Bed Posture Classification for Pressure Ulcer Prevention

R. Yousefi, S. Ostadabbas, M. Faezipour, M. Farshbaf, M. Nourani, L. Tamil
Quality of Life Technology Laboratory
The University of Texas at Dallas, Richardson, TX 75080
{r.yousefi, sarahostad, miad.fz, mxf104020, nourani, laxman}@utdallas.edu

M. Pompeo, M.D.
Presbyterian Wound Care Clinic
Dallas, TX, 75231
healerone@aol.com

ABSTRACT

Pressure ulcer is an age-old problem imposing a huge cost to our health care system. Detecting and keeping record of the patient's posture on bed, help care givers reposition patient more efficiently and reduce the risk of developing pressure ulcer. In this paper, a commercial pressure mapping system is used to create a time-stamped, whole-body pressure map of the patient. An image-based processing algorithm is developed to keep an unobtrusive and informative record of patient's bed posture over time. The experimental results show that proposed algorithm can predict patient's bed posture with up to 97.7% average accuracy. This algorithm could ultimately be used with current support surface technologies to reduce the risk of ulcer development.

Keywords: Pressure Ulcer, Pressure Image, Posture Classification, K-Nearest Neighbor.

I. INTRODUCTION

Pressure ulcer (PU) is usually developed over a bony prominence as a result of pressure and can be exacerbated by other factors like shear stress and/or friction [1]. Additional contributing factors include immobilization and malnourishment. Current cost of PU treatment in our health care system is estimated to be more than $1.2 billion annually [2]. Once developed, PUs represent an acute health condition that result in increased costs and suffering over many months and even years. Effective ulcer prevention and early detection will greatly reduce patient's suffering/discomfort. Strong motivation for this work comes from the growing shortage of trained health care providers and the ever-increasing cost of health care. In 2000, the shortage of nurses was estimated at 6%. This shortage is expected to grow to 20% by 2015 and, if not addressed, to 29% by 2020 [3].

To alleviate the interface pressure, care givers need to regularly (every two hours is often recommended) turn the patient. Practically this is not possible due to shortages of resources. A system that can monitor and record the patient's sleeping posture unobtrusively over time is quite useful for pressure ulcer risk reduction and better management of hospital resources. This system could be used to learn and extract optimal timing of repositioning of patients with different diseases and conditions on bed with different support surfaces [4]. It could also be used to measure repositioning care given to the patient for quality improvement and assurance.

Pressure sensors have been used for bed posture detection to meet the privacy issue in hospitals. A set of pressure sensors with a feed-forward neural net was presented in [5] for detection and distinction of body position. Harada et al. have proposed a template-based human posture detection [6] and a human motion tracking system [7]. A bed posture detection method is developed in [8] using Bayesian classification for the elderly where statistical kurtosis and skewness measures are estimated as feature vector to represent the shape of pressure contour. They have achieved an average of 78% classification accuracy on 3 postures. This technique suffers from lying angle and increasing number of stable postures will decrease the accuracy. To achieve a better performance, a multimodal approach to human sleeping posture classification, using pressure sensor array and video camera as complementary modalities was proposed in [9]. It should be noted that using camera in nursing units has different privacy issues which must be met.

Advancement in pressure sensing technology has provided opportunity to have pressure measurement in larger area with high resolution and low costs. There have been many companies using resistive and capacitive technologies who offer bed pressure mapping system [12][15]. Researchers are trying to reduce cost of pressure mapping systems and even make it disposable for use in a hospital setting [11]. Due to high treatment cost of PUs and shortage of nurses, we envision that in near future, pressure mapping system will be an economically justified part of hospitals and wound care clinics. The usage of high resolution pressure mapping system is not limited to posture classification. It can cover bed fall detection, appropriate support surface selection to optimum pressure redistribution on support surfaces, risk assessment and controlled healing process.

Considering this trend of pressure mapping system, there is a need for a new high accuracy processing unit for classification of bed posture which is general enough to be used with current and future commercial pressure mapping system. This processing algorithm should pave the road toward future usage of pressure mapping system. To the best of our knowledge, this has not been met in previous works due to lack of accuracy and low resolution pressure data or privacy issues (e.g. by using camera). So, in this work we have developed a high accuracy image-based algorithm which could be used with different pressure mapping system. Our work tries to fill the gap between previous research work and a commercial product for pressure ulcer management in the sense that it can ultimately be used in bed with automatic pressure redistribution capabilities [13][14]. A new algorithm is developed for classification of patient's posture on bed. An image-based preprocessing unit processes input pressure map and prepares it for classification using Principal Component Analysis (PCA) and Independent Component Analysis (ICA).

