Classifying Bed Inclination Using Pressure Images

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Abstract— **Pressure ulcer is one of the most prevalent problems for bed-bound patients in hospitals and nursing homes. Pressure ulcers are painful for patients and costly for healthcare systems. Accurate in-bed posture analysis can significantly help in preventing pressure ulcers. Specifically, bed inclination (back angle) is a factor contributing to pressure ulcer development. In this paper, an efficient methodology is proposed to classify bed inclination. Our approach uses pressure values collected from a commercial pressure mat system. Then, by applying a number of image processing and machine learning techniques, the approximate degree of bed is estimated and classified. The proposed algorithm was tested on 15 subjects with various sizes and weights. The experimental results indicate that our method predicts bed inclination in three classes with 80.3% average accuracy.**

I. INTRODUCTION

Patient's posture is one of the most important factors in developing pressure ulcer also known bed sore. In each posture, there are certain limbs which are in direct contact with bed surface and they will be under stress. These limbs are at risk if they are subject to high pressure for a long time. As a result of pressure, blood flow to those stressed areas gets disrupted and cells do not receive nutrients and start dying which leads to pressure ulcer. Pressure ulcers cause many difficulties to patients. They are difficult to heal and in some cases need multiple surgeries and long time (months or even years) to be cured. Also, bed sores are painful and very costly to heal. So, monitoring the patient's postures at the interface pressure dimension can be useful to evaluate the patient situation during the hospitalization time. In particular, once the posture is known, to decrease the interface pressure and pertinent stress on each limb, we need to reposition the patient body efficiently and preferably according to a time schedule [1] [2]. Nurses are commonly advised repositioning patients every 2 hours. But this is not practical due to shortage of nurses. On the other hand for completely repositioning of a patient, more than a nurse is sometimes needed. Having information about posture and high risk areas of patients can help us evaluate risk of pressure ulcer and schedule for repositioning. To utilize resources, automatic detection of body limbs and high risk regions is needed.

One of the most effective, but largely ignored, relevant factor in developing the pressure ulcer is bed inclination (back angle). In many cases patients are put in inclined bed for reasons like having the feeding tube, after surgery, watching TV, etc. As a side effect, the bed inclination can increase the pressure on lower areas of back and buttock and consequently amplify the chance of pressure ulcer on those areas. Therefore, automatic monitoring of the bed inclination is needed.

In literatures, there are a number of related works which explore issues pertinent to the pressure ulcers by use of pressure sensor mats. The Principle Component Analysis (PCA) of collected pressure distribution of body is applied to predict sleep postures in five prevalent postures [3]. Authors in [4] used a vector of extracted attributes of kurtosis and skewness measures of pressure distribution to represent the shape of pressure contour. In [5] a light-weight computation algorithm is proposed to calculate continuous in-bed patient posture in eight common sleep postures. An algorithm to detect of high-risk regions that are related to three common sleep postures, is proposed in [6]. In this work by use of segmentation technique, a unique template of each posture is extracted. Then, graph matching algorithms are applied to label the tree according to the relevant template. Authors in [7] proposed an on-bed exercise monitoring system to follow compliance to physical rehabilitation programs. Also, a specific metric is proposed to match manifolds to enable quantified measurement of coherence to prescribe exercises. Our main contribution in this work is to develop a novel and robust methodology for estimating bed inclination by use of a low resolution pressure mat. To collect the pressure data, pressure sensor mats are used to provide pressure images [8]. Our technique automatically classifies bed inclinations into three classes. Note that, practically exact bed degree is neither needed nor realistic. Caregivers need historical body tilting and bed inclination to effectively prevent bed sore. To the best of our knowledge, this work is the first to compute bed inclination using only pressure images. The proposed algorithm has shown a promising performance in practical testing and evaluation. It can be valuable as a part of a comprehensive patient monitoring (e. g. smart bed) platforms in hospitals, nursing homes and acute care centers.

II. METHODOLOGY

A. Pressure Image Model

Most pressure mat systems provide a two dimensional array of sensors using a few thousand sensors. A commercial pressure mat that covers the entire bed surface is used to collect the pressure data. We used a typical flexible pressure mat with $N = 2048$ pressure sensors. These sensors are uniformly distributed across a $32'' \times 67''$ mat almost 1 inch apart. The pressure mat with a sampling frequency of 1.7

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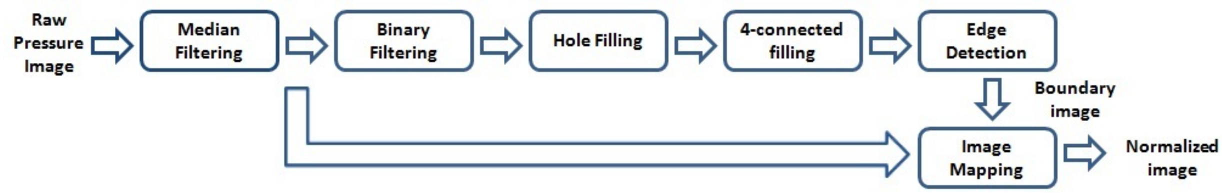


Fig. 1. Pressure image preprocessing operations.

