34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

Adaptive Cancellation of Motion Artifact in Wearable Biosensors

Rasoul Yousefi, Mehrdad Nourani, Issa Panahi
Quality of Life Technology Laboratory
The University of Texas at Dallas, Richardson, TX 75080
{r.yousefi,nourani,issa.panahi}@utdallas.edu

ABSTRACT

The performance of wearable biosensors is highly influenced by motion artifact. In this paper, a model is proposed for analysis of motion artifact in wearable photoplethysmography (PPG) sensors. Using this model, we proposed a robust real-time technique to estimate fundamental frequency and generate a noise reference signal. A Least Mean Square (LMS) adaptive noise canceler is then designed and validated using our synthetic noise generator. The analysis and results on proposed technique for noise cancellation shows promising performance.

I. INTRODUCTION

Wearable biosensors have the potential to become the center piece in healthcare technology by offering their capabilities for low-cost, pervasive and long term biosignal monitoring [1]. Wearable Biomedical Sensors and Systems (WBSS) are gaining momentum in both academia and industry. IEEE EMBS founded a technical committee on this topic in 2004. This committee has defined and characterized sensing of biomedical signals as a core function of a WBSS [2]. Extensive research on the topic has so far shown that signal integrity (quality) is one of the most important challenges in technical design of a wearable sensor system [3]. Photoplethysmography (PPG) biosensors is one of the main sensors with many applications in monitoring, diagnosis and assessment. The signal quality is specifically critical for wearable PPG-based systems [4]. PPG is a signal obtained by an optical sensor consisting of an emitting LED and a receiving photodiode. Briefly, a light is emitted towards blood vessels and the optical density received by photodiode reflects change of blood flow.

Despite various applications and proper form factor for wearable applications, PPG signal is highly susceptible to motion [5]. Overcoming motion artifacts presents one of the most challenging problems. One of the commonly used methods is adaptive noise cancellation using accelerometers as a noise reference signal [6][7]. A two-dimensional adaptive noise cancellation has been tried using the directional accelerometer data for finger PPG sensor [8]. Addition of a reflectance PPG sensor as the reference signal is also implemented in [4] but the reflectance PPG sensor is also susceptible to motion. The main drawback is addition of another extra hardware for the noise reference. Additionally, using 3-axis accelerometer data is computationally intensive [4] and they reflect motion (as opposed to noise). There is no direct and high correlation between acceleration data from accelerometer and motion artifact in PPG signal [9].

Our contribution in this paper is multifold. First, we have proposed a model for PPG signal and analyzed the effect of motion artifact on PPG signal using this model. Second, we have designed a motion-tolerant fundamental frequency estimator using special windowing approach. Third, we have proposed a synthetic noise generator using estimated fundamental frequency and designed an LMS adaptive noise canceler to extract PPG signal. Unlike other methods, estimation of the fundamental frequency and extraction of the PPG signal are all done by signal processing software. No extra hardware such as accelerometers or other reference vital sign sensor has been used in our approach. The proposed real-time adaptive noise canceler shows promising performance for extracting PPG signal. The developed model and fundamental frequency estimator, can serve as a preprocessing stage for signal enhancement techniques. Such techniques can effectively reduce motion noise and ultimately improve morphological features extracted from wearable sensors.
The remaining of this paper is organized as follows. In Section II, we propose a model for PPG signal production and motion artifact. Using this model, a robust technique is proposed to extract fundamental frequency in the presence of motion artifact in Section III. In Section IV, a synthetic noise reference generator and an adaptive noise canceler are explained to reduce motion artifact in PPG signal. Simulation results in Section V validate the advantages of our method. Finally, Section VI contains the concluding remarks.

II. PPG MODEL AND MOTION ARTIFACT

Inspired by speech processing research and technology, we have developed a model and a processing algorithm to reduce motion artifact on a PPG sensor system. This model enables us to characterize relation between PPG and motion artifact. Moreover, we will build an experimental platform to measure/reduce the effect of motion and test bench noise reduction techniques and tune their parameters. Here, we first introduce the model for PPG signal and then do experimentation with and without motion to see how motion artifact affects extraction and estimation of model parameters.

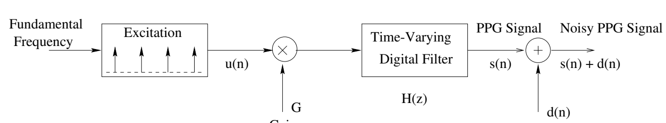

Figure 1. Proposed PPG model for characterization and experimentation.