The remaining of this paper is as follows. Our data collection platform and multistage algorithm developed for posture classification are described in Section II. Section III discusses experimental results and observations. Section IV contains concluding remarks.

II. Posture Classification

A. Data Collection Platform

Force Sensing Array (FSA) [15] is used to collect pressure data on the bed. The FSA system is a flexible mat that contains 2048 (32×64) uniformly distributed sensors which cover the total contact area between the subject and the bed. The FSA system can measure interface pressure between 0 to 100 mmHg per sensor. The sensor mat is light, thin and flexible. The electronic interface samples the sensor mat in 0.6 second. Sensor values are considered as a gray scale pressure image and this image is passed to our data processing unit which will be described in the next section.

B. Algorithm

Proposed processing unit has three main steps: Normalization, Eigenspace Projection and K Nearest Neighbor (kNN) Classifier. The normalization stage extracts the silhouette of the patient in the bed using binary image processing and prepares the training and input image with a fixed size for further processing. Figure 1 depicts an overview of the processing unit. Figure 2 shows the internal blocks of this stage where the upper path generates a binary image using thresholding. In order to improve the quality of the binary image, closing and bridging morphological operations [16] are applied on it. The resultant binary image is multiplied with filtered and equalized gray scale image and the body segment of image is scaled to a fixed size for Eigenspace projection. Smoothing is applied on gray scale pressure image using a rotationally symmetric Gaussian lowpass filter of size 10 with standard deviation 0.5. As an example, Figure 3 shows original images in two postures and corresponding normalized images.

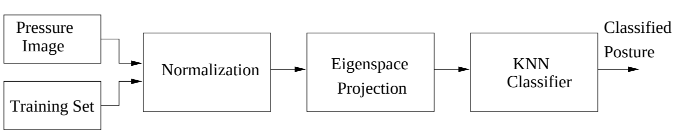


Figure 1. Overview of developed processing unit.

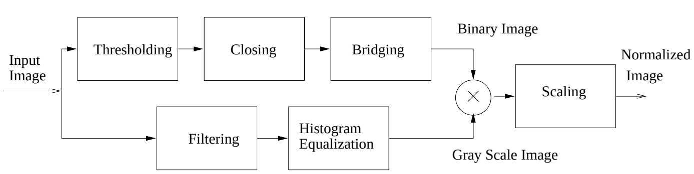
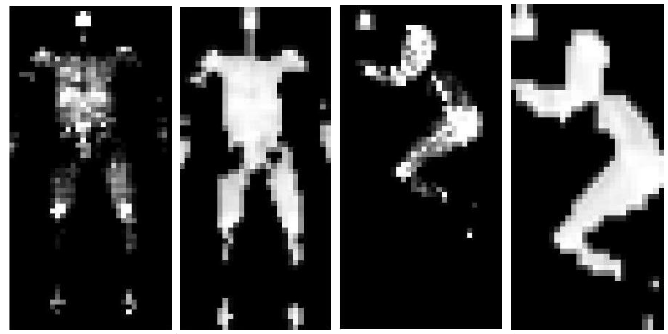


Figure 2. Normalization unit.

Projecting images into eigenspace is a procedure that could be used for appearance-based recognition algorithms. As a common application of eigenspace, Turk and Pentland used eigenspace projection for face recognition [17][18]. A pressure image is represented as a vector of pixels where the value of each entry is the pressure value of the corresponding sensor point. The pressure image is a point in an N-dimensional



a b c d

Figure 3. (a) Original image (supine) (b) Normalized image (supine) (c) Original image (left foetus) (d) Normalized image (left foetus).

space, where N is the number of sensor points (e.g. 2048 for this work). In this technique, we first select a subspace on which to project the pressure images. After subspace selection, all training images are projected into this subspace. Training set includes pressure images of different postures and different subjects considering variations within and between classes. Then, each new test image is projected into the same subspace. Projected test image is compared to all the training images by a kNN algorithm [19] and the training images that are closest to the test image are used to identify class of test image. In kNN technique, the distance from test image to each training sample is measured and the k smallest distances are chosen and the most matched class in these k classes is the final output representing class label.

