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 guaranteed 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...
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. 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 signature-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 ($64 \times 27$) 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 disturbing 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
to certain areas susceptible to bedsore (e.g. sacrum, back, and shoulder) that caregivers often inspect \[1,3\]. Small body parts (e.g. ankle and coccyx) are not considered in this work. Three common sleep postures (supine, left side and right side), nine different limbs (S1–S9) for supine and seven limbs (L1/R1–L7/R7) for left/right postures are considered. Table 1 depicts the most important at-risk limbs in target postures. Ultimately, we want to automatically identify and track each limb and compute the risk for each limb.

Let set $\{S_1, S_2, \ldots, S_n\}$ denote $N$ pressure sensors with non-zero pressure values (i.e. after filtering). There are two key assumptions: (i) the model of pressure distribution for any limb directly depends on the skeleton formation, shape and weight of that limb \[7\]. Obviously, sensors under a specific limb should have more experienced pressure affinity than sensors under other limbs, (ii) the sensors related to each limb are naturally closer to each other than sensors that capture other limbs. Consequently, each sensor is presented as a triplet $s_i = (x_i, y_i, p_i)$ where $x_i$ and $y_i$ are the coordinates and $p_i$ is the pre-processed pressure value corresponding to the sensor at $(x_i, y_i)$. To make the features homogeneous, all the three attributes of set $S$ are normalized to interval $[0,1]$.

### 2.2. Construction of limb graph (LG)

Our proposed clustering method aims to divide set $S$ into $K$ partitions indicating distinct limbs. Although most of the limbs may be considered as surfaces. However, we do not know how is the real shape of these body limbs in the space represented by $S$. Some of these limbs can produce convex or concave areas in $S$ space. Another hurdle is that some of these limbs with similar pressure distribution may be located very close to each other in real story (e.g. two feet in supine posture).

To overcome these problems, we propose to form a graph to represent geometry of the body limbs. We call this graph limb graph or LG. Let define $LG = \{V, E\}$ where $V = \{v_1, v_2, \ldots, v_n\}$ is the set of vertices and $E \subseteq V \times V$ denotes the set of edges among $v_i$. In LG, each sensor presents a node $v_i$. Each node is connected to its $k$ nearest neighbors via an edge whose weight is initially computed using a similarity among nodes. The nearest neighbors of each node are the most similar sensors to itself. Our hypothesis is based on the fact that sensors related to each limb are reporting similar average pressure values related to specific mass of body. When the limbs disjoin with related distinct synovial joints, the pressure model will change as well. When constructed, LG can be segmented into subsets of continuous interconnected regions indicating distinct body limbs.

Constructing LG requires defining a suitable similarity measure among $v_i$. We construct LG for set $S$ as follow: (i) model each $s_i$ with a node $v_i$ in LG and (ii) $k$ nearest neighbors of each $s_i$ are chosen using Euclidean distance:

$$u_{ij} = \| s_i - s_j \|$$ (1)
Using Eq. (1), \( k \) may have a large influence on the final segmentation performance. If it is considered too large, some of the small parts are merged in big parts. Similarly, if \( k \) is set too small, we will have the lack of connectivity within a single limb. Also, there is another shortcoming of just using Euclidean distance. If there are some close \( v_i \) that belong to different partitions, they may join two different partitions incorrectly. For example, green edge in Fig. 2(a) connects two close nodes \( v_i \) and \( v_j \) from different partitions strongly. This problem may be worsened by existence of partially concave partitions within the body pressure data.

To overcome the abovementioned shortcomings, we refine the LG structure. To do that, LG is considered as a weighted graph. In this weighted graph, the weight between each pair of \( v_i \) and \( v_j \) is defined based on the number of shared neighbors using Jaccard distance [22] as follows:

\[
w_{ij} = \frac{|n(v_i) \cap n(v_j)|}{|n(v_i) \cup n(v_j)|}
\]

(2)

where \( n(v_i) \) and \( n(v_j) \) indicate list of the \( k \)-nearest neighbors of \( v_i \) and \( v_j \), respectively, and \( i,j \) refers to the number of elements in the set. The Jaccard distance, as the similarity between two nodes of LG, will get maximum when their \( k \) nearest neighbors are the same \((w_{ij} = 1)\) and is proportional to the number of neighbors they share. This definition integrates the model of data distribution into the weights of LG. Also, this metric regulates the edges that span sparse areas between clusters (green edges in Fig. 2). For example, in Fig. 2(a), although \( v_i \) is the nearest neighbor of \( v_s \), \( w_{ij} \) of edge \( v_i - v_j \) will have very small weight using Eq. (2).

