It illustrates the force applied directions of three different torsion models

Adjustable difficulty design uses two parameters, that is, "torsion amplitude" and "torsion model" to guide the rehabilitation patient to perform elbow exercise training of different difficulties: (1) Torsion amplitude: It set up the rolling of the square and hollow obstacle, and it will decide the torsion amplitude of the elbow of rehabilitation patient for the completion of the task. (2) Torsion model: Based on the injury condition of the rehabilitation patient, this system has designed three different torsion models as in the figure to be used for the rehabilitation strategy planning: a. Guiding model: The flying controller will provide guiding and dragging force according to the rotational angle of the airplane and the angle of the target frame. The dragging force will become smaller when the difference of the angle between the airplane and the frame. b. Natural model: The flying controller does not provide any force. c. Resistance force model: Flying controller will provide resistant dragging force according to the rotational angle of the airplane and the angle of the target frame. The dragging force will become larger as the difference of the angle between the airplane and the frame becomes closer.

Fore arm exercise

The task is designed to use the task activity of the above mentioned "Flying across the barrier". Rehabilitation patient uses forearm exercise (Curving, stretching and left and right deviation) to control the left and right position as well as the height of the airplane in the virtual reality so as to move across a series of square hollow obstacles. These square and hollow obstacles possess respectively different left and right position and different height.

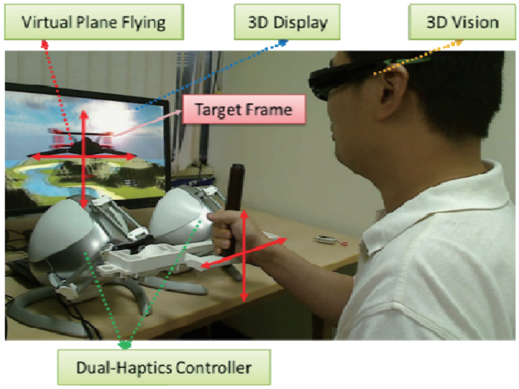

Figure 3. Game design and hardware equipment for forearm exercise

In the system design, 3D game engine is used to construct an interactive virtual flying scene. Meanwhile, 3D stereo screen accompanied with polarized stereo glasses are used to provide stereo depth of field. Moreover, double haptics simulation equipment is used to construct flying controller, through the characteristic of haptics simulator, collision and vibration can be simulated so as to provide force perception feedback to rehabilitation patient. Moreover, this system is accompanied with the measurement of brain wave to understand the correlation between wrist exercise (curving, stretching and left and right deviation) and brain wave under different force models.

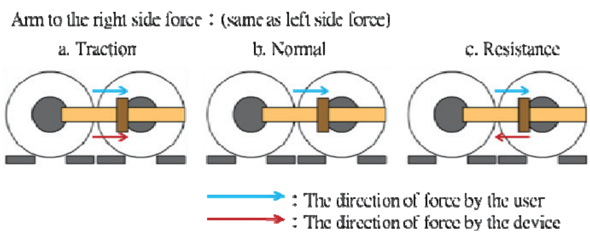

Figure 4. It illustrates the force applied direction of three different types of forced deviation models

In the adjustable difficulty design, two parameters are applied: "Deviation amplitude" and "Deviation force model" are used to guide the rehabilitation patients to perform wrist exercise training of different difficulties: (1) Deviation amplitude: It is to set up the deviation amount of the square and hollow obstacle, and it will decide the deviation amplitude of the wrist of the rehabilitation patient so as to complete the task. (2) Deviation force model: This system, based on the injury condition of the rehabilitation patients, has designed three different deviation force model as shown in the figure. It is to be used for the rehabilitation strategy planning: a. Guiding model: Flying controller will, according to the distance between the airplane and the target frame, give guiding and dragging force, and the guiding and dragging force will become smaller as the airplane gets closer to the frame. b. Natural model: Flying controller does not provide any force. c. Resistant force model: Flying controller will, based on the distance of the airplane to the target frame, give resistant force, and the resistant force will get larger as the distance between the airplane and the frame becomes closer.

In the above two exercise models, the force feedback output size of the guiding and dragging force are all calculated using linear algorithm. In the guiding model of the forearm exercise, to avoid sudden large force output in the guiding model, the maximal value of the guiding force will get increased gradually from small to large along with the closer straight line distance to the target frame. Then mixed with the frame planar distance, maximal force output proportion calculation is made. When the planar distance gets closer to the target, the force exertion will become smaller so as to avoid the generation of unnecessary bouncing and the subsequent rehabilitation injury due to over-sensitivity of the equipment. In addition, under the resistant force model, the force feedback maximal value and frame planar distance will be taken directly for force output proportion calculation. Since the force size is controlled by the user under the user's controllable range, there is thus no rehabilitation injury issue. Similarly, the force feedback algorithm design of the wrist exercise is the same as that of the forearm exercise, which is as shown in figure 5.

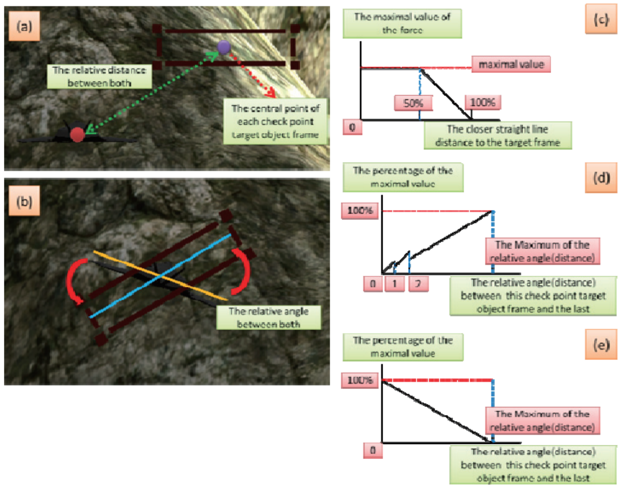

Figure 10. (a)The relative distance of forearm exercise, (b)The relative angle of wrist exercise, (c) The relationship between the force and the closer straight line distance, (d)The relationship between the relative angle(distance) and the force in guiding model, (e) The relationship between the relative angle(distance) and the force in resistant force model

4.RESEARCH METHOD: EXPERIMENTAL DESIGN

The received case and case receiving standard

The received case contains nine members, namely, three stroke patients in acute, sub-acute and chronic case respectively. The functions of the upper extremity of the patients all reach Fugl-Meyer Assessment with score in the range from 40 to 50, and all the patients are right handed.

