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Preventing Pressure Ulcers by Image based Posture Detection

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***Abstract*—Pressure ulcers, also known as pressure sores or bedsores, are a disease affecting the skin and underlying tissue that mostly occurs over bony parts of the body because of long-term exposure to pressure. Pressure ulcers most commonly develop in patients who are often bed- or chair-bound for long periods of time. When an ulcer occurs, its treatment is often complex and expensive. Relieving the pressure imposed on the patient skin is the most effective approach for preventing bedsores. Common practice in hospitals and nursing homes is to periodically repositioning the patient. Manually relieving patient skin pressure places a financial and physical burden on caregivers. In this paper, we are proposing a detection approach that optimally detects patient posture and spots at-risk locations on the body by using data from a pressure sensor array in a bed. Our novel ulcer detection solution is based on posture detection using an SVM-based classifier, whose performance was considerably boosted by the pre-processing pipeline we designed. The approach periodically generates outputs that can be used to trigger actuators in air-enabled mattresses to inflate and deflate the air in the target locations. This technique can also be used in robot-equipped beds to turn patients if needed to prevent bedsores. The generated outputs can also be used in reporting the patient's condition.**

***Index Terms*—Image Processing, Bedsore, Pressure Ulcers Prevention, Computerized Monitoring, Support Vector Machine.**

I. Introduction

Pressure ulcers (PUs), 'bedsores', or 'pressure sores' [1] are caused when an area of skin and the tissue below is damaged due to impaired blood flow, which is a result of being placed under constant pressure. Typically, they occur in a person confined to a bed or a chair by mobility problems or an illness.

Dealing with and preventing pressure ulcers is currently one of the most demanding daily challenges facing caregivers in nursing homes, hospitals, and long-term care facilities. Pressure ulcers are most prevalent in older adults, where PUs can cause severe health problems, which can result in sepsis and potentially death. The rate of pressure ulcers in hospital settings is high; the prevalence in European hospitals ranges from 8.3% to 23%, whereas the prevalence is 26% in Canadian healthcare settings [2]. In 2013, there were 29,000 documented deaths resulting from pressure ulcers globally [3]. According to the United States Centers for Medicare and Medicaid Services, pressure ulcers are one of the eight preventable iatrogenic illnesses. The spinal cord injury patient population is at the highest risk (25–66%) of developing a pressure ulcer due to the combination of immobility and decreased sensation. A prospective study of spinal cord patients not only found that sacral and ischial pressure ulcers were very common (43% and 15%, respectively), as might be expected, but also noted that the second most common location (19%) was on the heel [4], [5]. Nursing home patients have a prevalence of 11% pressure ulcers and are most likely to develop pressure ulcers over the sacrum or heels [6], [7]. Nursing home patients were also found to have contractures at a prevalence of 55% [8].

Pressure ulcer treatment is highly costly. One study [9] found that the cost to heal a pressure ulcer substantially increases with the severity of the ulcer, ranging from €24 ($32.16, Grade I ulcer) to €6,802 ($9,115, Grade IV ulcer) for patients treated in hospitals. In the National Health Service (NHS) in England, 24,674 patients were reported to have developed new pressure ulcers between April 2015 and March 2016, with an estimated treatment cost to the NHS of more than £3.8 million per day [10]. Early detection of pressure ulcers is crucial for effective prevention, but traditional methods such as tactile examination require continuous monitoring by medical professionals. Hospitals usually turn patients every 2 hours to prevent pressure ulcers, but the shortage of nursing staff makes it difficult to provide sufficient care. Therefore, efficient planning of pressure ulcer prevention is necessary to alleviate the nursing shortage and reduce the number of incidents. Automatic pressure ulcer prevention is an urgent need for patients who cannot receive continuous monitoring by professionals.