2.3. Limb graph partitioning

After constructing LG, we find all the communities (partitions) within this graph. Each community indicates area of group of \( v_i \) more connected with each other. There are several community detection methods studied in network research fields [23,24]. Community detection algorithms extract potential communities in a graph. The modularity for LG can be defined using the concept of modularity presented in [25]:

\[
Q = \frac{1}{2m} \sum_{ij} \left( w_{ij} - \frac{a_i a_j}{2m} \right) \delta(c_i, c_j), \quad m = \frac{1}{2} \sum_{ij} w_{ij}
\]

(3)

where \( a_i \) and \( a_j \) are the sum of all edge weights involving nodes \( v_i \) and \( v_j \), respectively. Also, \( c_i \) and \( c_j \) denote modules \( i \) and \( j \), respectively. Parameter \( \delta(c_i, c_j) = 1 \) if \( i = j \) and 0 otherwise. As explained in [25], modularity ranges in \([-1,1]\) for each graph. Since the modularity explains the quality of partitioning of a graph, it is used as an objective function maximized by a graph community detection technique.

Finding a set of partitions maximizing Eq. (3) is a combinational optimization problem which is NP-complete [25]. However, there are some efficient heuristics to approximate the maximum value of \( Q \). We employed a powerful and fast method proposed in [26] to partition LG. This greedy method works based on an iterative approach in two steps. Briefly, initially all the \( v_s \) of LG are located in different communities. At the first step, for a given \( v_s \) one calculates the gain in weighted modularity (Eq. (3)) by assigning \( v_s \) in the community of its neighbors \( v_k \) and choose the community of the neighbor giving the largest increase of \( Q \), as long as it is positive. Note that, in each step we obtain the modularity based on the original topology of the LG. In the next step, we use virtual supervertices instead of communities. Subsequently, we call any two supervertices connected if there is more than an edge between vertices of one particular community. In order to calculate the weight of the edge connected supervertices, we add all the weights of the edges between the corresponding communities at one lower level. These two steps need to be performed iteratively as far as no progression is observed on \( Q \) and process produce \( K \) partitions.

This method is extremely fast with complexity of \( O(m) \), when \( m \) is the number of edges in LG. Since the method performance may depend on the sequence of node to parse, we apply this partitioning on LG a large number of times (e.g. \( M = 100 \)) and select the result with the highest \( Q \) and \( K \) number of partitions. Fig. 3 shows the pseudocode of proposed approach to extract body limbs.

3. Automatic signature-based labeling

The ultimate goal is to employ the proposed clustering technique in an automatic monitoring system. In clustering phase (Section 2), we obtained \( K \) partitions but partition-limb mapping is not known. An intelligent method is needed to label the extracted clusters accurately. Manual labeling by an expert/physician is not efficient, as it is subjective and time consuming. In this section, we discuss how to automatically assign descriptive labels to clusters’ centroid in order to discriminate clusters from each others. To do this, we take advantage of the external knowledge (the reference points in bed location) to generate discriminative descriptors. Authors in [14,15] use a template-based labeling. Our proposed signature-based labeling has two main advantages compared to previous works. First, subject-independency: Subject’s body size varies among children and adults. But the basic structure (topology) of body is still the same for all people. So, when the size of body changes, the location of limbs would not change with respect to reference points. Second, shift-invariant: Subjects shift in bed time to time and may become close or far from mattress edges. In our technique, the relative distance of limbs from reference points

![Fig. 2. LG graph. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)](image)
is more consistent.

We want to automatically assign labels (limbs) to partitions \( L = \{ l_1, \ldots, l_K \} \) with coordination centroid set \( M = \{ \mu_1, \ldots, \mu_J, \ldots, \mu_J \} \) where \( \mu_j = (x_j, y_j) \) found in previous step. In this work, five reference points including four corners plus center of pressure mat are used. We define five reference points \( R = \{ r_1, r_2, r_3, r_4, r_5 \} \) where \( r_i \) is the location of \( i \)th reference point.

Fig. 4 illustrates an example of the cluster centroids \( \mu_j \)'s (\( \leq j \leq 19 \)) and reference points \( r_i \)'s for supine position.

