

Estimation of the Elderly Getting Out of Bed Using a Sheet-type Pressure Sensor

[Atsushi Hagihara, Fumiko Harada, Hiromitsu Shimakawa]

Abstract— In this paper, we propose a method of estimating the care recipient's posture on the bed in detail and predicting the care recipient's getting out of the bed. In order to grasp the movement and posture of the care recipient on the bed in real time, a classifier that estimates the posture of the care recipient on the bed is created by machine learning. The explanatory variables were the position of the center of gravity of each part of the care recipient, the average value of the velocity and acceleration of the position of the center of gravity over a certain period of time, and the variance and covariance of the position of the center of gravity, and 16 types of body positions were classified. As a result of Random Forest, we were able to classify with an F value of 0.72 or more. This suggests that it is possible to estimate the getting out of the bed of a care recipient in real time.

Keywords—Machine Learning, Elderly Care, Sensing, Pressure Sensor

I. Introduction

In Japan, the elderly population has been increasing rapidly, and the number of people need nursing care to live (Care recipients) has tripled in the past 15 years. However, hospitals and nursing facilities face a shortage of staff compared to the number of care recipients.

Many of the care recipients spend all day in bed. Beds are not only a place to sleep but also a place to live for care recipients. However, there are accidents, injuries and illnesses caused by living mainly in beds. At the bedside, care recipients frequently fall or become bedsores. In order to prevent the care recipient from falling at the bedside, measures such as installing a fence on the bed are taken. However, they often fall when they get out of bed due to dizziness or unstable posture. In addition, the care recipient stays the same posture for a long time, causing skin necrosis and bedsores. For this reason, body pressure dispersing equipment has been introduced, but the equipment is expensive, and it is difficult to permanently install it on the bed.

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In many hospitals and nursing facilities, caregivers regularly change the position of care recipients. However, due to the shortage of staff, it is difficult for caregivers to perform enough patrols and monitoring, which is a great burden for caregivers.

Therefore, in order to reduce the burden on caregivers, it is necessary for the system to monitor the care recipients instead of humans, detect accidents and illnesses, and inform the caregivers. There is a need for a support system that reduces the physical burden on care recipients.

II. Preliminary Survey

A. Interview with Caregiver

For a preliminary survey, we interviewed a caregiver about falls and bedsores. As a result of the interview, Accidents such as falls of care recipients frequently occurred from 20:00 to 6:00 a.m., and it was found that pressure sores could be prevented by performing regular postural changes every two hours. The causes of frequent accidents at night were that there were few nurses and caregivers working, unable to call caregivers because of consideration for other patients in the room, and poor visibility. For these reasons, the care recipient getting out of the bed by himself, and the caregiver rushes after the accident.

Therefore, it is necessary to detect before the care recipient getting out of bed and to gain time until the caregiver comes. And, it became clear that regular postural change puts a heavy burden on caregivers such as time management. Interviews with caregivers suggest that falls are more urgent than bedsores. And, it was found that preventing the care recipient from getting out of the bed alone would significantly reduce the risk of falling.

It is necessary to notify the caregiver when the care recipient getting out of the bed at night. On the other hand, false alarms make caregivers and nurses tired, so a highly accurate detection system is required.

In this paper, we focus on accidents such as falls, which are urgently required for coping. When the system detects that the care recipient getting out of the bed, it is necessary not only to notify the caregiver, but also to stop the care recipient until the caregiver comes. For example, a smart speaker installed on the bed talk to the care recipient, and the care recipient can be stopped, and an accident at the bedside can be prevented.

III. Existing Research

There are many studies that measure elderly people's posture, movement and biological information at the bedside to support nursing care. In addition, there are many studies that measure the behavior and actions in daily life and monitor where and what the elderly are doing.

A. Detection of Getting Out of the Bed

There is a bed that detects getting out of the bed of the care recipients, as a support system that is actually introduced in hospitals and nursing facilities [1]. In this system, a load sensor such as a weighing scale is installed under the bed to determine whether the care recipient is sleeping on the bed or getting out of the bed. The introduction of this system has been shown to have the effect of reducing accidents such as falls.

However, only detecting whether the care recipient is sleeping or getting out of bed cannot tell the detailed turnover and posture of the care recipient, so it cannot be notified until the care recipient has completely got out of the bed. Notifications after the care recipient has completely got out of the bed is too short for the caregiver to go to the care recipient. Therefore, there is a problem that it is not possible to prevent before the care recipient's accident occurs.

B. Measurement of Biological Information

In addition to posture and movement, there are studies that measure biological information such as the respiratory rate, pulse wave, and body temperature of the care recipient in bed [2][3][4]. Sleep disorder and arrhythmia can be detected by measuring the biological information of the care recipient using a conductive sheet or thermistor.