As shown in Figure 1, PPG signal is modeled and generated with two key elements, i.e., a linear time-varying digital filter and an excitation unit. PPG signal is produced using the following equation:

$$s(n) = Gu(n) + \sum_{k=1}^{p} a_k s(n-k) \tag{1}$$

where $s(n)$ is the PPG signal, G is the gain factor, $u(n)$ is a pulse train and a_k's are coefficients of time-varying digital filter of order p with z-domain transfer function of:

$$H(z) = \frac{S(z)}{G\,U(z)} = \frac{1}{1-\sum_{k=1}^{p} a_k z^{-k}} \tag{2}$$

The fundamental frequency, f_0, is defined as the lowest frequency of a periodic vital sign estimating the heart rate. PPG signal, $s(n)$, is modeled as output of a linear time-varying digital filter which is excited by a pulse input. Noise input $d(n)$ also represents noise due to motion artifact.

A. Linear Time-Varying Digital Filter

Linear time-varying digital filter in this model is an all-pole filter and the location of the poles determines system behavior over time. Figure 2 shows frequency domain representation of a sample stream of PPG signal collected using our finger PPG sensor with sampling frequency of 250 Hz. F1, F2 and F3 determine location of poles in all-pole model. F1, F2 and F3 are the frequencies where concentration of energy is high in wide-band spectrogram. Figure 2 shows the spectrogram of PPG signal and the location of F1, F2 and F3 over time when there is no motion of the hand.

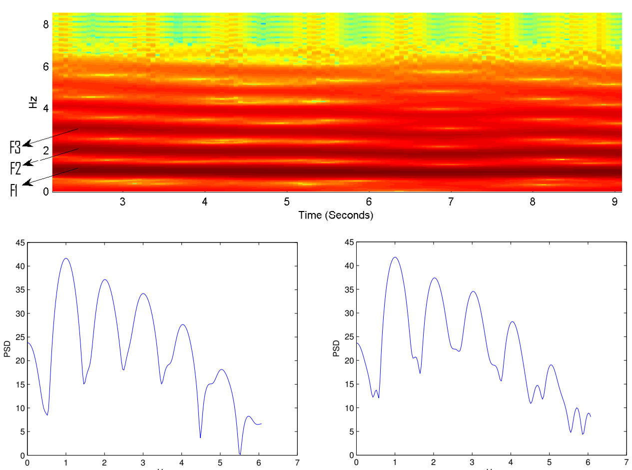

Figure 2. (Upper) Spectrogram of the clean PPG signal without motion (Lower left) Spectrum of clean PPG signal at t = 4 Sec (Lower right) Spectrum of the clean PPG at t = 8 Sec

Figure 3 shows the spectrogram of PPG signal and the location of F1, F2 and F3 for the left-right motion of the hand of wearer. Excitation unit produces a series of harmonics, those whose frequency is close to poles representing F1, F2 and F3 pass through the filter and creates these patterns showing high concentration of energy.

The locations of F1, F2 and F3, containing main component of the signal energy, can be clearly seen in Figure 2. In Figure 3, we can fairly observe location of F1, F2 and F3 but there are also new components due to motion artifact. Comparing these

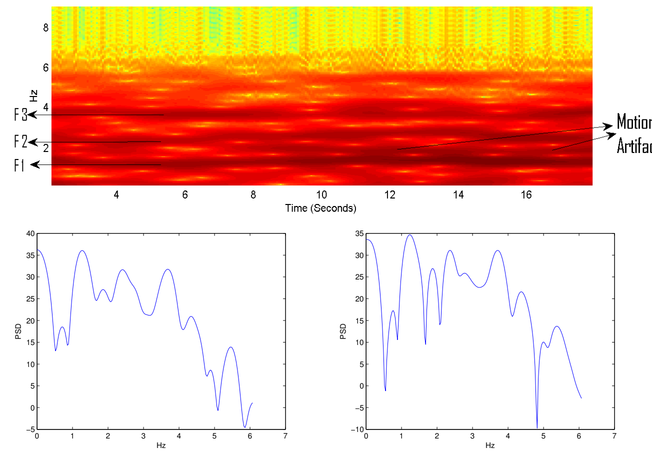

Figure 3. (Upper) Spectrogram of the noisy (motion corrupted) PPG signal (Lower left) Spectrum of the noisy PPG signal at t = 4 Sec (Lower right) Spectrum of the noisy PPG at t = 8 Sec