At first, we generate a \( K \times 5 \) distance matrix \( D \):

\[
D = \begin{bmatrix}
  d_{11} & d_{12} & \cdots & d_{15} \\
  \vdots & \vdots & \ddots & \vdots \\
  d_{51} & d_{52} & \cdots & d_{55}
\end{bmatrix}
\]

(4)

where \( d_{ij} \) is the Euclidean distance between each limb center \( \mu_j \) and each reference point \( r_i, 1 \leq j \leq K \) and \( 1 \leq i \leq 5 \). Afterwards, we create \( K \times 5 \) signature matrix \( SM \):

\[
SM = \begin{bmatrix}
  sm_{11} & sm_{12} & \cdots & sm_{15} \\
  \vdots & \vdots & \ddots & \vdots \\
  sm_{51} & sm_{52} & \cdots & sm_{55}
\end{bmatrix}
\]

(5)

where \( sm_{ij} \) is the order of each limb center \( \mu_j \) with respect to reference points \( r_i \) after sorting the columns of distance matrix \( D \). Each row of matrix \( SM \) represents signature of a limb. In other words, the limb signature denotes position of that limb with respect to the reference points. Table 2 presents the signature matrix for an example subject in supine position. For instance, limb \( l_5 \) is the 2nd closest limb with respect to reference point \( r_2 \), while it is farthest (9th) limb from \( r_1 \). As a whole, limb \( l_5 \) has a unique signature of \{9, 2, 8, 1, 8\}.

During training, we generate a signature matrix template \( T = \{ t_{ij} \} \) which includes signature of different limbs. During testing-phase, we define a similarity matrix \( Z \) representing number of common components in both new limbs and the templates:

\[
Z = | \{ sm_{ip} \} \cap \{ t_{ip} \} | \quad \text{for} \quad 1 \leq p \leq K \quad \text{and} \quad 1 \leq q \leq 5 \quad \text{and} \quad | \cdot | \quad \text{denotes} \quad \text{number of elements}.
\]

Finally, we find the maximum value in each row of similarity matrix \( Z \) and report its index as the corresponding limb label:

\[
L = \{(l_j) = \text{arg max}_{1 \leq j \leq K} (z_{l_j, \ldots, z_{l_j}})\}
\]

Algorithm 1 summarizes the proposed automatic limb labeling. In continuation of this paper, LGC refers to two step method: clustering and labeling.

**Algorithm 1.** Signature-based limb labeling.

Input: \( M = \{ \mu_j \}, R = \{ r_i \}, T = \{ t_{ij} \} \)

Output: \( L = \{ l_j \} \)

for all \( 1 \leq i \leq 5 \) do
  for all \( 1 \leq j \leq K \) do
    \( D = (d_{ij}) = || \mu_j - r_i || \)
    \( SM = \{ sm_{ij} \} = \text{Order of} \ d_{ij} \ \text{in} \ i \text{th column} \)
  end for
end for
for all \( 1 \leq p \leq K \) do
  for all \( 1 \leq q \leq 5 \) do
    \( Z = | \{ sm_{ip} \} \cap \{ t_{ip} \} | \)
  end for
end for

\( L = \{(l_j) = \text{arg max}_{1 \leq j \leq K} (z_{l_j, \ldots, z_{l_j}})\} \)

4. Assessment of ulceration using skin tolerance model

4.1. Review of SUP assessment model

There is a strong evidence that shear increases by accumulation...
of perspiration over the skin over time and speeds up ulcer development [17]. Ref. [18] presented an improved model (compared to their early work in [20]) to assess the effects of accumulating shear and temperature on the skin. Briefly, this study formulates the effects of most factors involved in development of superficial pressure ulcers (SPUs). Although a very accurate assessment of the shear is not practical, the shear stress can be modeled using the pressure experienced by limb using relationship $\phi = \mu \times P_l(x)$ [18]. Parameter $\mu$ is the shear coefficient between the skin and the covering sheet. Parameter $P_l(x)$ denotes the applied pressure on limb $l$ in posture $x$ for the time interval $\Delta t$. To have a more practical model, we consider the worst-case scenario to estimate $P_l(x)$. To do that, the maximum average pressure is applied to estimate this value:

$$P_l(x) = \max_{s \in s_l(x)} \left\{ \frac{1}{\Delta t} \int_0^{\Delta t} p_{s_l}(t) \, dt \right\}$$

