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Automatic limb identification and sleeping parameters assessment for pressure ulcer prevention

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ABSTRACT

Pressure ulcers (PUs) are common among vulnerable patients such as elderly, bedridden and diabetic. PUs are very painful for patients and costly for hospitals and nursing homes. Assessment of sleeping parameters on at-risk limbs is critical for ulcer prevention. An effective assessment depends on automatic identification and tracking of at-risk limbs. An accurate limb identification can be used to analyze the pressure distribution and assess risk for each limb. In this paper, we propose a graph-based clustering approach to extract the body limbs from the pressure data collected by a commercial pressure map system. A robust signature-based technique is employed to automatically label each limb. Finally, an assessment technique is applied to evaluate the experienced stress by each limb over time. The experimental results indicate high performance and more than 94% average accuracy of the proposed approach.

1. Introduction

1.1. Background

Pressure ulcers (bed-sores) are localized injuries on the skin and underlying tissues happening due to prolonged stress on those areas. Pressure ulcer occurs on a limb, once the regional vessels are blocked due to pressure experienced by that limb. In this situation, bed-sores gradually develop due to lack of sufficient blood flowing through some regions of that limb [1]. Bed-sores are common among elderly, bed-ridden and hospitalized individuals and often occur in specific limbs such as back, sacrum, head, heels, hips and elbows [1]. Although pressure ulcers develop gradually, if they are not addressed on time, they may lead to surgery, amputation or even death [2]. Pressure ulcers are very painful for patients and very expensive to cure for hospitals. The average cost of managing a single full-thickness PU is as much as $70,000. The annual cost of ulcer treatment in the U.S. is estimated to be more than $11 billion [3].

Although pressure is known as the main reason of pressure ulcer development, the effects of several other factors such as shear, moisture, and skin temperature have been investigated in recent studies. The U.S. and European National Pressure Advisory panels (NPUAP and ENPUAP) categorized PUs in four stages and regularly publish guidelines for inspection, prevention, and treatment [3,4].

Special beds with air mattress and passive pressure map/distribution devices [5] are well-known technologies to relieve the stress by repositioning the patients. Such approaches are practically useful for patients suffering developed pressure ulcers [6]. However, these methods are very costly and are not guarantied to work well for all at-risk patients. In addition, these technologies do not offer scientific assessment of each at-risk limb.

Intelligent analytics to evaluate the risk of pressure ulcers on patient's body are highly in demand. In-bed postures and the pressure experienced by each limb in that posture are known as main factors involved in bed-sores progress. Commercial pressure mats are able to continuously report pressure distribution of body. The pressure of at-risk limbs can therefore be relieved by turning the patient before it is too late. A robust assessment method depends on accurate posture identification and finding the corresponding body limbs [7,8].

1.2. Related work

Several works have employed pressure mats to identify sleep postures. Most of these methods use supervised machine learning approaches for sleep posture detection. A combination of video and pressure data is employed in [9] to classify patient's postures on the bed. Bayesian classification is applied on collected pressure map to identify sleep postures in [10]. In [11], a light

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computational method is employed to identify eight prevalent sleep postures. The proposed technique in [12] employed principle component analysis (PCA) and kNN classification to classify five common sleep postures.

Limb identification and tracking problem is more challenging than posture classification. In contrast with posture detection, limb identification can be formulated as an unsupervised problem. The reason is that some sleeping postures are very similar in terms of pressure distribution and shape. Thus, it will be difficult to distinguish these relatively similar postures without any labeling (training) information. So, "supervised learning" is preferred for posture detection problem. On the other hand, our side-knowledge on the limb detection data, like number of limbs and geometry information of the limbs in the body structure, let us detect limbs even without having any prior labels (training data). So, the "unsupervised learning" is often employed for limb identification. Human body is not rigidly geometrical and body weight-shift modeling cannot be easily captured. Another challenge in a limb identification system is to identify limbs by a system automatically and make it available for continuous assessment of sleeping parameters. In this paper, *sleeping parameters* refer to pressure, temperature, and shear collected at body–mattress interface.