However, measurement of biological information requires long-term monitoring and the wearing of complex sensors. In addition, in the measurement of biological information, it is not possible to confirm postural change or getting out of bed of the care recipient.

C. Monitor the Daily Activities of the Elderly

There are many studies that detect extraordinary behavior of the elderly [5][6][7]. In these studies, the system learns the pattern of the elderly's daily activities using cameras and location. And considers state transitions to determine whether the elderly's behavior is ordinary or extraordinary.

However, monitoring with a camera and wearing sensors has a mental and physical burden on the elderly. Care recipients are living mainly in beds, and it is difficult to detect extraordinary behaviors of care recipients from bedside location information.

IV. Prediction of Posture and Detection of Getting Out of Bed

A. Prediction of Posture Using a Sheet-type Body Pressure Sensor

In this paper, we propose a system that classifies the care recipient's posture on the bed in detail and predicts the care recipient's getting out of the bed. Figure 1 shows an overview of the process of predicting care recipient getting out of bed using this method.

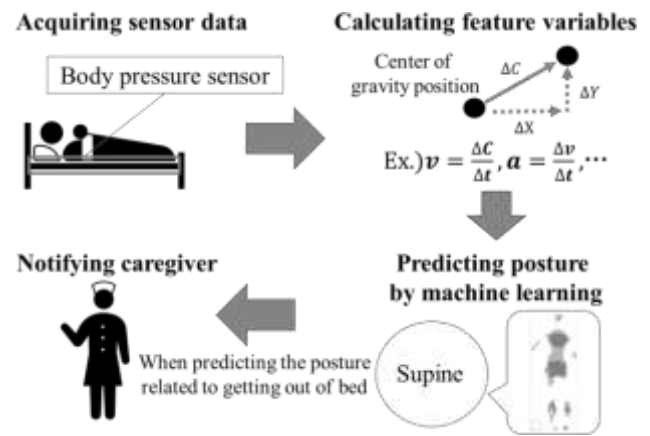


Figure 1. Overview of the prediction system

The body pressure distribution of the whole body of the care recipient on the bed is acquired by the body pressure sensor. Humans can easily identify body postures, such as supine, lateral, and long sitting positions, which are postures on a bed. Training the machine learning model using this information can improve the accuracy of the prediction process than using unsupervised learning. Therefore, a posture estimation model is constructed by supervised learning, and the posture of the care recipient in bed is predicted. It is not advisable to handle all these positions and pressure values because the number of body pressure samples acquired from the whole body is too many. The characteristics of body pressure on the bed are likely to appear in three parts: the back, the hip, and the legs.

In this paper, the body pressure distribution is divided into these three parts. The classifier for estimating the body posture is trained using the features of body pressure for each part acquired by the body pressure sensor and the label of the body posture identified by the human as training data. The body pressure features of the back, hip and legs are used as explanatory variables, and the following 16 postures are estimated by using machine learning. There are 16 types of postures for the care recipient on the bed, including 6 stable states and 10 transient states. The six stable states are: supine position (Supine), right lateral position (Right), left lateral position (Left), prone position (Prone), long sitting on the bed (LongSitting), sitting position on the bed. (EdgeSitting). The transient states are: from supine position to right lateral position (StoR), right lateral position to supine position (RtoS), supine position to left lateral position (StoL), left lateral position to supine position (LtoS), right lateral position to prone position (RtoP), prone position to right lateral position (PtoR), left lateral position to prone position (LtoP), prone position to left lateral position (PtoL), supine position to long sitting (StoLong), long sitting to edge sitting (LongtoEdge).

By applying machine learning, it is possible to predict in real time postures such as long sitting position and edge sitting position related to getting out of the bed. when this prediction system predicts the getting out of bed of the care recipient, it is possible to prevent accidents such as falls at the bedside by notifying the care recipient and stopping the care recipient using the smart speaker.

B. Outline of Body Pressure Sensor and Measurement of Body Pressure Features

In this paper, the position and movement of each part are calculated from the body pressure distribution on the bed of the care recipient acquired by the body pressure sensor, the posture of the care recipient is estimated, and the getting out of the bed is predicted. From Chapter 3, monitoring with a camera and wearing a wearable sensor put a great deal of physical and mental burden on the care recipient. Therefore, we measure the distribution of body pressure on the bed of the care recipient using a sheet-type body pressure sensor. The sheet-type body pressure sensor is thin and has excellent elasticity, and it can visualize and measure the whole-body pressure distribution with little load on the care recipient. The sheet-type body pressure sensor that we use has 25 sensors in the short side direction and 64 sensors in the long side direction arranged at 2.8 cm intervals. A total of 1600 points of body pressure can be measured from 15mmHg to 110mmHg.