two scenarios leads us to the potential benefit of application of an *adaptive comb filter* [10] keeping energy concentrated harmonics and reducing motion artifact component of Figure 3. Another observation here is that separating noise components of Figure 3, using an adaptive comb filter, from the main signal is useful in generation of a synthetic noise reference which is correlated to the motion artifact of the corrupted PPG signal. This is the principle behind synthetic noise generator proposed in this paper and to be described in Section IV.

B. Excitation Unit

The excitation unit generates a pulse train using fundamental frequency which changes in a limited range over time (i.e. typical human heart rate). A p-th order linear predictor estimates $s(n)$ in a system of the form:

$$\tilde{s}(n) = \sum_{k=1}^{p} \alpha_k s(n-k). \tag{3}$$

The difference between actual PPG signal and the predicted sequence defined by $e(n) = s(n) - \tilde{s}(n)$ is the output of a system with transfer function of:

$$A(z) = \frac{E(z)}{S(z)} = 1 - \sum_{k=1}^{p} \alpha_k z^{-k} \tag{4}$$

called residual error signal. Defining $H(z)$ to be an inverse filter for $A(z)$, the output of the all-pole filter, $H(z)$, to approximated residual signal is an approximation of the true PPG signal.

Motion artifact may significantly change shape of the signal. New excitation pulses are also generated in the residual error signal and consequently in the excitation signal. This fact limits application of conventional techniques such as Average Magnitude Difference Function (AMDF) [11], signal correlation in time domain or other peak searching techniques in time domain for estimation of fundamental frequency. To overcome these limitations, we have designed a novel real-time algorithm for fundamental frequency estimation.

III. Fundamental Frequency Estimation

The autocorrelation function $C(P)$ preserves periodicity information of the input signal and it can be expressed as:

$$C(P) = \frac{1}{N} \sum_{n=0}^{N-1} s(n)s(n+P) \tag{5}$$

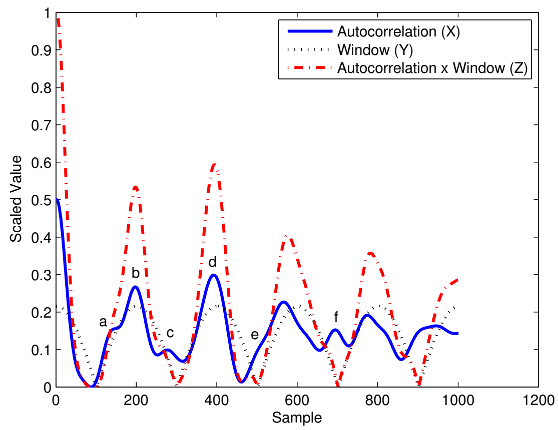

Figure 4. Example of autocorrelation and windowing.

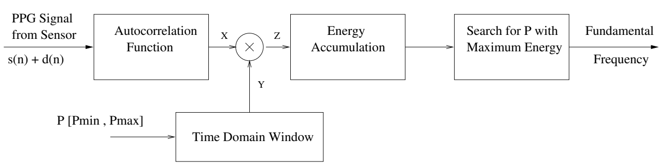

Figure 5. Real-time fundamental frequency estimator.

where $s(n)$ denotes PPG signal from sensor, P is lag value and n is discrete time. When $s(n)$ is similar to $s(n+P)$, $C(P)$ will have a large value. If $s(n)$ is periodic with period P_0, $C(P)$ has local peaks at P_0 and integer multiples of P_0. Location of the peak value at P_0 is an estimation of the fundamental frequency since $P_0 = \frac{F_s}{f_0}$ where F_s is the sampling frequency.
As shown in autocorrelation function of sample motion corrupted PPG signal in Figure 4, there are cases where the peak at $2P_0$ is larger than peak at P_0, or there are peaks corresponding to P's less than P_0 (e.g. point d and a). Also, there might be other peaks such as points labeled c, e and f due to motion artifact. So, in the presence of the motion artifact, autocorrelation function may not provide a robust estimation of fundamental frequency. The maximum likelihood method used for pitch detection in speech signals [12] works well when the signal is noisy. Adopting this technique from speech processing, we have developed a novel fundamental frequency estimator for wearable biosensors shown in Figure 5.