To enable automatic PU detection and prevention, researchers have proposed visual monitoring, which raises privacy concerns. Alternatives, such as automatic posture detection, are often not accurate enough. Progress in pressure sensing technology has made it possible to have pressure maps of the patients not only in high resolution but also with low costs. In this paper, we propose an effective PU detection algorithm for a smart bed, able to capture pressure data and act accordingly, to help bed-bound patients avoid developing Pressure Ulcers. The focus of the algorithm is to retrieve and process real-time data from pressure sensors embedded in the patient's bed. The algorithm is intended to provide the 2 main outcomes:

1) Detecting posture of the patient in the bed. The algorithm classifies the patient's posture in classes including Supine, Right and Left.
2) Pinpointing the spot of the patient's body that is at risk of excessive pressure. The algorithm detects the stressed part of the patient's body by calculating the average pressure imposed on the body skin during specific intervals.

Our approach can be used with a commercial and customized pressure mapping system. We use a machine learning (ML) based approach to detect the patient's posture train with a public data-set [11]. The data set contains pressure maps obtained from thirteen subjects in three main postures: supine left and right posture. Pressure maps are preprocessed by segmentation and dimension reduction before entering the ML algorithm stage to improve the performance and accuracy of the algorithm. In the evaluation of our posture detection pipeline, we will show that our approach achieves better detection performance than the current state-of-the-art approaches that have trained and tested their models using publicly available datasets [11], [12].

The remainder of this paper is organized as follows. In the next section, we review Related Work. The Detection Approach section includes a detailed discussion of the dataset, our intended mechanism to detect bedsores and its implementation. The Results and Discussions section displays the outcomes for at-risk parts of the body from our simulation experiments, shows the evaluation of the posture detection part, and contrasts this part with other existing work. Finally, we summarize our work in the Conclusions section.

II. Related Works

Pressure ulcer prevention based on posture detection has been studied recently. There have been different technologies employed by researchers to detect patients' in-bed posture, such as video cameras, wearable sensors, microphones, or pressure mattresses. In [13] researchers assess the risk of pressure ulcers by monitoring constant pressure, temperature, humidity, and movement using wearable wireless patches placed directly on the at risk areas. Authors in [14] collected data coming from a set of wearable non-invasive inertial sensors and designed a pressure ulcer prevention system using deep learning techniques. Authors in [15] present a smart remote monitoring system based on a ZigBee based sensor network with pressure sensors located on the bed for the prevention of PUs in patients with reduced mobility. Another technique utilized Electrocardiogram (ECG) measurements to estimate body postures [16]. The works using wearable sensors suffer from being uncomfortable since the sensors directly attached to a patient's body might often tend to be awkward. Aside from potential privacy violations, techniques using visual signals and video cameras are considerably affected by lighting issues during data collection.

Recently, there has been an increase in the number of works on in-bed posture recognition. Authors in [17] used a 48×128 sensor array of sensors embedded into a mattress for posture recognition based on weighted limbs, and in [18] authors used a 42×192 sensor array for classifying 4 major sleeping positions of Supine, Prone, Left, and Right. They propose a robust deep learning model capable of accurately detecting subjects and their sleeping postures using a publicly available data set acquired from a commercial pressure mapping system. In [19], the authors proposed the design of a smart bed which retrieves body pressure data from customized settings of two types of pressure sensors (FSR-408, FSR-406) to prevent ulcer pressure and issue fall detection alerts.

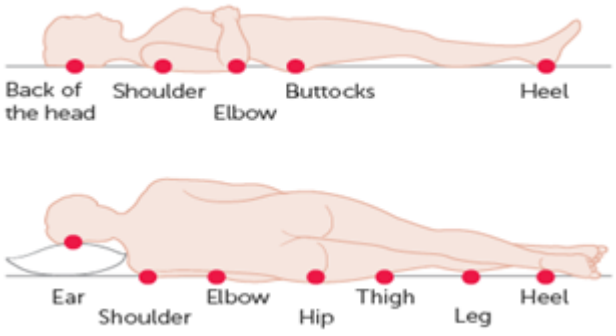


Fig. 1. Parts of the body where pressure ulcers commonly develop.

III. Detection Approach

In this section, we discuss the methodology and tools of our detection approach.

A. Dataset

The dataset we used in this study comprises a set of pressure maps obtained from thirteen subjects [11]. The characteristics are tabulated in Table I. For each subject, we have seventeen variations of three main postures: supine, and lateral (left and right) in the dataset. Each posture pressure map is captured for 2 minutes at a sampling rate of 1Hz, which leads to around 120 frames per posture. Pressure maps are obtained from a pressure mat, a 2-dimensional array of 2048 sensor points. These sensors are uniformly distributed across the 32" × 64" surface of the mat.

