A Smart Bed Platform for Monitoring & Ulcer Prevention

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***Abstract*— The focus of this paper is to develop a software-hardware platform that addresses one of the most costly, acute health conditions, pressure ulcers - or bed sores. Caring for pressure ulcers is extremely costly, increases the length of hospital stays and is very labor intensive. The proposed platform collects information from various sensors incorporated into the bed, analyzes the data to create a time-stamped, whole-body pressure distribution map, and commands the bed's actuators to periodically adjust its surface profile to redistribute pressure over the entire body. These capabilities are combined to form a cognitive support system, that augments the ability of a care giver, allowing them to provide better care to more patients in less time. For proof of concept, we have implemented algorithms and architectures that cover four key aspects of this platform: 1) data collection, 2) modeling & profiling, 3) machine learning, and 4) acting.**

I. Introduction

A. Motivation

Pressure ulcers (PUs) usually develop over a bony prominence as a result of pressure, or pressure in combination with shear stress and/or friction. Additional contributing factors include immobilization and malnourishment [1]. Groups known to have a high risk of developing PUs include bedridden patients, wheelchair-bound individuals, frail elderly persons [2] with no or limited mobility, as well as individuals with diabetes, poor nutrition, and chronic blood-flow diseases [3].

Pressure ulcers represent an enormous burden on our health care system and an enormous problem for health care providers [4]. In 1990, a large epidemiologic study reported that the 1-year incidence of PU development in nursing homes was 13.2%; a systematic review reported that in U.S. the prevalence ranged from 7% to 23% [5]. In hospitalized patients, the prevalence ranges from about 3% to 11% (approximately 1.5-3.0 million patients in the United States). Pressure ulcers result in both an increased length of hospital stay and increased hospital costs [6]. The current cost to our health care system resulting from PUs is more than $1.2 billion annually [7]. Once developed, PUs represent an acute health condition that results in increased costs and suffering over many months and even years. Effective ulcer prevention and early detection will greatly reduce patient suffering/discomfort.

B. Background and State of the Art

The current approach used to identify PUs relies on health care workers, primarily nurses. Diagnosis is made through a combination of actions. At the time of hospital admission, a physical examination is conducted and a medical history is taken, with a focus on physical and mental problems such as incontinence or confusion. The Braden Scale [8], which has been identified as the most reliable and valid tool for predicting ulcer risk, is used by nurses to assess the patient's risk of bed sores. Clinicians observe the patient's skin on a regular schedule to identify any discolorations or warmth indicating potential skin breakdown. Unfortunately, underlying tissue can be compromised by the time the skin actually opens. Additional concerns include the location of the bed sore, mobility, shearing, and the potential for exposure of the PU to urine or feces because of incontinence. Early detection of any compromised skin area is the first and the most important step to preventing an open sore [9]. However, because of higher patient acuity and increasing demands on nurses [10], it is difficult, if not impossible, for health care personnel to check their patients' skin several times throughout the day.

There are several hospital beds which perform various functions to assist in the care and prevention of pressure ulcers. The proposed bed is the first to provide a holistic solution to pressure ulcer care and prevention that address the four key aspects: data collection, learning, reasoning & deciding, and acting. Providing support for the hospital staff in all of these areas allows the bed to truly amplify their abilities such that they can be more efficient, and successful in caring for patients, especially with regard to pressure ulcers. The investigators have not found an existing or a research hospital bed that follows the proposed approach towards system design.

Various sensors have been used to record different signals but there is some research that goes further such as body pressure image, respiration rate, heart rate and even blood pressure information in a non-invasive manner [11]. A signal processing unit is often needed to extract the desired information.

Several attempts have been made to develop hardware and control of hospital beds for pressure ulcer prevention, including passive and active approaches. These include low air loss mattresses which showed some improvement over standard mattresses [12]. Also the DeCube mattresses have been shown to somewhat prevent the occurrence and accelerate healing of pressure ulcers [13]. However, there is no record as to why they are not currently used. Several other technologies were studied such as alternating pressure mattresses, air fluidized beds, and mechanically assistive beds. A review of these passive technologies mentioned shows that their actual benefits were unclear and inconclusive [14]. The one clinically proven method for preventing pressure ulcers is to turn the patient frequently, which none of these mattresses can do [15].