The three key steps involved in this technique are:

(1) The autocorrelation of PPG signal is computed (e.g. 1000 data samples sampled at 250 Hz), i.e. point X in Figure 5.
(2) For each P in the limited range of the period, a special window is generated (e.g. 10 window for 1000 data samples corresponding to 0.7 Hz to 1.9 Hz), i.e. point Y in Figure 5. Windows are multiplied with autocorrelation function in time domain. One sample shaped autocorrelation function and window can be seen in Figure 4.
(3) Step (2) results new modified autocorrelation function for each window in point Z in Figure 5. For all modified autocorrelations, summation of the autocorrelation function is computed and the window passing maximum energy defines period and thus fundamental frequency.

Since This technique searches the window passing maximum energy instead of searching for peaks in the autocorrelation function, this technique shows promising performance in noisy environment of wearable sensors. Different window types can be designed and optimized for PPG signal in the presence of motion artifact. In this paper, we have used a window whose shape in time domain is frequency spectrum of a comb filter. In the frequency domain, this window is a train of pulse with fundamental frequency f_w which reduces the leakage from motion noise components. Proposed technique in frequency domain can be interpreted as finding f_w such that maximum correlation exists between spectrum of the window and spectrum of PPG signal.

IV. Noise Reduction Using Synthetic Noise Reference

Adaptive filter and in particular Least Mean Square (LMS) adaptive filter has been used with accelerometers to reduce motion artifact in PPG signals [6][7]. Adaptive filters work based on the self adjusting of the their coefficients using an adaptive algorithm to minimize error cost function. As shown in Figure 6, the LMS algorithm requires a primary input signal, i.e. $s(n)+d(n)$, and a secondary reference noise source $g(n)$. Primary input signal contains the PPG signal corrupted by additive motion noise and the secondary noise source is correlated with the motion noise. The adaptive filter produces an estimate of the noise which is subtracted from the primary noisy signal to reduce the noise level. Researchers have used an extra hardware such as accelerometers to generate the noise reference signal [6][7]. Also, in [13] a synthetic noise reference is generated using concurrent usage of Singular Value Decomposition (SVD), Independent Component Analysis (ICA) and Fast Fourier Transform (FFT) methods.
To avoid using extra hardware for reference noise, we capitalize the estimated parameter of PPG model of Figure 1, fundamental frequency, to implement a novel noise reference generator. The quasi-periodic behavior of PPG signal leads to harmonic structure in magnitude spectrum of the PPG signal. Comb filters can be designed to have large values at the specified fundamental frequency of the signal, f_0 and its harmonics, and low values between them. The complement of this comb filter can be used to pass motion artifact of Figure 3, and reject signal component, $s(n)$. Different comb filters [10] [14] are investigated and the comb filter with transfer function $(1-z^{-P_0})/2$ where $P_0 = \frac{Fs}{f_0}$ performs well in generating a noise reference signal. The generated noise reference, $g(n)$ in Figure 6, is highly correlated with motion artifact. This transfer function is implemented with a time-domain shift and summation and despite its simple structure shows superior performance. Figure 6 depicts real-time algorithm developed for adaptive noise cancellation using generated synthetic noise reference based on the fundamental frequency.

The fundamental frequency estimator tracks fundamental frequency over time. Synthetic noise generator basically accepts current fundamental frequency and generates a noise reference using transfer function $(1-z^{-P_0})/2$. LMS algorithm minimizes output error to obtain the best estimation, $\hat{d}(n)$, of the true noise $d(n)$. Estimation of the true noise, $\hat{d}(n)$, and $d(n)$

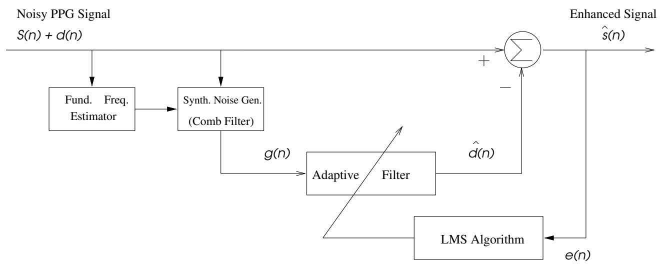

Figure 6. Proposed adaptive noise canceler using synthetic noise reference.

effectively cancel each other out. The proposed noise generator is by far more computationally efficient than concurrent usage of SVD, ICA and FFT and switching between outputs of these processing blocks as reported in literature [13].