Hz [8] [9] [10] can measure the pressure between 0 to 100 mmHg. Let us show the extracted pressure mat sensor values by matrix PM:

$$PM = \begin{bmatrix} p_{0,0} & p_{0,1} & \cdots & p_{0,N-1} \\ \vdots & \vdots & \cdots & \vdots \\ p_{M-1,0} & p_{M-1,2} & \cdots & p_{M-1,N-1} \end{bmatrix} \quad (1)$$

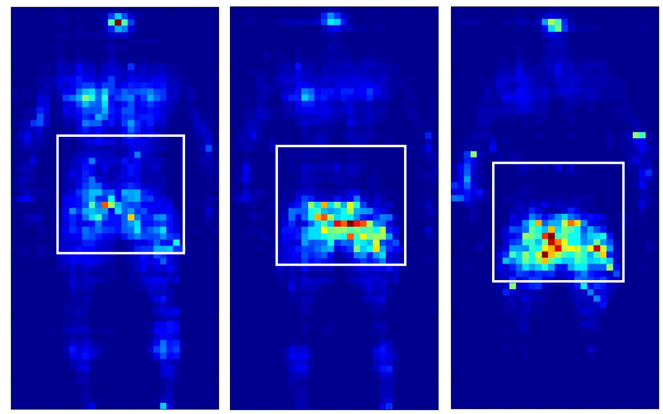
where $p_{i,j}$ is the pressure value reported by sensor in location (i, j), $0 \leq i \leq M$ and $0 \leq j \leq N$.

B. Pressure Image Preprocessing

To more accurate evaluate the bed inclination, we need first to pre-process the collected data from pressure mat. Since people are in different sizes and there are many sources of noises in our work (such as mat movement and saturated sensor value),in pre-processing phase, we apply different signal and image processing techniques for getting the normalized image. Preprocessing steps are shown in Fig. 1. To eliminate the background noise, a Median filtering is used. Binary image will be extracted by applying binary filtering on the image. Hole filling is used to remove holes and isolated pixels in the image. Afterwards, boundaries of image has to be filled by using a 4-connected filling process. In this method, from a given pixel, the region that can be reached is a set of 4 way moves (north, south, east, west). The filled pixels will be given the average value of their neighbor pixels in the last step (Mapping step) to reduce the effect of incorrectly non-sense pressure value in that sensor position. Boundary edge can be extracted by gradient edge detection algorithm [11]. The gradient approach detects the edges by looking for the maximum and minimum in the first derivative of the image [12]. Finally, by mapping the boundary image on the main image, we can extract the final normalized image that is more uniform, connected and noiseless.

C. Classifying Bed Inclination

Our goal here is estimating three levels (classes) of bed inclinations commonly used in hospitals for bed-bound patients. These inclinations are: (1) B0 degree, (2) B30 degree, and (3) B60 degree. Practically, bed inclination of more than 60 degree is never used. When inclination of the bed increases, according to the mechanical rule, the force on the inclined surface (back area) is going to decrease. But the force on the buttock area goes up. Also, pressure distribution in these two areas (buttock and back) is a robust feature in detecting these degrees. Fig. 2 shows the distribution of pressure on these areas for three considered degree classes



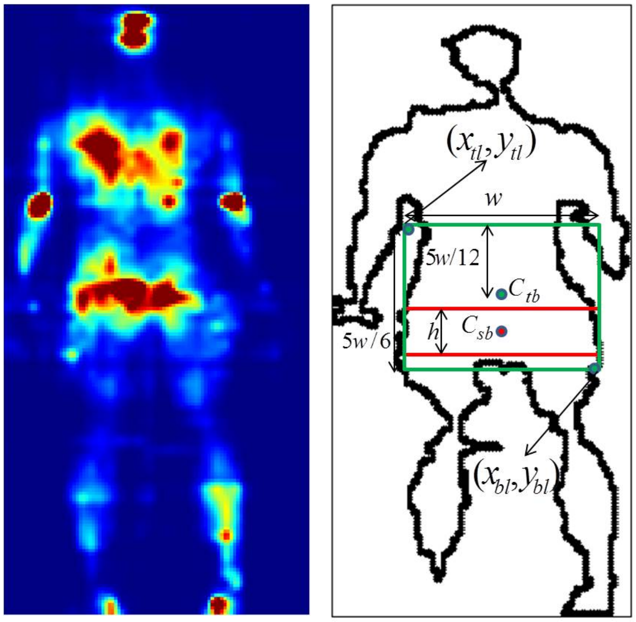
(a) (b) (c)

Fig. 2. Common bed inclinations: (a) B0 (0 Degree), (b) B30 (30 Degree), (c) B60 (60 Degree).

for a subject. Expectedly, with increasing the bed degree, the pressure moves from the upper back area toward the buttock area. The upper half of the white box in Fig. 2 gets darker (low pressure) and the lower half gets shinier (high pressure).