The mechanical solutions, including those offered by Hill-

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Rom, as well as other manufacturers, offer several assistive solutions, but none actually turn the patient. Another approach is the IANSiS bed, developed at the University of Wisconsin [16], comprised of 5724 plastic, pneumatically actuated, pins with a small head diameter of 15.6 mm. The drawback of this approach is that pins close together can apply very different forces which can increase shear forces in the skin. Still, none of these beds can provide the large rotations involved in turning, or achieve the same effect by other means. The proposed bed can achieve the pressure distributions associated with turning the patient using a lesser, although significant, amount of rotational motion than manual turning.

C. Key Contribution and Paper Organization

In this paper, we present implementation of a proof-of-concept platform for pressure ulcer monitoring and prevention. This platform has combined four key aspects of a support system, i.e. data collection, modeling, machine learning, and acting. Our platform has been successfully tested using pre-recorded data and favorable performance and accuracy have been observed. Due to lack of space, our discussion will be limited to the system level. The details of these algorithms are beyond the scope of this paper and will be reported in future publications.

The remaining part of this paper is organized as follows: Section II explains the four main units of the smart bed platform. Experimental results are outlined in Section III. Section IV contains the concluding remarks.

II. Smart Bed Platform

Since interaction with the hospital bed is a key cause of pressure ulcers, a smart bed can provide a first line of defense in preventing them. With this goal in mind, the hospital bed can be viewed as a source of biosignal data collection, because it is where patients spend a large amount of their time. The goal of this work, in general, is to enhance the capabilities of the bed with respect to its intellectual and physical characteristics, such that it can provide cognitive support to hospital staff. More specifically, the combination of a sensor network, machine intelligence, a morphable, tiled surface, and computer control can produce a smart bed capable of providing support to the staff that significantly improves the care, epidemiological analysis and prevention of pressure ulcers. The smart bed reduces the staff needed to turn patients. That means the nurse can spend more direct care time at the bedside assessing for complications or adverse events instead of looking for help to turn the patient. There are four aspects of interest related to a *pressure-ulcer aware* smart bed system as pictured in Figure 1 and to be explained next.

A. Data Collection & Monitoring

In order to measure pressure over the entire body, pressure sensors are distributed over the bed's surface in an array format. Resistive and capacitive sensors are the two main types of commercially available surface pressure sensors. The technology behind large area sensing using a sensor matrix has been advanced in the past decade and currently several pressure sensor arrays are offered in the market. Examples are Tekscan, Xsensor and Sensor Product Inc. that offer off-the-shelf sensor and/or body pressure measurement mats.

These devices are necessary but not sufficient. Off-the-shelf sensor arrays can be used to capture the pressure map, but the level and sophistication of the processing required for the smart bed application, is not commercially available. Specifically, a time-stamped pressure distribution image that can be constructed to facilitate body part identification, posture detection/classification and body movement analysis. To simplify the monitoring, we have also designed a GUI that facilitates access and visualization of relevant data.

B. Modeling & Profiling

This unit generates a profile from the initial, fused sensor data in order to capture the most important metrics such as the pressure map, level of moisture, temperature, mobility/activity, and blood pressure. As shown in Figure 1, the key units here include: (a) preprocessing and signal conditioning, (b) detecting body posture and limbs, and (c) extracting critical features from the sensed data (patient's profile/model). The most critical information for a patient likely to experience a pressure ulcer can be collected directly from the sensor readings or through data fusion such as deriving probabilistic models and/or Bayesian data fusion methods [17]. Fused data are expected to be more informative in terms of interpretation.

The Braden pressure ulcer risk assessment chart [8] is widely used by hospitals to informally estimate the risk of developing pressure ulcers for bedbound and chairbound patients. Typically, a nurse manually records his/her judgment as a number between 1 (highest risk) and 4 (lowest risk) for six categories: (1) sensory perception, (2) moisture, (3) activity, (4) mobility, (5) nutrition and (6) friction & shear. Patients with a total score of 12 or less are considered to be at risk of developing pressure ulcers, (i.e. 15-16=low risk, 13-14=moderate risk, 12 or less=high risk). Available Braden chart data is used for training and validation of the results produced by our support vector machine (SVM) approach [18].