The selection standard is the unilateral brain stroke patient of the first onset of the disease, and the period between stroke onset time and the participation time should not be more than one year, and the age is in the range from 20 to 85 years old. Meanwhile, the near end action functions of the upper extremity of the disease side should all be above the fourth term (included) of Brunnstrom's stage) and the patient should have exercise disorder of the upper extremity. Moreover, the patient should have no significant recognition function loss to follow simple command, to understand experimental objective and to act in accordance with research procedure and is willing to sign the agreement for person under test.

Each patient will be recorded with his age, gender, left handed or right handed, existed diseases (including hypertension, diabetes, hyperlipemia, arrhythmi, epilepsy), the location of the brain injury, stroke type (infarct type or hemorrhagic type), date of stroke onset, number of months of rehabilitation, and the score of Barthel's Index. A professional assessment person will be responsible for the assessment of the above data and scale.

Experimental process

This experiment is going to be designed in reversal replication design. In the beginning of the experiment, the person under test will be explained with experimental process and its objective, then the person under test will be asked to sign the agreement. In addition, we have to remind the person under test not to attend any other rehabilitation training activities during the test period.

The entire experiment lasts for 31 days. The first eight days will be the situation assessment of the patient, and the physiological and psychological state of the person under test before the experiment will be recorded. The medical personnel can, based on the assessment situation of the patient, make all kinds of rehabilitation training difficulties. During the test period, two major assessments and four simple assessments will be done. After eighth day, rehabilitation training lasting for 15 days will be carried out, and the therapy frequency for the patient will be three times a week. Select a game with difficulty meeting the capability of the patient, then collect the data for one hour of rehabilitation training, then record the game played, the performance, the gaming time and make sure there is no error in the game output for the person under test. The interval between therapy should be more than 24 hours to avoid the generation of fatigue on the patient. After the completion of the therapy, simple assessment will be performed for a total of eight times, at the last time of rehabilitation training, a major assessment will be performed so as to record the effectiveness after the patient has received the rehabilitation training. In the last eight days, no rehabilitation training will be carried out, instead, four simple assessments and one last assessment will be performed to observe if in this rehabilitation way, the patient can, without carry-out of any training, keep the level previously achieved just right before the ending of a series of rehabilitation training.

Data analysis and performance assessment method

The data type and format acquired in this research includes clinical assessment tool data, task performance data, exercise raw data and the psychological emotional data of subjective perception.

Clinical assessment tools include physical assessment and self assessment. We have used the following physical assessments: FM(first assessment), WMFT, TEMPA (four major assessment), and self assessment: MAL, CAHM, SIS(second and third major assessment). Moreover, the difference between pre-test and post-test will be used to assess rehabilitation effectiveness.

Game task performance includes task success rate, task completion time, response time and task score. Furthermore, statistical analysis will be performed to assess the improvement trend of the exercise performance.

The exercise raw data is the exercise locus information, and further exercise analysis will be performed to calculate different exercise indexes, which include stability, discontinuity, efficiency, oscillation and level of loading. Furthermore, the difference between the pre-test and post-test is going to be used to assess the rehabilitation effectiveness, in the mean time, statistical analysis will be performed to assess the trend of exercise function improvement.

The psychological emotional data of subjective perception is technological acceptance survey questionnaire, which will be used to do survey on user for the followings: awareness on the game content, presentences of virtual reality, usefulness of the training task, playfulness of the training task, intension to use of the training task and ease of use of the training task, the main objective is to obtain the assessment on this system from the person under test, and it is hoped that the result can be used as better system reference in the future design. In the mean time, related analysis will be done with the above mentioned data to investigate the correlation between psychological emotional factor and rehabilitation effectiveness.

5.RESEARCH METHOD: EXPERIMENTAL DESIG

In the experiment, nine patients are expected to be recruited to participate in the experiment. Currently, one person under test has been recruited, with data as: age 82 years old, female who is a patient of Ischemic Stroke, and the score obtained from FM assessment is 27, TEMPA and WMFT performances are all middle and low. According to the above mentioned experimental process flow, we have finished Pilot Test, in the followings, we are going to show all the experimental results of the person under test.

Exercise analysis

According to the spatial status data of the operation of virtual reality object through force feedback device from the patient under measurement, exercise analysis can be done to understand further and investigate the exercise model and behavioral strategy for the patient to complete the task.