Two specific subspaces which are used in this study are: (i) the subspaces created by principle component analysis (PCA) [18] and (ii) generalized form independent component analysis (ICA) [20]. PCA and ICA are two alternative methods that are investigated in this paper. To generate the subspace for PCA, each of the stacked images in training set must be centered by subtracting the mean value as in:

$$x^i = [x^i_1 - m_1,\ x^i_2 - m_2,\ \ldots,\ x^i_{N-1} - m_{N-1},\ x^i_N - m_N]^T \quad (1)$$

where x^i is the stacked training image i, m is the mean image and N is the number of sensor points. Then, data matrix X of size $N\times M$ where M is the number of images in training set is created. Each column of X is one stacked training image. The covariance matrix of this data matrix is:

$$C = XX^T \quad (2)$$

which is multiplication of data matrix and its transpose. The eigenvectors of square covariance matrix are the non-zero vectors which satisfy:

$$CV = \Lambda V \quad (3)$$

where V is defined as:

$$V = [v_1,\ v_2,\ \cdots,\ v_M] \quad (4)$$

V is the set of eigenvectors associated with the eigenvalues Λ which is a matrix of form:

$$\Lambda = \begin{bmatrix} \lambda_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \lambda_M \end{bmatrix} \quad (5)$$

Eigenvectors of V are ordered based on their eigenvalues λ_i and eigenvectors associated with eigenvalues which are more than a threshold are kept as basis images. Considering K eigenvector are kept, then we define V_K to be:

$$V_K = [v_1,\ v_2,\ \cdots,\ v_K] \quad (6)$$

All the training images is projected to this new eigenspace V_K by:

$$P^i = V_K^T x^i \quad (7)$$

and each new pressure image is also projected into this space and the result will be passed to kNN multiclass classifier. Pressure images are represented as a linear combination of basis images after projection. The value of this threshold depends on the reconstruction quality and classification accuracy. Figure 4 shows the process of reconstructing pressure images using basis images where I_1 through I_M are basis images extracted from V and B_1 through B_M are corresponding coefficients. Figure 5 shows a reconstructed posture image from 10 basis images of PCA.

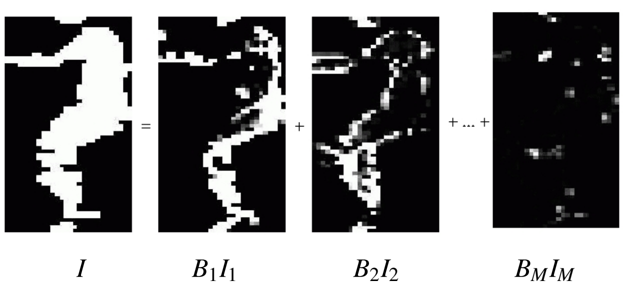


Figure 4. PCA representation of pressure images (postures) as a linear combination of basis images, i.e. $I = B_1I_1 + B_2I_2 + ... + B_MI_M$.

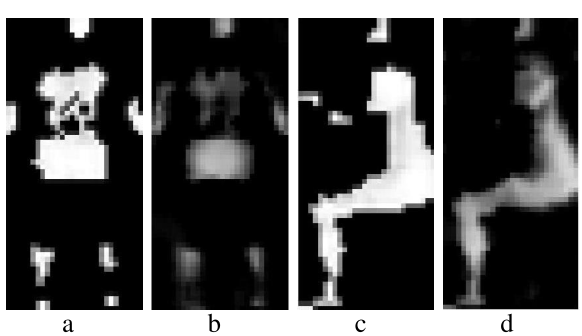


Figure 5. PCA reconstructed postures using 10 basis images: (a) original image (supine posture) (b) reconstructed image (supine posture) (a) original image (left foetus posture) (b) reconstructed image (left foetus posture).

In PCA model, since covariance matrix is used, second order statistics of data are captured which only have amplitude spectrum of pressure images. The phase spectrum which contains the structural information are hidden in higher order statistics. Unlike PCA which uses a Gaussian source model, the essential assumption in ICA is that the combining coefficient are nonGaussian and mutually independent random variables allowing higher order statistics in ICA. So, the optimization in PCA is the minimization of reconstruction error from the reduced dimension data, while the optimization of ICA is the minimization of statistical dependence between the basis images [20]. A variety of approaches formulate ICA technique and we used *informax* algorithm proposed by Bell and Sejnowski [21]. Similar to the PCA, the projection information is extracted during training phase and training database is created after projection. Cosine similarity measure is used to classify test postures in kNN.

III. Experimental Results

To evaluate our posture classification methodology, a complete set of pressure maps are collected for six different subjects in 5 different postures as shown in Figure 6. These postures are stable postures that patient could stay in for a long time. For each subject, data is collected in 0, 30 and 60 degree elevation of the head of the hospital bed in supine posture.