1) Body Posture Detection: Figure 2 depicts an overview of posture classification algorithm developed for this platform. The posture detection algorithm has two main steps, i.e. training and test. The goal in training phase is to generate required data set for classification. To build the training set, a complete set of pressure maps in 5 different postures are collected using our platform. Training set goes into preprocessing unit which extracts the body segment and enhances quality of pressure images. Dimension of data is reduced by projecting images from a correlated high dimension input space into an uncorrelated low dimension data space using Principal Component Analysis (PCA) [19]. During test, each new pressure image is projected into new dimension space. Distance between extracted features for new pressure map and the training set is measured in kNN classifier to assign labels.

2) Limb Detection & Tracking: Most of pressure ulcers form over bony areas of the body such as sacrum, over the hip bones, back of the head and shoulder. Limb detection allows us to track at-risk regions of the body and assess those parts more accurately. After classifying patient's posture on the bed, we fit a model to classified pressure map using an

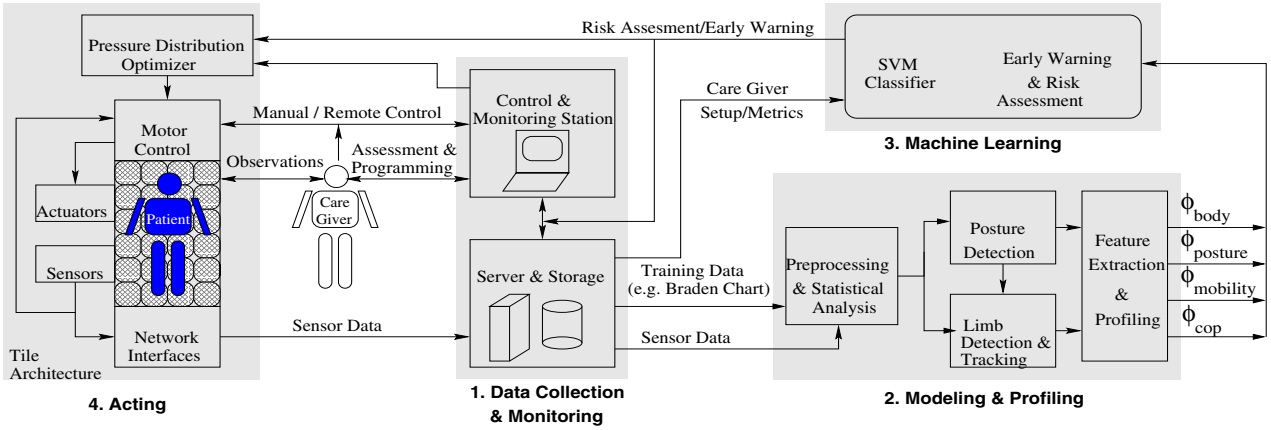

Figure 1. Smart bed system architecture.

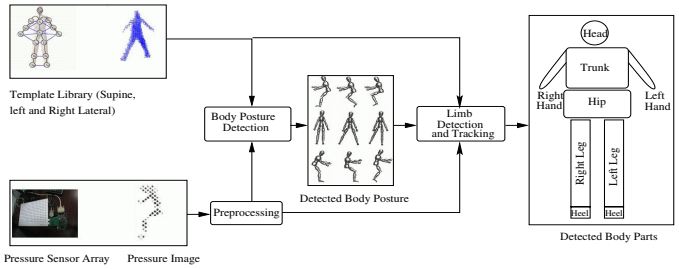

Figure 2. Posture Detection Process.

articulated human body model. Flexible and parametric human body model is developed for all postures. During the training phase a database of human body model is generated. During test, the most similar sample of classification algorithm will serve as the initial estimation of the model parameters. After initial estimation of location, size and angle of the assigned model, blob analysis is done to tune model parameters [19].