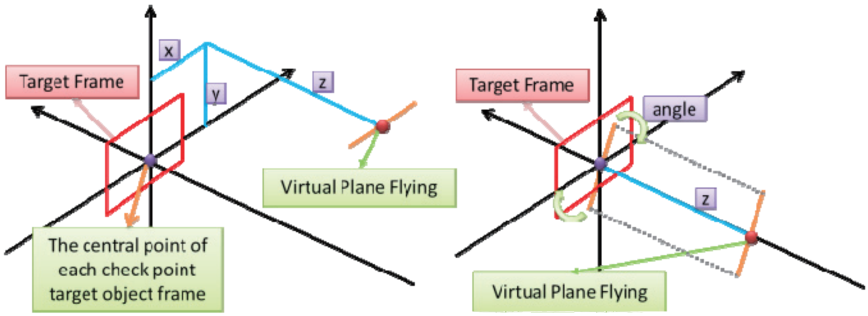

Figure 9. The coordinates schematic

For the training task regarding the use of forearm to operate the airplane to make up and down or left and right movement, the task goal is to use force feedback device to operate the airplane and to move it to designated direction so as to pass smoothly the target object frame. The location of the airplane in the virtual space in each time point is subtracted with the spatial location of the central point of the target object frame to get the relative distance between both of them. Meanwhile, Cartesian coordinate is used as basis to cut it into three partials (x, y, z) for the representation. The units are all the coordinates defined by game engine. The central point of each check point target object frame is used as coordinate origin. Wherein x represents the left and right direction distance of the airplane relative to the central point of the target object frame, y represents the up and down direction distance of the airplane relative to the central point of the target object frame, z represents the front and rear direction distance of the airplane relative to the central point of the target object frame. When the airplane passes through the target object successfully, x, y, z values will all approach zero (The airplane size will approach but is a little bit smaller than the target object frame), which is as shown in figure 9(left). Since z values are constantly accumulated using fixed value, then the x, y value at each time point of the task process is plotted into time-history diagram, which represents the approaching history diagram between the airplane and the target object, which is as shown in figure 5. It can clearly display the behavioral model of the forearm exercise in two directions of the

Cartesian coordinate for the patient in the task completion process, then a comparison can be made for the investigation of the behavioral strategy.

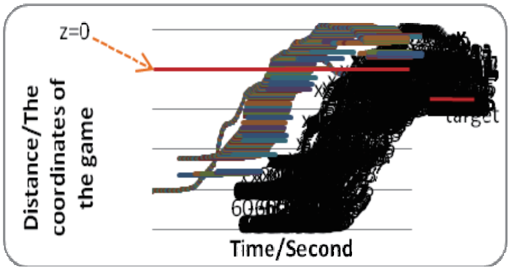

Figure 5. The distance approaching history diagram between airplane and target object using the check point of the left and right movement training as example.

For the training task regarding the use of wrist for the operation of the left and right rotation of the airplane, the task target is to use force feedback device to operate the airplane to rotate to the assigned angle so as to pass the target smoothly (frame). When we subtract the rotational angle of the airplane in the virtual space for every time point by the rotational angle of the target space, the relative angle between both of them can then be obtained; meanwhile, based on the Cartesian coordinate, Euler Angle and one partial z can be used for the representation, and the units are the coordinates defined by the game engine. Take the Euler Angle of the target object of each check point as basis, wherein the angle is the angle difference between the airplane and target object, z is the front and rear distance between the target object and the airplane, when the airplane successfully passes the target object, the relative angle and the z value will all approach zero, which is as shown in figure 9(right). Since z value is accumulated constantly from a fixed value, then the relative angle at each time point in the task process is plotted as time-history diagram, which then represents the approaching history diagram between the airplane and the target object as in figure 6. It can clearly display the behavioral model of Euler Angle of Cartesian coordinate of the wrist exercise of the patient in the task completion process. Then a comparison can be made and the behavioral strategy can be investigated.

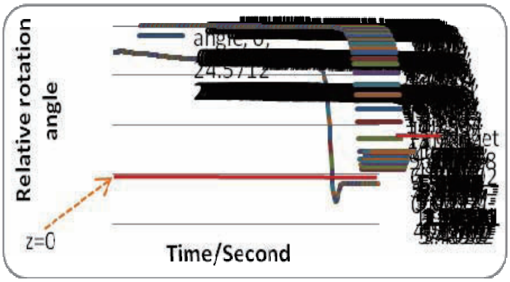

Figure 6. The distance approaching time history diagram between airplane and target object

Task performance

According to the measured patient's task performance, accompanied with the frequency of the training sessions, statistical analysis can be made on the time axis so as to evaluate the level of improvement and the development trend of the task performance. The task performances of two training tasks at different therapeutic processes are as shown in figure 7~ figure 8.

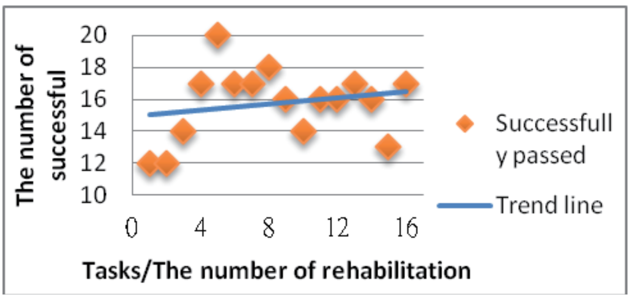

Figure 7. Task performance: Training task of wrist exercise

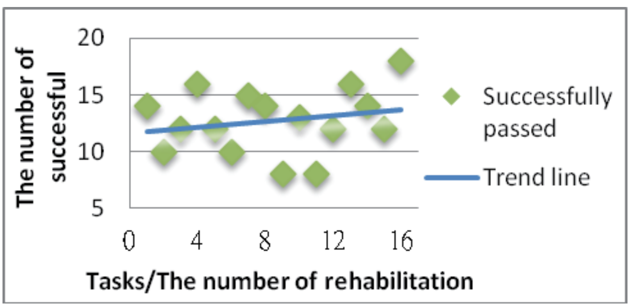

Figure 8. Task performance: Training task of forearm exercise

Psychological emotional data of subjective feeling

The measurement result of the psychological emotional data of subjective feeling is as shown in table 1. The result shows that in two items of playfulness and intention to use, scores of more than 4 can be obtained, which shows that this system can indeed make the patient continuously involved in rehabilitation therapeutic process that is based on this training system and have fun from it. However, in the usefulness part, lower score is obtained, and the main reason is because in this part, the issues are mostly on whether the force or endurance training has brought some significant effects. However, the hemiparalysis level of this patient still cannot afford, in the rehabilitation training process, training with resistant force model, hence, lower score is obtained, and in this case, it shows that this part of survey questionnaire design has room to be improved. In the playfulness and Ease of use parts, pretty good scores are obtained, which show that such training game can increase patient's fun in the rehabilitation process, and it worth of being recommended to other patients. However, Ease of use item does not reach the score level of 4, the reason might be due to the defect in the operation hardware and equipment. Moreover, due to lower adaptation of the higher age patients on the stereo display equipment, the patients can easily feel less direct and obvious operation easiness of the system, and this is also the part of the system that needs to be improved continuously.