V. Experimental Results

To evaluate our real-time fundamental frequency estimator, corrupted and noisy PPG signal named a44091c dataset from MIT MIMIC II waveform database [15] is used. The sampling frequency of this database is 125Hz and total number of simulated samples is 360000, 48 minutes of data gathered from an Intensive Care Unit (ICU) monitor. Figure 7 shows a small portion (72 sec) of noisy signal of this database. This sample of data includes noise-free segment (approximately $t = 18$ to $t = 30$ sec) and noisy part ($t = 50$ to $t = 72$ sec). Figure 8 shows raw PPG signal, extracted fundamental frequency using our real-time fundamental frequency estimator and autocorrelation method. Note that, in autocorrelation technique, the corresponding autocorrelation function is computed and a peak searching is used to find the fundamental frequency between 0.6 Hz and 3.3 Hz. In this experiment 2000 data samples are used for computation of autocorrelation. The heart rate is almost stable and the fundamental frequency is around 1 Hz as it can be visually confirmed in Figure 7. As we discussed earlier, the autocorrelation function does not provide a robust estimation of fundamental frequency. Some of erroneous outputs are marked by "*" on bottom plot in Figure 8. The result of our estimator is shown in middle plot of Figure 8. It can be seen that our estimator has no error providing a robust estimation of the fundamental frequency.

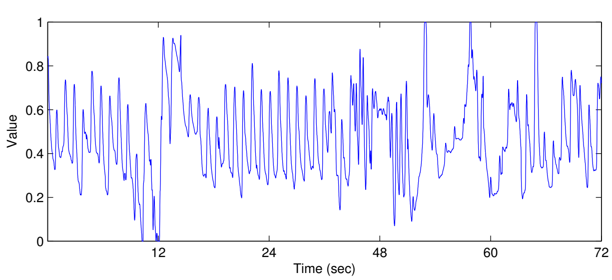

Figure 7. Portion of noisy and corrupted PPG signal in "a44091c".

A data collection platform is developed using a finger probe with Red LED and Infrared LED working on 660nm and 895nm, respectively. Analog conditioning circuit limits bandwidth of the signal to 70 Hz and it is acquired with sampling rate of 250 using TMS320C5515 Evaluation Module

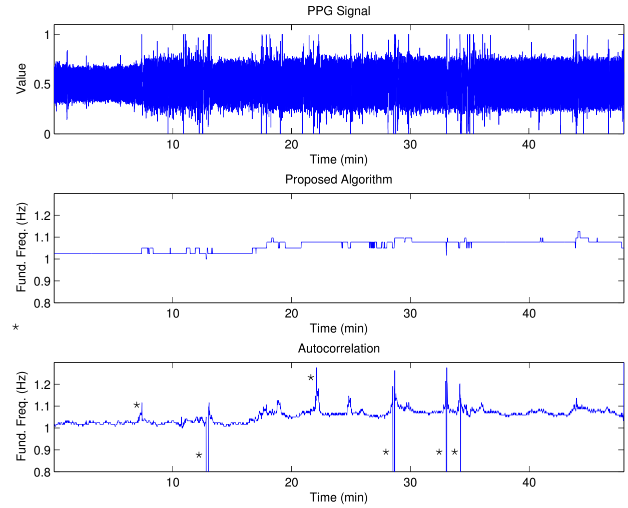

Figure 8. Simulation of fundamental frequency estimator on PPG signal from MIT MIMIC II database.

by Texas Instrument [16]. FIR hamming window low-pass filter with cutoff frequency at 10 Hz attenuates the unwanted signals.

To validate proposed methods on real data, PPG signal from user with different motions is collected for 12 minutes as shown in Figure 9. This data includes clean data without motion (No Motion), vertical movement of the hand (UP-Down Motion), horizontal movement of the hand (Left-Right Motion), bending of the finger (Bending) and walking. Movements have different accelerations and variations within each segment. 2500 samples of data is used for computation of autocorrelation function in both autocorrelation and our proposed algorithm and results are shown in Figure 9. The proposed method shows superior and robust performance compared to autocorrelation function in which many errors have occurred (see bottom plot in Figure 9) during bending of the finger and walking.