3) Feature Extraction: We want to extract relevant information from the data collection unit that can be used in the machine learning unit. There are two types of sensor data: (1) posture-independent (e.g physiological) data such as blood pressure, and (2) posture-dependent values such as pressure, temperature or moisture on each point of body in contact with bed. Posture-dependent values will be obviously limb-dependent too. For uniformity, we assume each metric is sampled periodically but the sampling period for each may be different. We assume there are M posture-independent, N posture-dependent metrics and L limbs to monitor. The temporal resolution of the posture-independent metrics is bounded by the sampling frequency of the data collection system. The spatial resolution of the posture-dependent metrics is confined by the distance between every two adjacent sensor nodes in the array of sensors. We use the concept of *moments* (m) to uniformly extract features. In mathematical modeling, moments are widely used to extract quantitative measures of the shape for a set of points. In general, the kth bounded moment of a real value function $f(t)$ is defined by $\mu_k = \int_t t^k f(t)dt$. The first four moments are *mean*, *variance*, *skewness* (a measure of the asymmetry) and *kurtosis* (a measure of the peakedness).

The development of bed sores is directly influenced by the time duration the patient stays in each posture and how the whole body is exposed to the risk factors. For a given period of time, Δt, we construct a vector of the first to the fourth moment or variation of the moment for both posture-dependent and independent data metrics.

(1) Posture-Independent Features:
Suppose $g_j(t)$ $(1 \le j \le M)$ indicate the posture-independent samples (e.g. blood pressure) taken over a period of time. For a given period of time, Δt, the feature vector for each function will be the combination of four moments:

$$\vec{G}_j = [m_{1,g_j},\ m_{2,g_j},\ m_{3,g_j},\ m_{4,g_j}] \qquad 1 \le j \le M \tag{1}$$

The extracted feature vector can now be defined as a combination of the above feature vectors:

$$\vec{\Phi}_{body} = [\vec{G}_1,\ \ldots,\ \vec{G}_M] \tag{2}$$

(2) Posture-Dependent Features:
There are at least three metrics to consider, i.e. based on limb's posture, mobility and center of pressure. For the first metric, let $f_{i,l}(x,y,t)$ represent the biosignal value $(1 \le i \le N)$ sampled for limb l $(1 \le l \le L)$ at bed-coordinate (x,y) at time t. For each function in a given time interval, Δt, we can compute:

$$\vec{F}_{i,l} = [m_{1,f_{i,l}},\ m_{2,f_{i,l}},\ m_{3,f_{i,l}},\ m_{4,f_{i,l}}] \quad 1 \le i \le N \quad 1 \le l \le L \tag{3}$$

And the overall extracted feature vector can now be defined as a combination of the above feature vectors:

$$\vec{\Phi}_{posture} = [\vec{F}_{1,1},\ \ldots,\ \vec{F}_{N,1},\ \ldots,\ \vec{F}_{1,L},\ \ldots,\ \vec{F}_{N,L}] \tag{4}$$

The second and third metrics (based on mobility and center of pressure) are associated with the limb's movement (i.e. large displacement shown in x and y axes) and limb's repositioning (slight movement that redistribute forces but does not make any large displacement), respectively. In order to obtain a numerical discrete level feature vector of the mobility level of patient, motion analysis [20] and center of pressure (CoP) [21] techniques are used. For mobility, we obtain two mobility functions $p_{x,l}(t)$ and $p_{y,l}(t)$. Similarly, for the second type of mobility, CoP for each of L limbs of interest (e.g. trunk, hip, leg, head) are computed and mapped to horizontal and vertical axes to give us $q_{x,l}(t)$ and $q_{y,l}(t)$. Briefly, for an area of interest

with K pressure value (v_i) points, CoP is formally defined as: $(x_{cop}, y_{cop}) = (\frac{\sum_{i=1}^{K} x \cdot v_i}{\sum_{i=1}^{K} v_i}, \frac{\sum_{i=1}^{K} y \cdot v_i}{\sum_{i=1}^{K} v_i})$.