(6)

where $s_{l}(x)$ indicates set of sensors belong to the limb $l$ in posture $x$. Also, $p_{s_l}(t)$ reports the pressure by sensor $s$ at time $t$. For simplicity, we use $P_l$ instead of $P_l(x)$. It was previously proven that $\mu$ increases with accumulation of perspiration over time on the skin using $\mu = 0.5V_t + 0.4$ [18, 27]. Parameter $V_t$ is the rate of accumulated perspiration within space $V$ of the skin over time $t$. To have a meaningful measurement resolution of perspiration, we consider $t$ based on a practical hourly repositioning guidelines in hospitals [28]. In general, the skin breaks down once the shear stress $\phi$ surpasses $\phi_{w}^s$ [18], hence:

$$\begin{cases} \phi = (0.5V_t + 0.4) \times P_l \\ \phi_{w}^s = (1 - 0.8V_t) \times \phi_{w}^s \end{cases}$$

(7)

where $\phi_{w}^s$ is the shear strength of dry skin. Since the perspiration rate directly depends on the temperature, it can be modeled as [18]:

$$V_t = \left[ \alpha \frac{T_a - 30 \, ^\circ\text{C}}{T_{a_{\text{max}}} - T_{a_{\text{min}}}} + \beta \frac{T_s - T_{s_{\text{min}}}}{T_{s_{\text{max}}} - T_{s_{\text{min}}}} (1 - R_b) \right] t$$

(8)

where $T_a$ denotes the ambient temperature, $T_s$ shows the skin temperature, and $R_b$ is the evaporation rate of water between body and sheet coverings. Parameters $\alpha$ and $\beta$ are two dimensionless factors related to rate of production and evaporation of respiration, respectively [18]. The perspiration rate is found to be a factor proportional to $T_a - 30 \, ^\circ\text{C}$ [29].

4.2. Assessment model

Fig. 5 presents the general behavior of $\phi_{w}^s$ and $\phi$ over time. We call this plot decision plot (DP). In DP, point $t_c$ denotes critical time at which shear stress under effect of perspiration surpasses the shear strength. Hence, this accumulated model enables us to assess the risk of ulcer over time for each limb. To have a more practical model, we propose to consider thresholds to divide DP into three decision regions (green, yellow, and red). We acknowledge that practical thresholds need extensive clinical experiments. In this work, we define thresholds based on $\phi(t) - \phi_{w}^s(t)$. More specifically, $t_{30}$ and $t_{90}$ are the levels that $\phi(t) - \phi_{w}^s(t)$ are reduced compared to $t=0$ by 60% and 90%, respectively. Also, the skin tolerance $t_c$ can be found as the intersection point of $\phi$ and $\phi_{w}^s$.

Note that the studies on the off-loaded recovery interval indicate that recovery increases with load duration and load pressure. For example, 15 min recovery time after 40 min of a steady heel pressure has been measured for heel blood perfusion by laser Doppler imaging in [30]. Unfortunately, there is very little, if any, clinical human data in the pressure ulcer formation. To the best of our knowledge there is no proven recovery model. In our work, we consider the instantaneous recovery model.

5. Experimental results

5.1. Setup and comparison metrics

Extensive experiments have been performed to assess the performance of the proposed approach. Fifteen healthy adult subjects with different weights, heights and ages were chosen for our data collection phase under UTD-IRB approval. For each subject, 600 pressure image samples were recorded for each considered posture (supine, left and right sides) in various turns over 10 min experiments. A visual inspection of the extracted limbs and scoring the match (in range of [0–10]) by an independent expert compared to the camera-recorded videos. Fig. 6 depicts an example of clustered bodies using LGC. All the compared algorithms were implemented by MATLAB R. 2013b and R language version 3.2.1. All experiments were performed using a desktop computer with 3.2 GHz CPU and 6 GB RAM.

The accuracy of limb detection is computed as follows:

$$\text{Acc} = 1 - \frac{N_{\text{miss}}}{N_{\text{total}}}$$

(9)

where $N_{\text{total}}$ is the number of frames analyzed and $N_{\text{miss}}$ is the number of times a limb is misclassified. In this assessment, the limbs are considered misclassified if any of the following occurs: (i) algorithm incorrectly segments the corresponding limbs, (ii) in an identified limb, more than 5% of its sensors visibly belong to different limbs. Note that, the recognition of a whole limb (not small stressed regions) is considered in our work similar to others [15]. Our target was not identification of partial limbs such as elbow and shoulder as identified in prior work [13]. The performance of our algorithm is compared against four existing algorithms reported in literature.

5.2. Experiments

Tables 3, 4, and 5 report the average accuracy for identification of different limbs in right, supine, and left postures, respectively. As Tables 3–5 show LGC achieves more consistent accuracy than others in different postures. Identification of head in side postures is challenging, a confusion may happen between head and shoulder. Tables 3 and 5 indicate the LGC performance to identify the head area in side postures much better than other methods.
Compared to this work, the GMM clustering may not fit well into Gaussian model for some limbs and it engenders misidentification of limbs. Fig. 6 depicts the extracted limbs for one subject in three different postures.