TABLE I
Individual Characteristics

User	Age	Height (cm)	Weight (Kg)
1	19	175	87
2	23	183	85
3	23	183	100
4	24	177	70
5	24	172	66
6	26	169	83
7	27	179	96
8	27	186	63
9	30	174	74
10	30	174	79
11	30	176	91
12	33	170	78
13	34	174	74

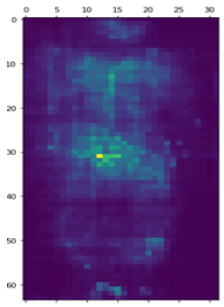


Fig. 2. Example of a body pressure map visualization .

Figure 1 represents the areas of the body where pressure ulcers commonly develop. Figure 2 shows the visualization of an example of the body pressure map of the supine posture.

B. Processing Pipeline

The primary goal of our method is to find and monitor the PU-prone locations of the patient's body while lying on the bed in three standard postures: supine, right and left. The present approach uses the two-dimensional matrix of pressure measurements laid over the bed's surface.

This method is aimed to be used for monitoring, prevention and management of pressure ulcers. The flowchart is illustrated in Figure 3.

a) Segmentation: The segmentation unit extracts the body segment and improves the quality of pressure images. As shown in Figure 4, the segmentation unit is a preprocessing section for both the posture classification ML algorithm and the at-risk detection points unit. Training and test sets need to go through the segmentation unit. Since noise in images are smoothed and reduced in the segmentation process, the performance of our classification model is considerably enhanced.

The segmented image is used both in posture detection and to find at-risk points. Figure 4 represents the sequences of the steps in the segmentation unit. According to Figure 4, the segmentation unit is composed of two pipelines: binarization and filtering. Their results are multiplied to create the final segmented image. Binarization includes preprocessing, thresholding, and post-processing units. The binarization's preprocessing includes histogram equalization and Gaussian filtering. Histogram equalization increases global contrast. Applying a Gaussian filter to the pressure map is the next step in binarization, which smooths the image, and reduces noise. The filter helps the thresholding algorithm in finding a more accurate threshold value.

The combination of histogram equalization and Gaussian filtering as binarization preprocessing improves the quality of the image and alleviates damages that can occur during the retrieval and storage process. Accordingly, thresholding performance will be enhanced. After pre-processing, thresholding binarizes the pressure image. The algorithm uses Otsu's method for thresholding [20]. We applied closing morphology as post-processing to fill holes in the binary-segmented body's pressure image caused by binarization. Figure 5 illustrates one of the pressure images along with its corresponding segmented image.

b) Dimensionality Reduction: A pressure image is represented as a sequence of pixel intensities whose values are the pressure measurements of the corresponding sensors. The vector of pixels is a point in N-dimensional space with N the number of sensors (e.g. 2048). The main problem associated with high dimensionality in machine learning is model overfitting, which lowers the generalization ability. Principal Component Analysis (PCA) [21] is the selected dimension reduction technique. It projects each data point onto only the first few principal components to obtain lower-dimensional data while preserving as much of the data's variance as possible. The model also becomes more efficient, as the reduced feature set boosts learning rates and diminishes computation costs by removing redundant features. In this technique, a subspace on which to project the pressure images is first selected. After subspace selection, all training images are projected into this subspace. Given the fact that PCA is sensitive to the scale of the data, data standardization is applied before going through dimension reduction. Scaling each dimension to fit a standard normal distribution is known as data standardization, a standard normal distribution is defined as a distribution with a mean of 0 and a standard deviation of 1.