TABLE I. PSYCHOLOGICAL EVALUATION

Grading items	Awareness	Presence	Usefulness	Playfulness	Intension to use	Ease of use
Average score	4	4.72	2.53	5	4	3.56

6.CONCLUSIONS

In this research, trainings are going to be provided for the upper extremity rehabilitation items, which include the endurance, stretching and flexibility of the forearm and the wrist. Moreover, game technology, force feedback technology and stereo image technology are associated to develop body perceptive training task in virtual reality. In the mean time, this research has designed rehabilitation therapeutic session for right handed patient with

Fugl-Meyer Assessment score in the range 40 to 50, and pilot test has been successfully completed. The experimental result has proved the functionality of this set of rehabilitation training task in all aspects. Through the exercise analysis of the historical data of exercise locus and the statistical analysis of the task performance of the past therapeutic sessions, this system can successfully acquire reliable and valuable information to be used in the future for verifying medical care effectiveness and for developing new clinical assessment method. In the mean time, according to the measured psychological emotional data of subjective perception, it can be seen that this system can indeed urge the patient to continue getting involved in rehabilitation therapeutic session based on this training system and enjoy it. Meanwhile, it makes the patient more confident on the rehabilitation effect possibly generated by these two training tasks.

In the future, the pilot test of this research is going to be used as the basis to perform the system improvement, and large scale clinical test is going to be conducted continuously so as to verify the medical care effectiveness of this system, in the mean time, clinical assessment method will be developed too.

We would like to thank the researchers, teachers, and students who participated in the system design, implementation, and experiment. We are also grateful for the support of the National Science Council, Taiwan, under NSC 100-2221-E-008-043- & NSC 100-2631-S-008-001.

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Miniaturized Cortex Cooling Device and System for Hypothermia Therapy Application on Freely Moving Rat

Chih-Wei Chang[1], Kuan-Chou Hou[1], Yun-Wen Tsai[2],
Lei-Chun Chou[1], Jin-Chern Chiou[3] and Jeng-Ren Duann[3]

1. National Chiao-Tung University, Hsinchu City, Taiwan,
2. National Cheng-Kung University, Tainan City, Taiwan
3. China Medical University, Taichung City, Taiwan

(e-Mail:chihwei@nctu.edu.tw)

Abstract — This paper presents a miniaturized brain cortex cooling device and system using thermoelectric (TE) cooler for hypothermia therapy application on freely moving rat. Two type of cooling electrodes including planar and micro-needle structures are fabricated and studied by EEG recording. Comparing to prior arts, our approach can be applied under freely moving behavior. The cooling temperature is designed as 2°C to avoid permanent injury in brain. Packaged planar or needle electrode with TE cooler consumes only 2x2mm2. EEG recording electrodes and thermocouple are implanted for observation as well. Simulation result shows that TE-cooler with needle type electrode behaves deeper effective cooling depth and faster cooling response in rodent cortex range (~2mm deep). Long term EEG monitoring on freely moving rat also presents no extra side effects with continuously cooling.

Keywords — EEG signal, brain cooling

1.Motivation

To date, different approaches have been developed for seizure treatment including dose, electrical stimulation, resection surgery and hypothermia therapy. Brain resection is the pis aller. Comparing to electrical stimulation, cooling stimulation shows less invasive since there is no any charge exchange between implanted device and neurons but only lower down the environmental temperature to alleviate the extraordinary discharge in neuron by depressing its activities. Also, EEG signal can be continuously monitoring without disturbing by the stimulating currents Currently, brain cooling have been studied by TE cooler [1-3] and heat exchange [4-5] methods but only under anesthesia model or after brain slice. This paper presents a miniaturized cooling device with varied cortex contact structure for related animal hypothermia studies.

2. Results

Fig.1 illustrates the overall brain cooling device and system structure design. EEG, thermocouple and the current driver are recorded and control by a laptop via DAQ and LABVIEW. Practical experiment setup is shown in Fig.2. Note that the cooling device and EEG recording are tested under awake and freely moving status. To investigate and compare the planar and needle type electrode performance, a TE cooler-cortex interface model is built by ANSYS. Comparison of the simulation result of lateral and vertical temperature distribution between planar and needle type electrodes are displayed in Fig.4, while Fig.5 exhibits the cooling response in different depth in cortex in the same time period. The simulation boundary is limited in 2mm, which is an usual cortex thickness of a rat. Results shows that needle type electrode achieves deeper and faster cooling response. Detailed in-vivo test is still undergoing.

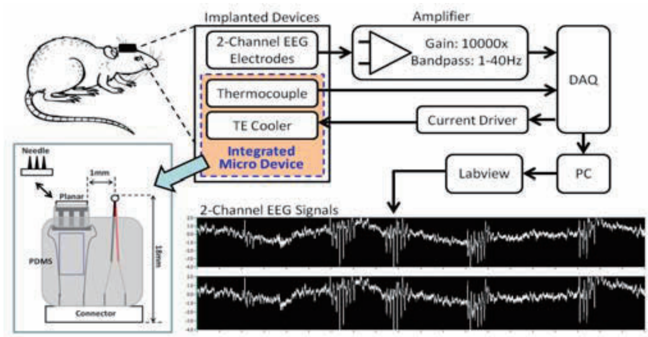

Figure 1. Brain cooling device and system for hypothermia therapy application. TE cooler and Thermal couple are packaged and implanted together with 2 channel EEG electrodes.