The hypothesis test was performed to show statistically significant differences between LGC and other methods in identification of limbs in three common postures and p-value is reported in Table 6 to quantify the differences [31]. A small p-value (p ≤ 0.05) in Table 6 denotes the LGC method is more robust than other algorithms to identify the limbs correctly (i.e. LGC’s result is statistically significant).

Fig. 7 presents the average result of limb identification of 7.5 h of a subject’s sleep for three different methods at night. As depicted, the accuracies of GMM and FCM methods are low, but LGC was able to keep accuracy of limb detection around 89% in a real-time experiment.

LGC approach is more reliable than other techniques applying natural image processing and structural body part formulations for real-time application. LGC was tested with three different setting of k (the number of nearest neighbors) for 100 running on the collected dataset. The results are shown in Fig. 8. Small interquartile ranges denote robustness of LGC to selection of parameter k.

After extracting and labeling the limbs in each posture, the average pressure experienced by each limb is computed. Table 7 reports these average values for one subject for a time window of 20 s. In general, our experiments show that sacrum, shoulder, and hip areas experience the highest pressure rate in supine and side postures, respectively.

To have a practical analysis, we set parameters $T_a = 35 ^\circ C$, $\phi_a = 70$ kpa, $a = 2$, $\beta = 1$, $T_{s}^\text{max} = 40 ^\circ C$, $T_{s}^\text{min} = 30 ^\circ C$ and RH = 0.5 as they were recommended in [18,32,33]. Note that $T_a$ is different with room temperature. Body of patient continuously heats the small area around limb of interest, the temperature of this close area is called ambient temperature. Hence, $T_a$ can be considered close or a bit smaller than body temperature ($T_a = 35 ^\circ C$).

We apply the proposed process to calculate limb pressure values in Table 7. Figs. 9–11 present the situation of each limb at different time intervals ($\Delta t_1 = 20 $ min. $\Delta t_2 = 30 $ min. and $\Delta t_3 = 50 $ min) in three different postures. The levels of risk are shown using colorful limbs (green, yellow, and red) in these

**Table 3** Comparing accuracy (in %) of various limb detection algorithms for right side.

<table>
<thead>
<tr>
<th>Alg</th>
<th>R1</th>
<th>R2</th>
<th>R3</th>
<th>R4</th>
<th>R5</th>
<th>R6</th>
<th>R7</th>
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<td>–</td>
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<td>86.1</td>
<td>91.0</td>
<td>87.5</td>
<td>97.7</td>
<td>100</td>
<td>100</td>
<td>91.6</td>
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<tr>
<td>[14]*</td>
<td>–</td>
<td>84.5</td>
<td>–</td>
<td>92.1</td>
<td>92.1</td>
<td>–</td>
<td>–</td>
<td>89.6</td>
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<tr>
<td>[13]</td>
<td>–</td>
<td>96.7</td>
<td>–</td>
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<td>90.0</td>
<td>96.7</td>
<td>96.7</td>
<td>90.3</td>
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<tr>
<td>LGC</td>
<td>93.2</td>
<td>93.5</td>
<td>95.0</td>
<td>90.4</td>
<td>92.6</td>
<td>96.6</td>
<td>98.5</td>
<td>94.3</td>
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</tbody>
</table>

*a Based on our implementation of [14].

**Table 4** Comparing accuracy (in %) of various limb detection algorithms for supine.

<table>
<thead>
<tr>
<th>Method/limb</th>
<th>Algorithm</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
<th>S5</th>
<th>S6</th>
<th>S7</th>
<th>S8</th>
<th>S9</th>
<th>Avg</th>
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<tr>
<td>[15]</td>
<td>GMM</td>
<td>87.3</td>
<td>93.7</td>
<td>93.7</td>
<td>100</td>
<td>88.4</td>
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<td>92.1</td>
<td>92.1</td>
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<td>[16]</td>
<td>FCM</td>
<td>90.4</td>
<td>100</td>
<td>100</td>
<td>95.0</td>
<td>94.2</td>
<td>94.5</td>
<td>94.0</td>
<td>93.7</td>
<td>93.7</td>
<td>95.0</td>
</tr>
<tr>
<td>[14]*</td>
<td>Geometrical</td>
<td>–</td>
<td>89.4</td>
<td>–</td>
<td>95.0</td>
<td>94.2</td>
<td>94.5</td>
<td>94.0</td>
<td>93.7</td>
<td>93.7</td>
<td>92.7</td>
</tr>
<tr>
<td>[13]</td>
<td>Geometrical</td>
<td>86.7</td>
<td>84.0</td>
<td>89.8</td>
<td>–</td>
<td>–</td>
<td>93.3</td>
<td>–</td>
<td>80.0</td>
<td>80.0</td>
<td>85.7</td>
</tr>
<tr>
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<td>94.5</td>
<td>96.2</td>
<td>95.7</td>
<td>96.2</td>
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<td>95.5</td>
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<td>95.1</td>
</tr>
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</table>