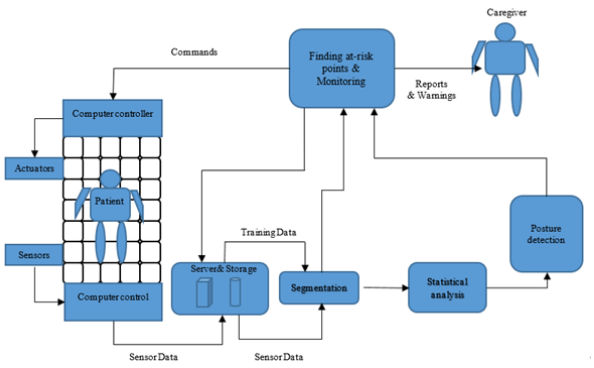


Fig. 3. Diagram for the monitoring and preventing pressure ulcers process. Retrieved pressure maps are processed and classified based on the patient's posture to find at-danger parts of the body.

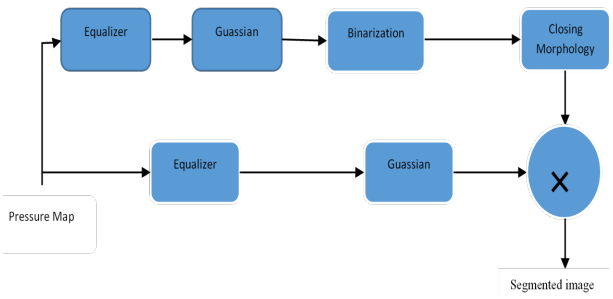


Fig. 4. Sequences of process steps in segmentation unit.

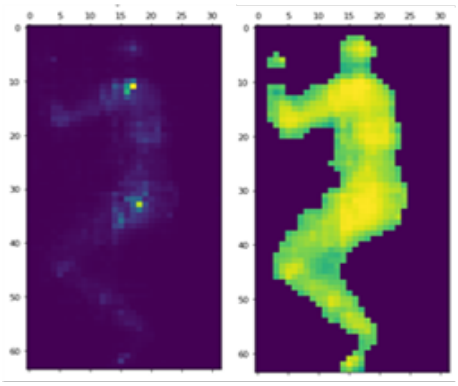


Fig. 5. Pressure image along with its corresponding segmented image.

c) Posture Detection: To classify the pressure images based on the patient's posture, we chose to use Support Vector Machine (SVM) owing to the fact that we are dealing with high-dimensional data-points. SVMs are able to find the optimal boundary between different classes in high-dimensional feature spaces. This is particularly useful for posture detection, where the data may have many features and the boundary between different postures may be non-linear. SVMs are able to handle non-linear boundaries by transforming the data into a higher-dimensional space and then finding the optimal boundary in that space. Additionally, SVMs are also able to handle imbalanced classes, which is a common issue in posture detection where one class may be much more common than the others. Postures are classified into three types: Supine, Right and Left. The machine learning model is trained with the training set, which includes the number of pressure maps with the three mentioned postures.

d) At-risk areas detection and monitoring: In the At-risk areas detection and monitoring unit, the developed approach detects the at-risk regions using segmented pressure images based on the patient's posture. Figure 6 represents the flowchart of the method's at-risk areas detection and monitoring unit. The first step is to segment the pressure image through the segmentation unit, not only to detect the posture but also to find the most stressed parts of the body. After detecting the patient's posture, depending on the posture: supine or lateral (left or right) the algorithm will find N sub-matrices (26 for supine and 29 for lateral) with most sum of the pressure values. The sub-matrix size can depend on the patient's body dimensions and posture.

The next step is to map the regions found into the mattress cells. In this work, the cell size is considered to be 4x4 sensors. Having 32x64 sensors embedded, a mattress covers 8x16 cells (128 cells in total). The next step is to update sigma, which stores the cumulative average of sensor readings for the mapped cells. Each cell is associated with a flag with on and off status. When the flag is on, it indicates that the corresponding sigma value of the cell exceeded P_{max}, a threshold for the cumulative pressure imposed on a cell, for a period T (for example 30 minutes), and the region is stressed. The flag is off when the cell is not stressed or the pressure is relieved, which means the sigma average value should fall under P_{min}, the cumulative pressure which is defined as relief for a stressed region. Flag values are updated according to equation 1. When the status of the flag is off but the average value of the cell pressure in the last period exceeds P_{max}, the cell's flag status changes to on, and it will remain on until the average pressure of a future period falls under P_{min}. Flag values, which are based on the patient's position and pressure, can be thought of as commands issued to actuators, whether they operate air inflators and deflators or robot step motors. These values can also be exploited to create the reports for the associated caregivers.