Similar to Equation 3, functions Ps and Qs are computed and the extracted feature vector for limb's mobility and CoP and are defined:

$$\begin{cases} \vec{\Phi}_{mobility} = [\vec{P}_{x,1}, \vec{P}_{y,1}, \ \ldots, \ \vec{P}_{x,L}, \vec{P}_{y,L}] \\ \vec{\Phi}_{cop} = [\vec{Q}_{x,1}, \vec{Q}_{y,1}, \ \ldots, \ \vec{Q}_{x,L}, \vec{Q}_{y,L}] \end{cases} \quad (5)$$

The final feature vector is a combination of vectors shown in Equations 2, 4 and 5. It's easy to verify that the total number of features will be $4[M + LN + 2L + 2L] = 4[M + L(N + 4)]$. Ultimately, the most relevant features will be chosen for machine learning unit.

$$\vec{\Phi}_{overall} = \vec{\Phi}_{body} \cup \vec{\Phi}_{posture} \cup \vec{\Phi}_{mobility} \cup \vec{\Phi}_{cop} \quad (6)$$

C. Machine Learning

The primary goal of this unit is to apply machine learning techniques to train a model for assessing a patient's risk of developing pressure ulcer, by combining the features extracted in the modeling and profiling unit. The predictions made by this model will enable us to (1) issue an early warning (alert) flag indicating the existence of high risk of developing ulcer and (2) control command/data for pressure redistribution around high-risk limbs (i.e. provided to the care giver or the actuation unit).

To train this risk assessor, we have employed SVM [18], a learning algorithm that achieved state-of-the-art results on a variety of tasks, both within and outside the health-care domain. In our training set, each instance corresponds to the data collected from a particular body part of a patient at a particular time step, and is represented as a vector composed of the features discussed in the previous subsection. The label of an instance, which is manually assigned by a health-care professional, can be either a simple binary classification (i.e. whether the patient is at high risk of developing PU or not) or one of the three classes (e.g. high, moderate and low risk). Given this training set, we can use an SVM in combination with a variety of kernels to assign one of the risk levels to a test instance (if the label is one of its three classes) or a classifier for determining whether a patient has a high risk of developing ulcer (if the class label is binary). One may argue that the binary decision returned by a classifier is not particularly useful in practice, since what we typically desire is a real value that indicates the risk of developing ulcer. In fact, this real value can be easily derived from an SVM classifier. Hence, we derive a risk function R that computes the risk associated with a test instance based on its distance from the hyperplane in SVM, assigning the highest (lowest) risk value to the instance that is farthest away from the hyperplane in the positive (negative) region.

D. Acting

The general requirements on the design of the bed hardware are to provide a means for moving and manipulating the patient. The bed uses *soft, non-grasp* manipulation for this purpose. The non-grasp approach is used because it is safe in that there is no attempt to grasp or constrain the patient's body. The "soft" aspect allows for fine control of the contact/pressure forces along the patient's skin. Manipulation is the key issue here because manipulating/moving the patient is the most-effective current practice used by nurses to prevent pressure ulcers, referred to as "turning the patient".

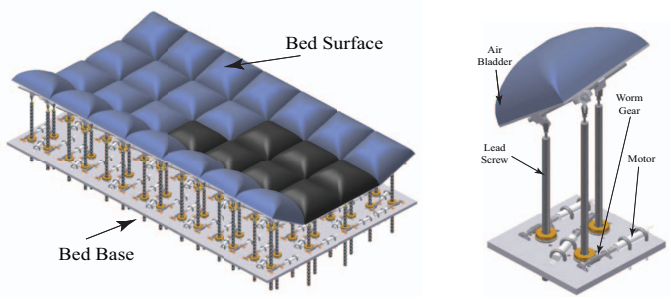

Figure 3. Tiled architecture: (a) base and surface, (b) one tile and its 3 DOF.

In this work, soft manipulation is accomplished using a combination of mechanical and pneumatic actuation; pneumatically controlled, air mattresses are often used in pressure ulcer prevention. Thus the idea here is to add mechanical actuation, enhancing the bed's ability to finely control the pressure along the patient's skin.

The overall design of the bed consists of a segmented or tiled surface where each tile can be actuated independently or in concert with the others. This creates a movable surface that can manipulate a patient without grasping her/him. A preliminary version of the bed, along with a closeup of an individual tile, is shown in Figure 3. It consists of 1 foot x 1 foot units yielding a bed approximately 7 foot in length x 4 foot in width, which would accommodate a wide range of patients. It is designed to handle a wide range of patients, including bariatric ones, up to 315 kg.