• **Step 1 (Boundary Identification):** Our approach to classify an image to one of these common degrees includes a two-phase detection process. In the first step, we find the approximate locations of the two key areas (back and buttock). By analyzing a large number of boundary images, we realized that often the shoulder area is the widest. The second widest continuous area of body is the buttock area. The width of the body in this area can be found by calculating the continuous horizontal distance of body (border to border) for all length of the body. For this work, a *scan box* with size of $h \times w$ is considered. For a fixed height (e. g. h=4 rows), we scan the image top-down to see what is the second largest $h \times x$ rectangle that can be embedded within the boundaries of a normalized image. Empirically, $h = 4$ has produced excellent results since smaller value of h causes more ambiguities and large values makes the circumscribed rectangle not to fit and not accurate. Afterwards, the center of extracted region is calculated and called $C_{sb}(x_{sb}, y_{sb})$. Now a *target box* with $w \times 5w/6$ and the center $C_{tb}(x_{tb}, y_{tb})$ can be detected. To detect the correct size of *target box*, we empirically define the following relationship between C_{sb} and C_{tb}:

$$\begin{cases} x_{tb} = x_{sb} \\ y_{tb} = y_{sb} - w/4 \end{cases}$$



(a) (b)

Fig. 3. (a) Raw pressure image. (b) Extracted boundary image.

where w is the width of scan box. Fig. 3 shows these boxes. Matrix TB is then used to indicate *target box* of size $H \times W$:

$$TB = \begin{bmatrix} f_{1,1} & f_{1,2} & \cdots & f_{1,W} \\ \vdots & \vdots & \ldots & \vdots \\ f_{H,1} & f_{l,2} & \cdots & f_{H,W} \end{bmatrix} \tag{2}$$

where $f_{i,j}$ is the pressure value of located sensor in the ith row and jth column of *target box*.

• **Step 2 (Feature Extraction):** Let us show the summation of pressure values extracted from pressure mat for entire body and *target box* by S_P and S_t, respectively. They can be calculated as:

$$S_P = \sum_{j=0}^{N-1} \sum_{i=0}^{M-1} P_{i,j} \tag{3}$$

$$S_t = \sum_{j=y_{tl}}^{y_{br}} \sum_{i=x_{tl}}^{x_{br}} f_{i,j} \tag{4}$$

Three important features using pressure values captured by *target box* are extracted. These two features, called F_1, F_2 and F_3, are defined as follows:

$$F_1 = \frac{\sum_{i=H/2}^{H} \sum_{j=H}^{W} f_{i,j}}{S_P} \tag{5}$$

$$F_2 = \frac{\sum_{i=1}^{H/2} \sum_{j=H}^{W} f_{i,j}}{S_P} \tag{6}$$

$$F_3 = \frac{\sum_{i=H}^{(H/2)-1} \sum_{j=H}^{W} f_{i,j}}{\sum_{i=H/2}^{H} \sum_{j=H}^{W} f_{i,j}} \tag{7}$$

Intuitively, F_1 indicates changing pressure rate between buttock area and entire body. Similarly, F_2 shows changing pressure rate between back area and entire body. Feature F_3 indicates changing the pressure rate between upper bound area of *target box* (back) and lower bound area (buttock). The pressure distribution on *target box* is changed with increasing in bed inclination. Therefore, we define the fourth feature as:

$$F_4 = \sqrt{\frac{\sum_{i=1}^{H} \sum_{j=1}^{W} (f_{i,j} - \mu)^2}{H \times W - 1}} \tag{8}$$

where $H \times W$ (see Eqn. 2) is the total number of pressure sensor values in the extracted target box and μ is the $mean$ value of the pressure value in this set. F_4 indicates the *standard deviation* in the target box region and in general implies dispersion of pressure values around the $mean$ value of TB.

• **Step 3 (Classification):** After extracting the four features, a classification approach is applied to identify a new sample class. Four classifiers have been tied to classify new instances. The *k-Nearest Neighbor* (kNN) has shown a superior performance in comparison with $PART$, $C4.5$ and *Naive Bayes* classifiers. By applying kNN multiclass classifier on extracted features, we can distinguish class B60, B30 and B0 from each other. Fig. 4 depicts an overview of the bed inclination classification approach. The same algorithm is applied on the training set instances to extract F_1 through F_4.