$$flag = \begin{cases} 1, & \frac{1}{T}\sum_T P \geq P_{max} \text{and } flag = 0 \\ 0, & \frac{1}{T}\sum_T P \leq P_{min} \text{and } flag = 1 \end{cases} \quad (1)$$

e) Implementation: The implementation is structured into five modules: data fetching, binarization, filtering, PCA and machine learning and monitoring. Before fitting the model, the training set must go through standardization and dimension reduction. The standard score of sample x is calculated by equation 2.

$$x = (\frac{(x-u)}{s}) \quad (2)$$

where u is the mean of the training samples and s is the standard deviation of the training samples. Our SVM machine learning model was tuned using Grid Search method. Grid Search was executed in a loop over different PCA values in order to find the best values for both PCA and model parameters. RBF (Radio Basics Function) was chosen as our model kernel. C (penalty parameter) and Gamma were set at 50 and 0.0001, respectively.

IV. Results and Discussions

In the following, we present the main results achieved and compare our results with other implementations. Our model

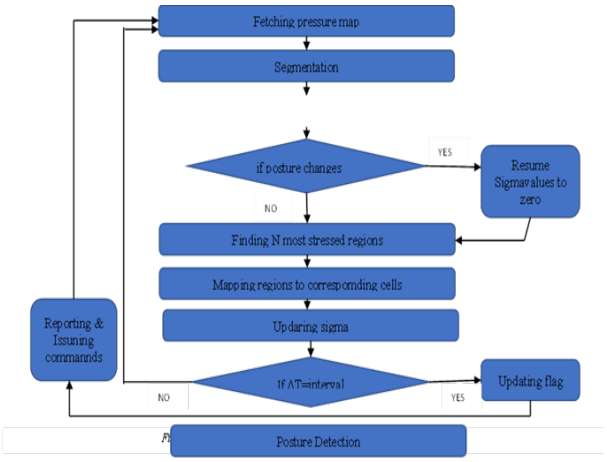


Fig. 6. The flowchart of the algorithm's at-risk areas detection and monitoring unit.

performance was evaluated by different metrics for a range of PCA values, which are presented in Table II. For each posture recall, specificity and precision were calculated. Overall performance of the model for the test set was computed by the accuracy metric. Based on the patient's posture, the at-risk parts of the body are detected in the monitoring unit on the segmented image of the patient's body. Based on experiments performed with different subjects, the numbers of at-risk regions for supine and lateral postures are set respectively at 26 and 29 with region sizes of 4*4 inches. Figure 7 represents the examples of a supine and lateral posture of a subject whose at-risk parts were located by our method.

The average measurement values of the active at-risk region sensors are accumulated in their corresponding entry in the sigma variable. The average pressure of the regions, which is obtained from dividing the corresponding sigma value by the number of fetching maps during a specific period of time (30 minutes in our experiments), is compared with $P_{max} = 50$mmHg, which we set as a reference in this work. When the pressure exceeds P_{max}, the corresponding entry for the measured region of the alarming array will be set to *True*, and it will remain *True* until the pressure, in the following period, falls below $P_{min} = 30$mmHg (also parameterizable), thus implementing a hysteresis behavior.

We implemented a performance verification experiment by feeding the present algorithm every second with image pressure frames of the dataset. Frames of the patient's body in two supine and lateral postures were fed to the algorithm. Figure 8 visualizes the snapshots of sigma for the 16x8 array selected, which keeps the accumulated pressure measurements of at-risk found regions, and also for Flag, which presents the corresponding alarm points on the mattress surface which means those cells of the mattress (in yellow color) are in touch with at-danger parts of the patient's body. Therefore, for example in the case of using the self-inflating and deflating air mattress, the corresponding actuators must be activated to relieve the skin pressure.

To compare the performance of our posture classification with other existing works, we use another publicly available dataset [12]. The researchers in this work have simultaneously used 4 different modalities: RGB camera, LWIR camera, a depth camera and pressure mat to collect data from 45 variants of three main postures of 102 subjects. This dataset provided us with 4950 pressure maps. We dedicated 4/5 of the dataset to train our model and tested the model performance with 1/5 of the remaining dataset. Our model obtained 99.2 per cent accuracy on the test set. The confusion matrix of the test set for three main postures is shown in Table III.