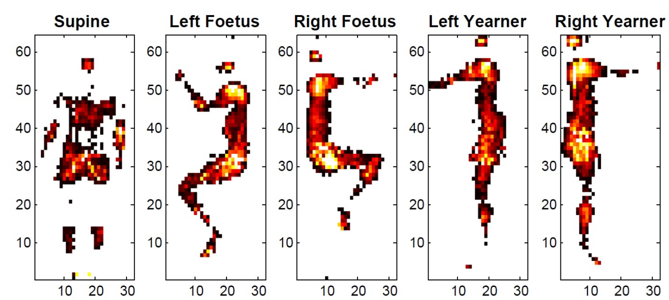


Figure 6. Pressure image of five postures considered in our experimentation.

Data is split into two non-overlapped parts and test data (30% of data) is held out during the training phase of eigenspace projection. Table I and II summarizes experimental results extracted for both PCA and ICA. Different number of basis images are evaluated by their predictive accuracy and ten basis images are used in K nearest neighbor algorithm. For the PCA approach, cityblock distance measure, sum of absolute differences, is used to classify projected pressure.

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		

Confusion matrix contains information of predicted and actual classes. 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. *Recall* is the percentage of positive labeled instances that were predicted as positive and *precision* is the percentage of positive predictions that are correct. *Accuracy* is the percentage of predictions that are correct. The accuracy of the PCA and ICA with kNN classifier are 94.3% and 97.7% and the recall rate of PCA in different classes ranges from 90.7% to 99.8% where the left yearner has the highest value and the right yearner has the lowest recall. Classification accuracy of ICA is less than PCA but it has less variation and the lowest recall value belongs to right foetus class which is higher than the lowest recall value in PCA. Our approach is compared to others in Table III. Note that different works in this table have different number of postures, modalities and testing strategies and a full-fledge comparison is not possible. In [8], 78% accuracy is reported but it is limited to 3 upper body postures for only immobile and inactive patient. It is also sensitive to lying angle as it is stated in [8]. Huang et al. [9] achieved 94.05% accuracy using both pressure and video modalities. This approach has different privacy issues in nursing environments and higher computational load and integration cost for real scenarios in hospitals and nursing units. Reference [10] employs a more complicated support vector machine classifier to reach 78% classification with minimum accuracy of 72% in right foetus posture. As mentioned in [10], this algorithm is sensitive to noise because it works on the raw data and objects on bed (e.g. pillow) interfere with posture recognition in real scenarios. Minimum accuracy in our work is 91.3% while the overall accuracy is 97.7%. The preprocessing unit in our algorithms eliminates sensitivity to noise and our algorithms is tested on real hospital bed with support surface on the bed with subjects with high level of mobility. In our work a high resolution pressure mapping system is used which is commercially available with reasonable cost. Application of this pressure map is not only posture classification and it could be used for turn scheduling [4], support surface selection, optimizing pressure redistribution surfaces, risk assessment and other controlled treatment of PUs.

TABLE II
ICA CONFUSION MATRIX(%)

	Right Foetus	Left Foetus	Right Yearner	Left Yearner	Supine
Right Foetus	92.1	0	5.1	0.2	0.1
Left Foetus	1.1	95.1	.5	3.6	0
Right Yearner	4.4	0.2	93.2	0.6	1.8
Left Yearner	0.7	3.5	0.4	94.3	1.5
Supine	1.7	1.2	0.8	1.3	96.6
Recall	92.1	95.1	93.2	94.3	96.6
Precision	84.4	94.8	93	94	95.1
Accuracy			94.3		

IV. CONCLUSION

In this work, an algorithm is proposed for unobtrusive patient's bed posture classification to manage and reduce the risk of pressure ulcer. Our work is an efficient and highly accurate algorithm based on the data provided by a commercial pressure mapping system. This method can be used for patient monitoring, turning schedule, pressure redistribution and ultimately pressure ulcer prevention and time utilization of nursing staff. Experimental result indicates that PCA approach can predict patient's bed posture with up to 97.7% average accuracy. The future work is to get benefit of high resolution pressure map and employ developed image-based posture classifier in a hierarchal approach and implement an algorithm for limb detection to predict at-risk regions of body for developing pressure ulcer.

TABLE III
COMPARISON

Work	Modality	Number of Postures	Sensor Points	Accuracy(%):
Ref. [8]	Pressure Sensor	3	16	78
Ref. [9]	Pressure/Video	9	60	94.05
Ref. [9]	Pressure Sensor	9	60	46.86
Ref. [10]	Pressure Sensor	6	56	83
Our Work, ICA	Pressure Map	5	2048	94.3
Our Work, PCA	Pressure Map	5	2048	97.7

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