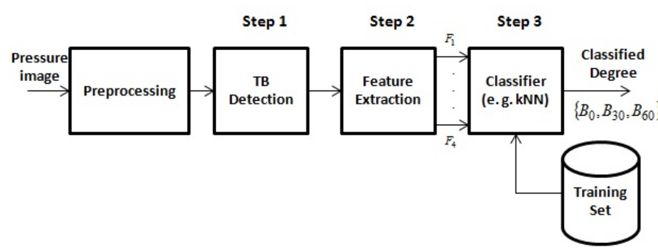


Fig. 4. The bed inclination classification process

III. EXPERIMENTAL RESULTS

The proposed approach in this work for classifying bed inclination has been well tested by a diverse set of collected pressure maps. 15 subjects with different sizes and weights have been chosen for data collection procedure. Ten-fold cross-validation (10-CV) technique [13] is used to get the overall results. For $bed\ inclination$ problem, three classes are: 1) 0 degree (B0), 2) 30 degree (B30), and 3) 60 degree (B60).

The complete classification results of our work for bed inclination by use of kNN classifier are summarized in Table I. In this table, *Confusion Matrix* has been used to demonstrate the performance of our algorithm. In this table, $Recall$ (also called sensitivity) is the percentage of the cases correctly predicted positive out of all positive cases in our gold set, i. e. $TP/(TP + FN)$. $Precision$ is

TABLE I

BED INCLINATION CLASSIFICATION RESULTS (%).

Class	B0	B30	B60
B0	80	13	0
B30	20	74	13
B60	0	13	87
Recall	80	73	86
Precision	86	69	87
F-measure	83	71	86.5
Accuracy		**80.3**	

the percentage of the cases correctly predicted positive out of all cases predicted positive, i. e. $TP/(TP + FP)$ and $Accuracy$ is the percentage of predictions that are correct, i. e. $((TP + TN)/(TP + FP + FN + TN))$. TP, TN, FP and FN represent "true positive", "true negative", "false positive" and "false negative". $F - measure$ calculated by a combination of recall and precision is computed by $(2 * Recall * Precision)/(Recall + Precision)$ [13].

For instance, the entries of the second column of Table I illustrates that 80% of B0 cases are predicted correctly and 20% are mis-classified as B30. Table I indicates that the accuracy of our proposed bed inclination algorithm to distinguish $B60$ is better than two other classes. For bed inclination classification, class $B60$ has the highest value for recall, precision and F-measure and $B30$ has lower accuracy than other inclination classes.

Note that accuracy of around 80% should be considered excellent in our applications. Two practical reasons are: 1) the computation is solely based on pressure images and no additional sensor (e. g. accelerometer used in some works [14]) is attached to bed or patient's body. So, it can be easily integrated with any patient monitoring system that works only with pressure mat data to do risk assessment. 2) bed/mattress and human body are conforming (not solid) objects and exact relative degrees cannot be even well defined.

To have a full evaluation of our method, four classifiers have been tried. Table II compares the performance of different classifiers based on the extracted features. The kNN classifier has the highest accuracy. This is expected as other methods need much more instances (e. g. hundreds of subjects) to learn a definite model in training phase.

TABLE II

COMPARING ACCURACY OF FOUR CLASSIFIERS (%).

Classifier	Recall	Precision	F-measure
kNN	**79.6**	**80.7**	**80.1**
Naive-Bayes	62.0	64.5	63.2
C4.5	75.7	78.3	76.9
Part	73.5	75.2	74.3

To analyze the effect of subject's weight (wt), Table III summarizes our experimentation for different subjects. The subject set includes of three groups with approximately equal number of samples: (i) *wt≤160 lbs*, (ii) *160 lbs≤ wt≤190 lbs*, and (iii) *wt≥190 lbs*. Interestingly, our work shows better performance for lighter group of patients. This is due to the fact that accurate extraction of TB and consequently related features for heavier bodies is harder than lighter bodies. In other words, heavier body often produces more uniform pressure distribution on target box that reduces the accuracy of classification.

TABLE III

TOTAL ACCURACY OF SUBJECTS GROUPED BY WEIGHT (%).

	wt≤160 lbs	160 lbs ≤ wt≤ 190 lbs	190 lbs≤ wt
# Patients	5	6	4
Accuracy	89.5	85.4	75.9

IV. CONCLUSIONS

In this paper, an efficient and novel algorithm for robust classification of bed inclination for bed-bound individuals was proposed that can be helpful in pressure ulcer monitoring, prevention and risk assessment. The average accuracy of our methodology has been 80.3% for three commonly-used bed inclination classes that is practically excellent considering the fact that we only use low resolution pressure images for non-geometrical conforming human body.

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