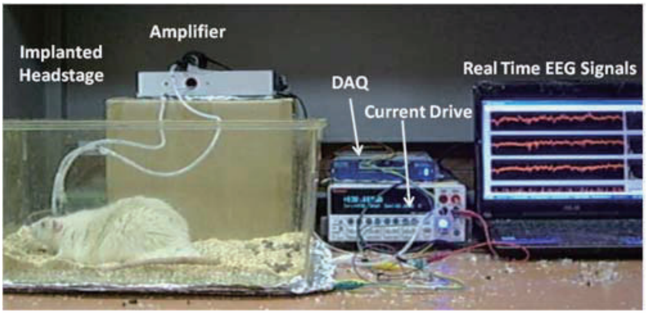

Figure 2. Practical experiment setup optical photograph. Note that the cooling device and EEG recording are tested under awake and freely moving status.

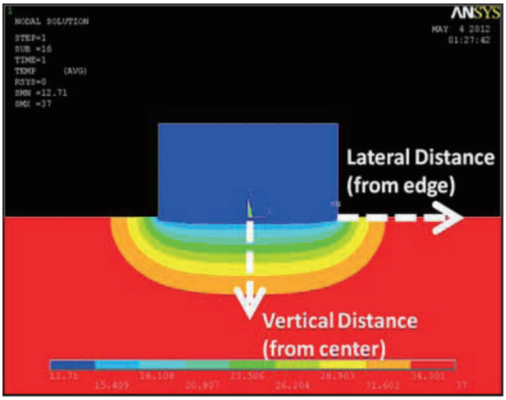

Figure 3. Simulation model of proposed TE-cooler. Both planar and needle type electrode are studied for temperature response.

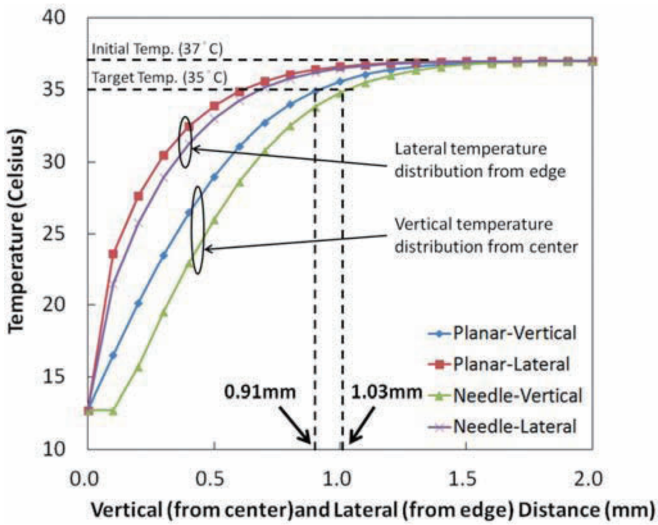

Figure 4. Comparison of the simulation result of lateral and vertical temperature distribution between planar and needle type electrodes.

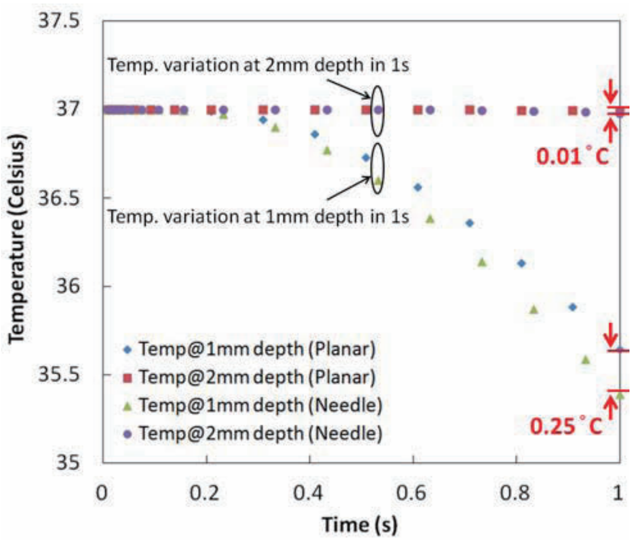

Figure 5. Comparison of the simulation result of effective cooling response at 1mm and 2mm of depth between planar and needle type electrodes.

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Cloud Computing Electrocardiographic System Using Xenon RF & GPRS Transmission Technique

Guo-She Lee[1] and Terry B.J. Kuo[2]

1. Faculty of Medicine, School of Medicine, National Yang-Ming University and Director of Department of Otorhinolaryngology, Taipei City Hospital, Taipei
2. Institute of Brain Science and Team for Developing Cloud Computing Health Care System, National Yang-Ming University

(e-Mail:gslee@ym.edu.tw)

Abstract — General electrocardiography (ECG) system tends to have several drawbacks so that it is difficult to apply an ECG system in home base. Here, we designed a home-based ECG system having the advantages of inexpensive equipment, cloud computing technique, and real-time monitoring. The hardware is smaller, portable, but sensitive. The ECG signals of a user can be transmitted and stored in a medical information cloud waiting to be monitored, retrieved and reviewd in world wide. And the signals can also be monitored by a server and the trained personnel in the call centers. The cloud computing ECG system can be used for every one at home and can significant reduced the risk of sudden cardiac accident and the mortality in the future.

Keywords — ECG, RF system, GPRS, internet

1. Introduction

General ECG system tends to have several drawbacks: first, it usually have to be performed and interpreted by a trained medical personnel in hospital; second, the ECG machine costs lots of money, and usually not available in our daily life. However, we here designed a home-based ECG system having several advantages: first of all, the equipment is inexpensive; second, the signals are cloud computed and stored; and the last, also the most important, the signals are real-time monitored. Our hardware is much smaller, portable, but sensitive. The ECG signals transmitted by the users will be stored in a medical information cloud. And the signals will also be monitored by a server and the trained personnel in the call centers.