Each unit is comprised of a parallel mechanism with an air bladder attached to the top; however, many configurations are possible. Each unit has 3 degrees-of-freedom (DOF) of movement, and an infinite number of DOF from the deformable bladder on top; the actual bladder will have a flatter, more square surface with more area. The pneumatic pumps required to inflate the air bladders are not shown in Figure 3. Pressure sensors are embedded in the surface and/or underneath the air bladder to provide force feedback to the motor controllers. Currently, a tile can tilt a maximum of 60.9°, which, in addition to the other features of the bed, should be sufficient to achieve the same effect as turning the patient.

III. Experimental Results

A. Posture Detection

Table I summarizes experimental result extracted for our posture detection algorithm. Each column of this matrix represents instances in actual class while each row of this matrix represents the instances in a predicted class. For example, the entries of the first column of the above confusion matrix have the following meaning: 99.2% of actual Right Foetus instances are predicted correctly while 0.7% of actual Right Foetus instances are erroneously predicted as Right Yearner and 0.1% as Supine. The overall accuracy (correct predictions) of the method with kNN classifier is 97.7% .

TABLE I

PCA CONFUSION MATRIX(%)

	Right Foetus	Left Foetus	Right Yearner	Left Yearner	Supine
Right Foetus	99.2	0	9.3	0	0.1
Left Foetus	0	99.6	0	0.2	0.1
Right Yearner	0.7	0	90.7	0	0.3
Left Yearner	0	0.4	0	99.8	0.2
Supine	0.1	0	0	0	99.3
Recall	99.2	99.6	90.7	99.8	99.3
Precision	91.3	99.7	98.9	99.4	99.9
Accuracy			97.7		

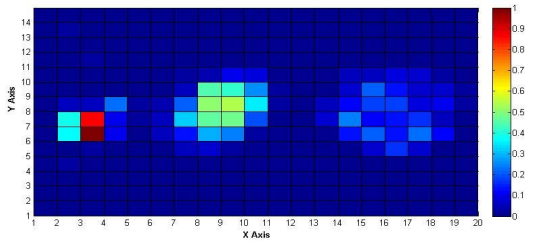

Figure 4. Effect of tissue (layer) softness on pressure distribution: hard (left), medium (middle) and soft (right).

B. Risk Assessment

The next experiment is a simulation study to conduct comparison between the risk factors for different body limb tissues. Figure 4 shows the pressure image of three identical objects with the same weight and shape over pressure mat. For each object, we used a different layer underneath in terms of softness to mimic the role of various body tissues and be able to show the risk factor. We simulated the bony limbs with harder layer and muscles with softer one. The left object had the hardest layer underneath and the right one has the softest layer. The overall pressure of all three objects is the same since the weight and the contact area are the same. However, the pressure distribution is expectedly different. Table II shows the extracted features (four moments) for these three objects. As expected, the mean values are approximately the same for all. The harder the layer, the higher the variance over the surface. To calculate the risk factor (R), we applied a simple normalization method to compute relevant weight (ω_i) for each feature (i.e. moments m_i). The last column of this table shows the risk factor ($0 \leq R \leq 1$) for each scenario. The results indicate the harder the layer or tissue, the higher the risk factor. While simple, this experiment shows that we can certainly assess the risk associated with various limbs and the whole body.

IV. CONCLUSION

Design and implementation of a proof-of-concept platform of a smart bed that will monitor a patient's in-bed body pressure and other parameters is presented. Machine intelligence is used to analyze data, assess the risk and alert care-givers to intervene at an early stage to prevent pressure ulcers. Specifically, the key algorithms for posture detection, limb tracking and risk assessment and also the architectural structure of the platform are discussed. In near future, we hope to report a life-scale sensor-actuator network with embedded computation, intelligence and networking capabilities that is ready for clinical trial.

TABLE II

FEATURES AND RISK FACTORS (R) FOR THREE SCENARIOS.

Tissue Softness	Mean (m_1)	Variance (m_2)	Skewness (m_3)	Kurtosis (m_4)	Risk (R)
Hard	0.0138	0.0074	9.4657	98.6307	0.8460
Medium	0.0135	0.0065	4.7368	25.4770	0.4995
Soft	0.0129	0.0016	3.6443	16.4165	0.2712

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