Figure 10 and 11 show a portion of results on collected

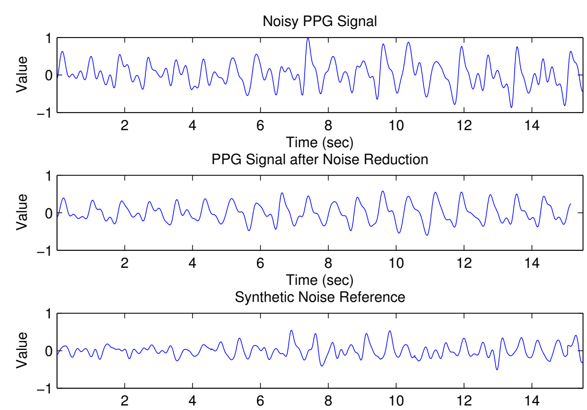

Figure 10. Noise reduction in PPG signals.

data of Figure 9 during left-right movement of the hand. Figure 10 shows motion corrupted PPG signal, improved PPG signal, $\hat{s}(n)$, at the output of adaptive filter and synthetic noise reference in time domain. Spectrum of motion corrupted PPG signal, improved PPG signal and synthetic noise reference is

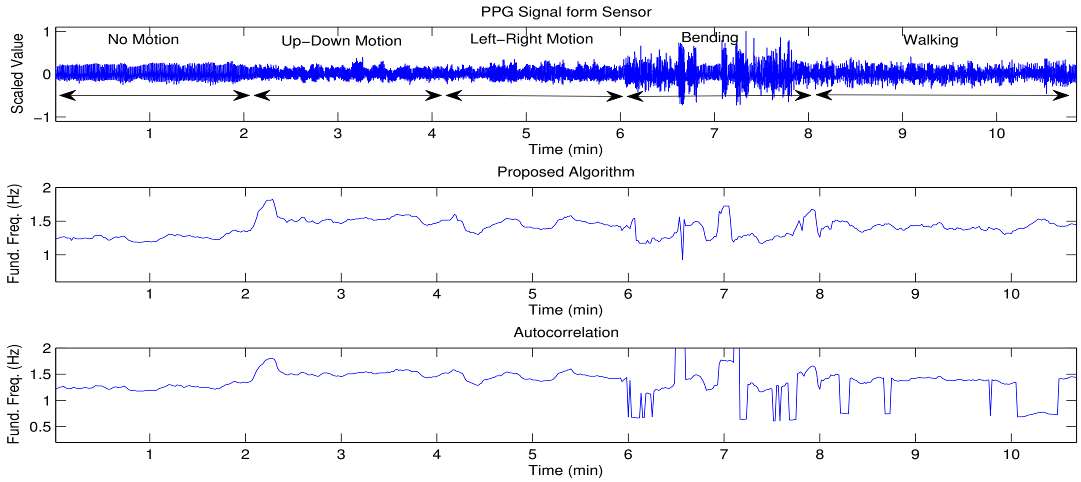

Figure 9. Simulation of fundamental frequency estimator on data from finger sensor.

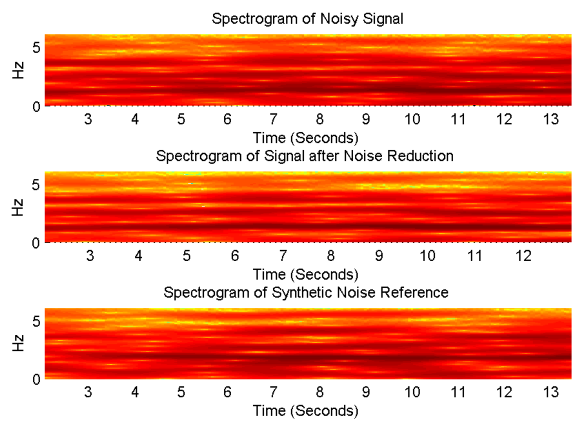

Figure 11. Spectrogram of noisy signal, enhanced signal and synthetic noise reference.

shown in Figure 11. As shown, motion artifact components are picked up by comb filter and the adaptive LMS filter significantly improves the signal spectrogram by reducing noise components of the spectrogram. Normalized LMS adaptive filter of order 20 is used in this experiment.