2. Methods

Figure 1 is the scheme of our home-based ECG monitor system using GPRS network. There are many Xenon ECG sensors that can be used at home, every user has his personal sensor, and each sensor is coupled with a GPRS gateway. The sensor and gateway together is called a home-based unit. For using the system, the Xenon ECG sensor obtains the heartbeat signals and converts them to a digital format. Then the signals are transmitted to a GPRS gateway in a distance of less than 10 meters from the sensor. Second, the gateway would once again pass the signals to the GPRS network for further uploading to the internet. The coverage of GPRS network is usually national-wide, and even in rural area, the gateway can be attached to the network to transmit the ECG signals. After uploading the signals to GPRS network, the resources of internet can be easily reached, and the signals are relayed world-wide to a server and/or a call center that can be in any place of the world. The signals are accessible to the call center and the users themselves. Also, the signals are computed by a risk-evaluation-software. Once the signals show a high risk of disorder, the nurses or doctors in the call center will get a pop-up message and recheck the signals. Then the medical staff may contact the users, evaluate and make the proper actions for the users. If any consultation is necessary, the signals can be sent to another specialist using multimedia messaging service (MMS) of the mobile phone. An activation of emergent calling system can be done by the call center or the specialist if the users need emergent medical attentions.

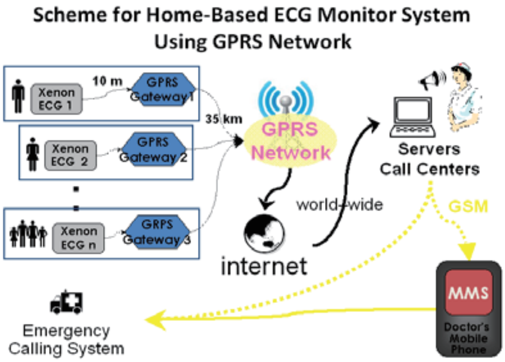
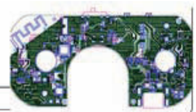


Figure 1.

The hardware design for Xenon ECG sensors is micro-controllers based. The 8051 MCUs are used as the control core because of low-power consumption and of low-cost on mass production. The weigh of sensor is less than 10 gram, the size is less than 6 by 4 by 1 centimeters (Figure 2). The sensor can be driven by a single 3-volt lithium battery. On stand-by, the power consumption is 8 micro-watt and the stand-by period can be as long as several months. On full-working, the power consumption is 4 milli-watt, and the working period is nearly 40 hours. The ECG sampling rate is adjustable from 250 Hz to 1 kHz. Figure 3 shows the ECG sensor and the electrodes. The electrodes can be fixed with the buttons on the sensor. Or the electrodes can be replaced using a specially designed belt. The belt has two patches of conductive fabric, and the belt is also washable to keep it clean and conductive.

Device Speciation



Weight (case not included)	8.9 g
Dimension	5.7 x 3.5 x 0.5 cm
Radio frequency	2.4 GHz
Power supply	3-V Lithium Battery (CR2032)
Continuous operation time	40 hours
Power consumption (full working)	≤4 mW
Power consumption (stand by)	8 μW (≥6 months standby)
RF range	10 m
ADC	16 bit
Sampling rate	250 ~ 1000 Hz
Signals	Electrocardiogram, HRV
Maximal node	Active 100, Sleep 65000

Figure 2.

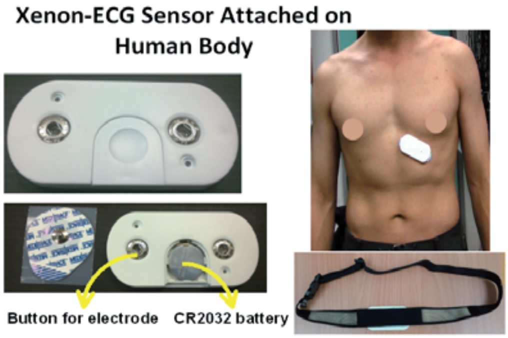


Figure 3.

The GPRS gateway (ETHCOM) was developed using the 8051 micro-controllers to receive the ECG signals from the sensors (Figure 4). The gateway transmits the signals to GPRS network. The Xenon receiver and the GPRS module is bound together on a mother board.

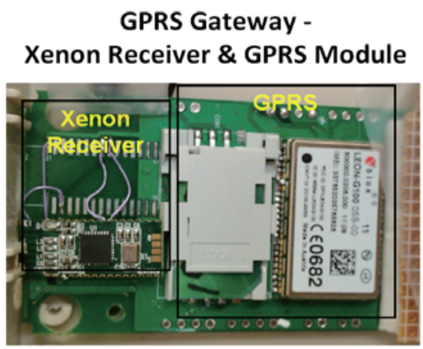


Figure 4.

3. Results

The Xeono and Ethcom Gateway ECG system was tested in a large scale in the Taipei 101 climb up racing 2011(Figure 4). There were over one hundred of participants taking part in this program. The runners had to climb stairs high up to the 84th floor. The height is close to 400 meters. Every participant wear a sensor on the chest to get the ECG signals. (Figure 5) (right half) shows the gateway box running for signal transmission and the monitoring program at the call center. Because the gateways can receive the signals only whthin a distance of 10 meters, a gateway was set at every 3 floors throughout the racing route. A total of about 30 gateways was set after all. The real-time heart rate, QRS width & amplitude of ECG waveform were all transmitted to the monitoring center (Figure 5 right most part)

Figure 5.

Another application of this system is illustrated in Figure 6 that showing the ECG signals of an user at his home. The signals are not real-time displayed, but can be recalled by the medical staff in the call center of a distant or a nearby hospital. The system can be integrated into the Health Information System of a hospital, and the doctors can easily check the past ECG records of the user.