Table IV shows the results of the other works in which their approaches are trained with the same dataset as in [12]. As can be seen in Table IV our classification approach has remarkably better performance.

V. Conclusions

In this paper, we present a method to detect a patient's posture, based on a signal processing pipeline using machine learning algorithms to pinpoint the at-risk parts of the body in terms of pressure ulcer disease development. We address the problem related to the generation of PUs when the skin is under constant pressure for a long time. In such a context, pressure sensor arrays embedded in the patient's bed can be exploited to prevent bedsores, which in turn helps to elevate the patient's quality of life and reduce nursing and treatment-related costs.

Our approach is composed of preprocessing units for segmentation and dimension reduction that considerably improve the machine learning model's performance. Our evaluation shows better results than related work using the same dataset. We also implemented a technique using the segmented image accompanied by detected posture to locate the PU-prone body's location. In the monitoring unit of the algorithm, alarms are raised for long stressed PU-prone parts of the body that can trigger actuators or be used to report caregivers.

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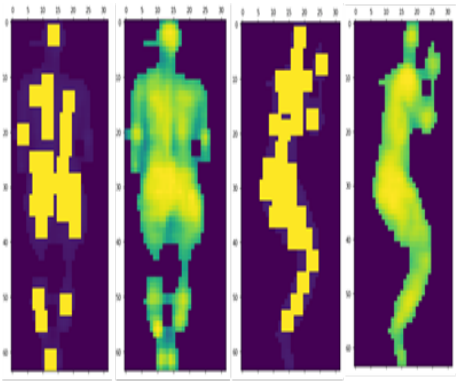


Fig. 7. Visualization of found at-risk points for supine and lateral posture along their corresponding segmented image

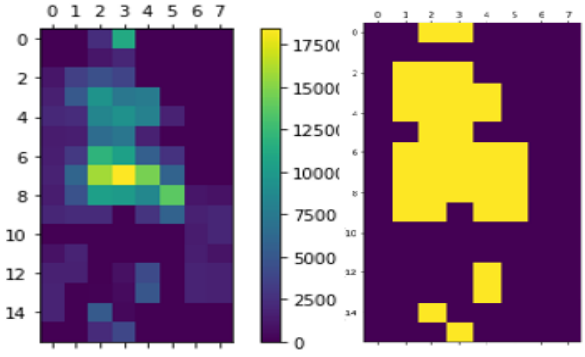


Fig. 8. Visualization of Sigma (left) and Delta values (right)

TABLE II
EVALUATION OF THE MODEL PERFORMANCE FOR A RANGE OF THE PCA VALUES

Posture	Metrics \ PCA	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65
Supine	Recall	92.9	94.7	96.4	96.4	100	100	98.2	100
	Specificity	92.3	94.3	96.1	96.2	100	100	98.1	100
	Precision	89.8	93.1	93.2	94.8	98.2	98.2	98.2	100
Right Side	Recall	95.2	95.2	95.2	95.2	100	100	100	100
	Specificity	98.8	98.8	98.8	98.8	100	100	100	100
	Precision	98.3	83.3	90.2	86.9	100	100	95.4	100
Left Side	Recall	84.8	87.8	90.9	90.9	96.9	96.9	96.9	100
	Specificity	93.9	95.1	96.2	96.2	98.7	98.7	98.7	100
	Precision	100	100	100	100	100	100	100	100
	Accuracy	90.9	92.7	94.5	94.5	99.0	99.0	98.1	100

TABLE III
TEST SET CONFUSION MATRIX OF THREE MAIN POSTURES

Actual \ Predicted	Supine	Left	Right
Supine	299	3	1
Left	1	301	0
Right	2	0	309

TABLE IV
COMPARISON OUR RESULT WITH OTHER WORKS

Approach	Accuracy
Sun et al. [22]	84.3
Xiao et al. [23]	86.8
Gkioxari et al. [24]	88.5
Chu et al. [25]	88.1
Yang et al. [26]	90.7
Newell et al. [27]	90.1
Present model	99.2

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