Recently, some methods have been proposed to identify body limbs in sleep postures using pressure mat data. For example, a technique is presented in [13] used cascaded image processing techniques to define a tree-skeleton model of body pressure image using Delaunay triangulation (DT). Briefly, each branch of the extracted tree is compared with a predefined body's tree-skeleton using dynamic time warping (DTW) to identify high-risk body points. The method heavily depends on the initial body template. Also, this method just detects high pressure points instead of whole limbs. Another problem is that the extracted pressure image from pressure mat is low resolution. In this situation, image filtering techniques may generate a fragmented tree-skeleton and it may cause a low quality skeleton of the body. The approach presented in [14] employs a pictorial structure model for identifying structured objects in pressure images. This approach makes it possible to keep track of all predefined body parts using a dynamic updating process. A predefined template of body with corresponding limbs for each posture is defined in [15]. A mixture of k Gaussian distributions (one for each limb) is trained using pressure mat's data. The required parameters of each Gaussian is estimated using expectation maximization (EM) process. Finally, a GMM clustering algorithm segments the pressure image into k different areas. Note that applying predefined Gaussian models on pressure mat data with limited number of pressure sensors to extract several body limbs may not be accurate due to fixed parameters required for each Gaussian. Since human's body sizes are very different (e.g. male, female, and children), fixed pre-defined values for each Gaussian will not be accurate when the number of corresponding sensors for each limb is very limited. The sleep pattern and the resulting pressure distribution of each limb vary among different subjects and this can cause another factor of inaccuracy. Also, the GMM-based approaches highly depend on the number of data points (sensors which experience pressure) in each limb which make it difficult to identify small size limbs (e.g. head). In [16], researchers proposed to apply a *fuzzy-C-means* (FCM) algorithm to pressure mat data to segment body pressure image to predefined limbs. Although applying FCM has shown higher accuracy than GMM and *k-means*, some misclassification have been observed specially for limbs in side postures.

None of above limb identification methods can efficiently be used in a real time system due to low performance and the lack of an intelligent limb labeling phase. Since sleeping postures of patients change over time, manual identification (labeling) of limbs is not practical. Conventional techniques did not offer an automatic limb labeling. Although some methods [15] apply a predefined template for their limb identification, this is still inaccurate as patients have different sizes and body shapes. With clustering techniques, a labeling mechanism is needed to find the cluster–limb correspondence.

PUs are known as a direct outcome of exposed pressure and microclimate factors like shear and accumulated perspiration [17,18]. Risk level is usually determined using Braden pressure ulcer risk assessment chart [19]. Although this chart is practically useful, its shortcomings include being subjective and observation based. Additionally, it cannot address deep tissue injury (DTI) that happens when underlying tissue can be compromised long before the injury is visible. In [20], authors used a pressure–time cell injury model of rats to model stress and recovery of each limb. This study has been used in [7] to model PU's risk-assessment. In this model, other factors like induced shear and temperature are not considered.

1.3. Main contribution and paper organization

This paper extends the state of knowledge in PU monitoring in three directions. First, we apply an efficient graph-based partitioning technique to identify body limbs in three prevalent sleep postures (left side, supine, and right side as shown in Fig. 1). Second, a signature-based labeling method is proposed to automatically label the extracted limbs accurately. Finally, a novel risk-assessment modeling based on microclimate effects [18] is applied to assess risk of PUs in different limbs which considers the combined effect of shear, pressure and temperature. The proposed method can be integrated in any monitoring system to effectively track limbs and evaluate the risk of pressure ulcer occurrence.

This paper is organized as follows: In Section 2, an effective body segmentation is introduced using graph clustering. In Section 3, a signatured-based labeling technique is introduced to automatically label extracted body limbs. The assessment of sleeping parameters using skin tolerance model is explained in Section 4. The experimental results and validation of the proposed approach are presented in Section 5. Finally, Section 6 highlights the concluding remarks.

2. Limb identification

2.1. Pressure map model and preprocessing

A commercial non-invasive pressure-sensitive mat platform is used to capture pressure data continuously [21]. This pressure measurement system provides a 2-D array of adjacent pressure sensing elements almost 25 mm apart. The flexibility and thickness of pressure-sensitive mat make it suitable to be easily integrated on top of the bed mattress. The pressure mat used in this work has 1728 (64×27) pressure sensing elements distributed uniformly to collect data with sampling rate of 1 Hz.

Sensing elements (e.g. resistive, capacitive, and piezoelectric) used in pressure mats commonly inject noise to the final sensor reading. To reduce this disrupting noise effect, a symmetric Gaussian low pass filter of size 10 with standard deviation 0.5 is applied. Some abnormal noisy points are observed from time to time caused by dynamic charging and discharging behavior of capacitors. A median filter is applied to remove this type of noise. This is actually a non-linear filtering which keeps edges of image and remove noise simultaneously. In other words, the median filter removes the noise by updating the value of each pixel with the median value of its adjacent pixels.

The body can be divided into meaningful at-risk limbs for each sleep posture. In this paper, the term "limb" is broadly used to refer