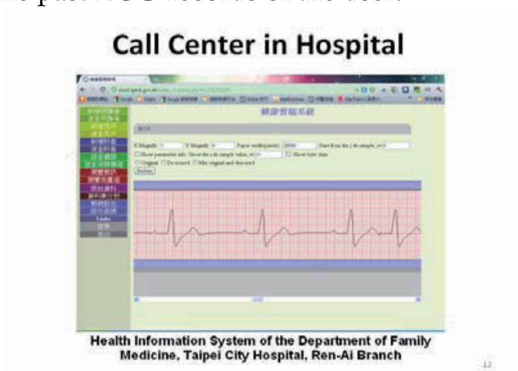
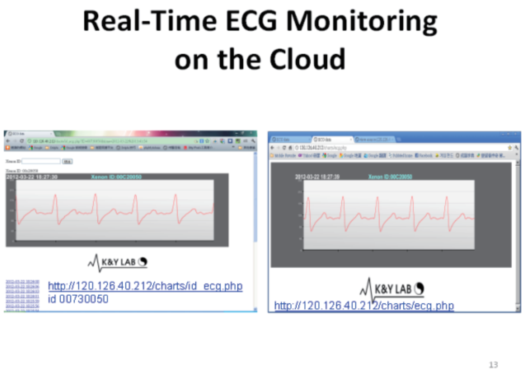


Figure 6.

Besides, the ECG signals can also be monitored in real-time and on the medical cloud computing system. An interavtive and webpage based link can be provided to the users and the medical staff to check the ECG in real time and also recall the ECG signals at any time and any place with the internet resource.



4. Conclusion

One of the most common killers for sudden death is cardiac arrest. However, if a prompt detection of arrythmia and an immediate CPR and defibrillation are done in 6 min, a victim can survive the cardica arrest at a very high survival rate of 60%. But if the detection and emergent emergent procedure are not done in that golden time, the outcome may be a disaster. There is a possibility to make the thing happen, and that is if a victim is monitored by a CLOUD COMPUTING ECG SYSTEM at home, he might get an early warning from a medical personnel and then the victim might have a chance to avoid a serious attack. The crucial twist for the man from "DEADWOOD" to "LIFE" will be the CLOUD COMPUTING ECG MONITORING SYSTEM.

HEALTH & TECHNOLOGY: Applications in Pediatric Medicine

Jeannie Huang

Department of Pediatrics, Division of Gastroenterology
University of California, School of Medicine

(e-Mail: jshuang@ucsd.edu)

Abstract — In recent years, healthcare is beginning to undergo a transformation that incorporates new technologies to improve quality and delivery of care. This is evident in the recent funding of healthcare electronic medical record systems in order to improve care via improved communications. This transformation also offers opportunities to regulate and provide new methods to deliver care via electronic systems. However, there are currently other technologies universally used by the public that offer additional potential arenas for health monitoring as well as intervention. In particular, the now ubiquitous use of mobile phones not only in the United States but in many countries, including China and India (Wikipedia, June, 2012), which currently top the list of cell phone users world wide. This ubiquitous use of mobile technologies allows for additional communications and sharing of information like never before.

Pediatrics is a unique field in medicine. It serves a population with a broad range of ages and developmental phases. For the very young, it is a field associated with care by proxy – both in regards to information obtained and information/care delivered. However, as youth mature, the by proxy nature of the relationship between the health professional and the patient should evolve and mature into an active and direct conversation between clinician and patient. The extent to which this happens depends on a number of factors including patient maturity, cognitive and developmental level and capability, parental withdrawal and ability to allow the evolution of this relationship, and clinical team awareness of these issues.

Because of this changing relationship over time, pediatric clinicians have learned to rely on not only self-report and by-proxy report, but also objective data to determine clinical status but also to identify clinical issues. In the past, this has been limited by data that can be collected via patient/parent interview and intermittent laboratory assessments. However, in the current age of medicine and health technologies, the potential to utilize technology tools in this process is promising. We discuss two of our projects to date that exemplify the potential for technology tools to collect data and deliver important health messages and intervention.

1.THE MORPHMED PROJECT

Reference to the following publication:

Huang JS, Becerra K, Golnari G, Fernandez S, Opalach A, Andres del Valle A. Digital facial image modification and its effects on body image and parental support for dietary and physical activity behaviors in children. J Pediatr 2009, 154: 74-8.

INTRODUCTION

Parental involvement and encouragement has been shown to be essential for children's adoption of healthy eating and physical activity behaviors [1, 2]. Crucial to parental involvement and readiness for action are parental recognition of overweight in their children and a heightened level of health concern for their overweight children [3].

Interventions to correct the weight perceptions of parents regarding their children have been deemed necessary [4] and yet difficult to develop owing to concerns of inducing psychological injury to children. Such concerns stem from the association between media portrayal of certain body types as ideal and body image dysphoria [5-6] and eating disturbances [7] among children, particularly among young girls. Others have voiced similar concerns regarding weight loss programs among children, although recent evidence suggests that these concerns may be overstated [8].

Formal evaluation of the effects of visual images on children's body image and on parental support for weight-related behavioral modification in their children was deemed necessary to perform to address these issues.

2.STUDY SUMMARY

The MorphMed study was a cross-sectional evaluation to determine the effects of facial image modification on weight and weight-related health perceptions among youth 10 to 17 years old and their parents. In particular, we examined the effect of the

MorphMed images on child participants' body image and on parents' support for their children's healthy dietary and physical activity behaviors. Our a priori hypothesis was that viewing MorphMed images would negatively impact children's body image but increase parents' support for their children's healthy dietary and physical activity behaviors.

3.METHODS

Study Performance

A convenience sample of eighty-one children 10 to 17 years old and their parents were recruited at local pediatricians' offices throughout the Greater San Diego area. Only one parent-child pair per family was recruited. Informed consent was obtained from parents and assent was obtained from children before study performance. All aspects of the study were reviewed and approved by the UCSD IRB.

The study was performed at the pediatricians' offices in a separate room. Parent participants answered surveys regarding support for their children's healthy dietary and physical activity behaviors, and child participants answered a body image survey. Child participants then had their faces photographed and images were uploaded into the MorphMed program created by Accenture Technology Labs (ATL). The MorphMed program altered facial photographs to realistically simulate varying degrees of weight gain and weight loss [Examples of digital alterations were provided in the slide show]. Both parents and children were then presented facial photographs of the child reflecting varying degrees of weight loss or gain (as well as their original photographs) and asked about their weight and weight-related health perceptions of each photograph. Subsequent to this computerized photograph survey, parents and children were then asked to again answer the same surveys on parental support and body image. Weight status was measured, calculated and categorized according to NCHS definitions [9, 10].