*a Based on our implementation of [14].
In the next experiment, we computed the skin tolerance curve of each limb based on its experienced pressure \( P_t \) at different levels of \( T_c \) in each posture (Fig. 12). Using Eq. (7), we can find the critical time in which \( \phi \) exceeds \( \phi_w^{\text{up}} \) as presented in the following equation:

\[
t_c = \frac{700 - 4P_t}{(0.5P_t + 56)(0.5T_c - 7.5)}
\]  

(10)

This equation enables us to estimate how to control the manageable parameters like pressure and skin temperature to increase the skin tolerance and minimize the risk of PU development for each at-risk limb.

5.3 Discussion

We investigated an automatic at-risk limb identification technique and theoretically modeled ulcer development based on important factors such as pressure, shear, and temperature. Extensive experimentations showed that our approach has the following characteristics:

- **Target areas:** In three prevalent sleep postures, we considered certain areas of body (limbs) susceptible to bedsore (e.g. sacrum, back, and shoulder) that caregivers usually inspect for pressure ulcer development. Small body parts (e.g. ankle and coccyx) are not considered in this work.

- **High performance:** Our proposed graph-based approach outperforms previous limb identification approaches. All previous techniques lack the automatic limb identification module. Some techniques identify limbs in supine posture more accurately in comparison with side postures. Although the proposed methods in \([15,16]\) show good performance of identification, the performance of these technique is highly dependent on the patient

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Table 7

<table>
<thead>
<tr>
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<td>18.6</td>
<td>13.2</td>
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</table>

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Fig. 7. Online performance of three approaches.

Fig. 8. Effect of \( k \) (numbers of nearest neighbors) on LGC performance.
Fig. 9. Assessment of $\Delta t = 20$ min. No limb is at risk (green). (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

Fig. 10. Assessment of $\Delta t = 30$ min. Back (in supine) and hip (in sides) are at mid-risk (yellow). (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

Fig. 11. Assessment of $\Delta t = 50$ min. Back (in supine) and hip/shoulder (in side) are at high risk (red), other limbs are at mid-high risk (yellow). (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)
Fig. 12. Scaled skin tolerance metric.
posture. This can reduce the robustness of these methods in real applications in hospitals. Also, model-based clustering like GMM can be more effective when there are sufficient number of pressure sensors to learn and accurately determine Gaussian parameters. Our experimental results verify that the head identification in side posture is still a challenge since the head is often merged with neighbor limbs such as a shoulder. LGC leverages the notion of graph-based clustering (which use shared nearest neighbor strategy of LG) to tackle this kind of problems. In this work, we also applied a mathematical model to include microclimate changes in pressure ulceration development which was ignored in previous works.

- Limitation: Identifying small at-risk areas is one of the limitations for any time interval.
- Sensitivity: We have not observed any correlation between subject’s weight (in range of 63–100 kg) and the performance of our method. However, a comprehensive sensitivity analysis with a larger dataset and various pressure mats is needed.
- Need for validation: Although pressure ulcers have been extensively studied, there is no particular stress-recovery or skin break model proven by clinical data. Such validation model is still an open question for researchers.

6. Conclusion

In this work, we proposed a fast and robust technique to automatically extract body limbs and assess risk of ulceration for bed-bound individuals. The graph-based structure is used to model the key metrics and perform automatic clustering and labeling. Then, a theoretical model of induced shear stress by pressure and skin temperature is employed to assess the chance of SBF development on each limb. We collected data from 15 subjects in three common in-bed postures to validate our technique and compare to other methods. The average accuracy (in %) for considered limbs in right side, left side, and supine were 94.3, 93.2, and 95.1, respectively. Our method will be ultimately used in a patient monitoring system to continuously assess the patients situation for any time interval.

Conflict of interest

None declared.

References