VI. Conclusion

We have studied the effect of motion artifact on the proposed PPG model for wearable PPG sensors. An algorithm is developed for robust estimation of the fundamental frequency using motion corrupted PPG signal. This parameter is used to generate a synthetic noise reference for adaptive noise cancellation of motion artifact. The proposed real-time adaptive noise canceler is validated through extensive experimentations that show promising performance eliminating the need for extra hardware such as accelerometer for reference noise.

References

[1] M.Z. Poh, N.C. Swenson, R.W. Picard, "Motion-Tolerant Magnetic Earring Sensor and Wireless Earpiece for Wearable Photoplethysmography," *IEEE Trans. on Information Technology in Biomedicine*, vol. 14, no. 3, pp. 786-794, May 2010.

[2] P. Bonato, D. De Rossi, A. Dittmar, S. Jayaraman, I. Korhonen, A. Lymberis, E. Mc Adams, Y. Zhang, "IEEE EMBS Technical Committee on Wearable Biomedical Sensors and Systems: Position Paper," BSN, pp. 212-214, 2006.

[3] http://tc-wearable-sensors.embs.org/index.html

[4] H.H. Asada, P. Shaltis, A. Reisner, S. Rhee, R.C. Hutchinson, "Mobile monitoring with wearable photoplethysmographic biosensors," *IEEE Engineering in Medicine and Biology Magazine*, vol. 22, no. 3, pp. 28-40, May-June 2003.

[5] S. Rhee, B.H. Yang, H.H. Asada, "Artifact-resistant power-efficient design of finger-ring plethysmographic sensors," *IEEE Trans. Biomed. Eng.*, vol. 48, no. 7, pp. 795-805, July 2001.

[6] L.B. Wood and H. Asada, "Low variance adaptive filter for cancelling motion artifact in wearable photoplethysmogram sensor signals," in Proc.Conf. IEEE Eng. Med. Biol. Soc., pp. 652-655, 2007.

[7] S.H. Kim, D.W. Ryoo, C. Bae, "Adaptive noise cancellation using accelerometers for the PPG signal from forehead," in Proc. Conf. IEEE Eng. Med. Biol. Soc., pp. 2564-2567, 2007.

[8] H. Han, M.J. Kim, J. Kim, "Development of real-time motion artifact reduction algorithm for a wearable photoplethysmography," in Proc. Conf. IEEE Eng. Med. Biol. Soc., pp. 1538-1541, 2007.

[9] H.H. Asada, H. Jiang, and P. Gibbs, "Active noise cancellation using MEMS accelerometers for motion-tolerant wearable biosensors," in Proc. Conf. IEEE. Eng. Med. Biol. Soc., vol. 1, pp. 2157-2160, 2004.

[10] N.I. Cho, S.U. Lee, "Tracking analysis of an adaptive lattice notch filter," *IEEE Trans. on Circuits and Systems - II: Analog and Digital Signal Processing*, vol. 42, no.3, pp. 186-195, Mar. 1995.

[11] M.J. Ross, H.L. Shaffer, A. Cohen, R. Freudberg, H.J. Manley, "Average magnitude difference function pitch extractor," *IEEE Trans. Acoust, Speech, Signal Process.*, vol. 22, no. 5, pp. 353-362, Oct. 1974.

[12] J.D. Wise, J.R. Caprio, T.W. Parks, "Maximum likelihood pitch estimation," *IEEE Trans. Acoust., Speech, Signal Processing*, vol. 24, pp. 418-423, Oct. 1976.

[13] M.R. Ram, K.V. Madhav, E.H. Krishna, N.R. Komalla, K.A. Reddy, "A Novel Approach for Motion Artifact Reduction in PPG Signals Based on AS-LMS Adaptive Filter," *IEEE Trans. on Instrumentation and Measurement*, pp. 1-13, 2011.

[14] S. Elliott, P. Darlington, "Adaptive cancellation of periodic, synchronously sampled interference," *IEEE Trans. on Acoustics, Speech and Signal Processing*, vol. 33, no.3, pp. 715-717, Jun 1985.

[15] G.B. Moody, R.G. Mark, A.L. Goldberger, "PhysioNet: a Web-based resource for the study of physiologic signals," *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 3, pp. 70-75, May-June 2001.

[16] http://www.ti.com/tool/tmdxevm5515.