For additional details re: measures, please refer to the referenced published article above.

4.RESULTS

Eighty-one children and their parents participated. Demographic data were presented.

Preliminary analyses of participants' survey responses prior to exposure to MorphMed images revealed significant differences in body image and parental support to increase physical activity and to reduce sedentary activities according to sex and weight status.

Lower body image satisfaction scores were reported by girls and overweight children, as compared to category counterparts. In regards to parental support, parents reported providing more support to boys than girls to increase physical activity and reduce sedentary activities. Participant responses did not vary according to participant age, race or ethnicity.

Comparison analyses between body image survey answers prior to and after child participants viewed MorphMed-altered images of themselves demonstrated no significant differences in scores. Comparison analyses between parental support survey answers prior to and after parents viewed weight-altered images of their children demonstrated significant increases in parental support for their children to perform physical activities, reduce sedentary habits, and increase intake of fruits and vegetables. Of note, parental support increased significantly more among parents of AROW and OW children as compared to parents of normal weight children.

5.DISCUSSION

In this study, we demonstrate that image technology may be useful as a motivator for parental support for weight-related behavioral change among children without associated negative effects on children's body image. Parental support increased for all weight-related health behaviors after parental viewing of MorphMed photographs, and particularly for the intended group of overweight children.

Our finding that altering facial images to reflect various weight states does not increase body or facial image dysphoria among children is reassuring and supports the use of such images in future pediatric obesity interventions to increase parental support. Exposure to the MorphMed photographs did not increase body image dysphoria.

The findings of this study are subject to a number of limitations. First, participants were only exposed to facial photographs. Second, we did include a wide age range of children in our study and thus a range of cognitive and social development. Lastly, our study assessed the effect of digital facial images on body image and parental support in the immediate post-exposure period. Further study will be required to determine whether documented increases in parental support are enduring and result in real behavioral change.

In summary, we demonstrate improved parental support for weight-related health behaviors without adverse effects on body or facial image among children after parent and child exposure to weight-altered facial photographs of participating children. These results suggest that image technology may enhance parent participation in and promotion of family-oriented behavioral interventions targeting healthy weight among children that promote physical activity, reduce sedentary behaviors, and improve diet. Our results also suggest that exposure to weight-related images as part of a weight management program may be safely undertaken among children and their families without adverse psychological consequences in the short-term.

A Technology Intervention on Disease Self-Management and Self Advocacy among Adolescents with Chronic Disease

Huang JS, Gottschalk M, Pian M, Dillon L, Norman G, Bartholomew LK.
Effects of a Technology Intervention on Disease Self-Management and Self Advocacy among Adolescents with Chronic Disease. Pediatric Academic Societies Annual Meeting, Boston, MA. April, 2012. E-PAS2012: 3550.2
.
(e-Mail: jshuang@ucsd.edu)

1. Introduction

Adolescents with chronic disease have been identified as a particularly vulnerable population at youth [1]. Data to date have demonstrated poor health and psychosocial outcomes in this at-risk population. Transition is the purposeful, planned transfer of adolescents with chronic and medical conditions from child-centered to adult-oriented health care systems. The Institute of Medicine (IOM) describes the health care transition for children with chronic disease from pediatric to adult health care services as crucial to future health care outcomes [1]. Healthy People 2020 lists transition planning as a major objective for youth with special health care needs [2]. However, data to date suggest that there remain notable deficits in the transition experience for many adolescents with chronic disease [3].

Common objectives among transition guidelines are to inform young patients adequately regarding their illness and for these patients to obtain skills to manage their condition independently [12]. In order to achieve these goals, adequate health literacy, defined by the U.S. Department of Health and Human Services as the patient being able "to obtain, process, and understand basic health information and services to make appropriate health decisions" [10], is required. Currently, there are no standardized programs provided to adolescents with chronic disease that can be easily distributed across clinical sites. The widespread use of technology among youth provides a potentially important distribution modality for transition-based programs for youth with chronic disease.

2.STUDY SUMMARY

We developed a theory-based, technology intervention, MD2Me, to improve disease self-management (DSM) skills and patient self-advocacy (PSA). MD2Me was designed as an intensive, 2-mo intervention during which DSM skills (self-monitoring and self-care) and PSA (active role in health) are promoted via a web and SMS curriculum. We hypothesized that adolescents with chronic disease exposed to our intervention would improve their disease self-management skills and patient self-advocacy.

3.METHODS

Study Performance

Eighty-one adolescents age 12-24 with inflammatory bowel disease, cystic fibrosis, or Type 1 diabetes were recruited from subspecialty clinics at a tertiary-care pediatric center in San Diego and randomized into either the treatment or control group. Randomization to treatment and control groups was stratified by disease. Health literacy, DSM, and PSA assessments using validated measures were performed at baseline and 2 months.

4.RESULTS

Randomization groups (treatment N=40; control N=41) did not differ by age ($p=0.97$), gender ($p=0.57$), racioethnicity ($p=0.73$), or literacy level ($p=0.85$). Repeated measures analyses using all available data from baseline and 2 months indicated a significant treatment effect (group x time) on DSM ($p=0.01$) and PSA ($p<0.01$). Health literacy did not significantly change by group over the study period but did appear to affect improvements in PSA in the active treatment group.

5.DISCUSSION/CONCLUSION

We demonstrate improvements in DSM and PSA among adolescents with chronic disease who received a technology-based chronic disease management intervention. These improvements validate the capability of currently available technologies to improve health via intervention among vulnerable clinical populations. Further study is needed to determine whether such effects are durable.

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Lecture Notes on Wireless Healthcare Research

作　　者／Kevin Patrick and Mu-Chun Su

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wingip@astro.ncu.edu.tw

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