The posture in the sitting position can be estimated by installing a body pressure sensor on the back or seat of the chair and measuring the body pressure distribution on the back and the hip [8]. Examination of the distribution of body pressure collected from a sheet-type body pressure sensor showed that the back, hip and legs were the sites where body pressure was particularly likely to concentrate when sleeping. Therefore, we focus on the position and movement of the legs in addition to the back and waist for estimating the posture of the care recipient on the bed and predicting getting out of the bed.

In order to calculate the position and movement for each part of the back, hip and legs, the body pressure distribution of the whole body acquired by the body pressure sensor is divided into three parts. Let the short side direction of the body pressure sensor be the Y axis and the long side direction be the X-axis. The X-axis is divided in the Y-axis direction so that the number of sensors is 21, 22, and 21 each, and legs are from $x = 0$ to $x = 20$, hip are from $x = 21$ to $x = 42$, and back are from $x = 43$ to $x = 63$. As an example, Figure 2 shows the body pressure distribution in the supine position and the dividing method.

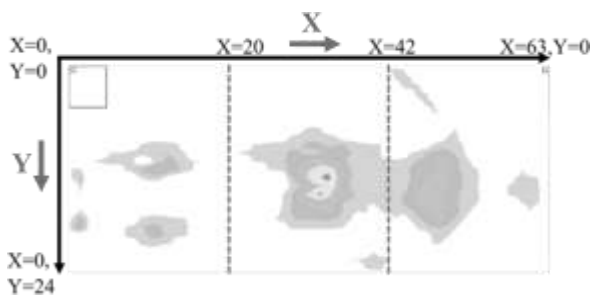


Figure 2. Body pressure distribution

In order to acquire the position and movement of each part, the center of gravity of each part and the velocity and acceleration of the center of gravity are calculated from the body pressure distribution divided into three parts.

C. Estimating the Posture by Machine Learning

In order to grasp the movement and posture of the care recipient on the bed in real time, we generate a

The position of the center of gravity of each part acquired by the body pressure sensor every 200ms is defined as (x_g, y_g) and expressed by the formula (1).

$$x_g = \frac{x_n m_n + x_{n+1} m_{n+1} + \dots + x_k m_k}{m_n + m_{n+1} + \dots + m_k}, y_g = \frac{y_1 m_1 + y_2 m_2 + \dots + y_{24} m_{24}}{m_1 + m_2 + \dots + m_{24}} \quad (1)$$

m_i is the pressure value (mmHg) measured by the sensor located at the coordinates (x_i, y_i) . k and n are the x coordinates of the sensor, $n = 1, k = 20$ for the legs, $n = 21, k = 42$ for the waist, and $n = 43, k = 63$ for the back. Let Δc be the moving distance of the center of gravity position for Δt seconds, v be the velocity, and a be the acceleration. It is expressed by the formula (2)

$$\Delta c = \frac{\Delta x^2 + \Delta y^2}{g}, v = \frac{\Delta c}{\Delta t}, a = \frac{\Delta v}{\Delta t} \quad (2)$$

Since the spread of body pressure in each part differs for each posture, the variance-covariance matrix S at the center of gravity position (x_g, y_g) for a certain time is calculated for each part. For example, in the supine position, the spread of the waist pressure is wide and circular, whereas in the lateral position, the spread of the waist pressure is long and elliptical. Let $V(x)$ be the variance of x and $Cov(x, y)$ the covariance of x and y . The variance-covariance matrix S is shown, and the components of S are shown (3).

$$S = \begin{bmatrix} V x_g & Cov x_g, y_g \\ Cov y_g, Xx_g & V y_g \end{bmatrix} \quad (3)$$

classifier that estimates the posture of the care recipient on the bed from the body pressure features of each part by machine learning.

The body pressure features are the center of gravity of the back, hips and legs, the velocity v and acceleration a of the center of gravity, and the variance-covariance matrix S of the center of gravity for a certain time calculated in section IV-B. To calculate the variance-covariance matrix S of the center of gravity, several data are required. Therefore, a set of variance-covariance matrices S is calculated from the five data of the center of gravity acquired for every 200ms. In addition, the average of the center of gravity position, velocity v and acceleration a at the center of gravity is calculated from the five data.

The explanatory variables used for machine learning are 21 types of center of gravity position of three parts, velocity v of the center of gravity position, average of acceleration a for 1000ms, and variance-covariance matrix S of the center of gravity position for 1000ms. Table I shows the explanatory variables.

Table I. Explanatory variables

Calculate the following 7 types for each part	
Average of the center of gravity x_g on the X-axis	Average of the center of gravity y_g on the Y-axis
Average of velocity v at center of gravity position (x_g, y_g)	Average of acceleration a at center of gravity position (x_g, y_g)
Variance $V(x_g)$ of center of gravity position x_g	Variance $V(y_g)$ of center of gravity position y_g
Covariance $Cov(x_g, y_g)$ of the center of gravity position (x_g, y_g)	

The objective variables are 16 postures in total, including 6 stable states and 10 transient states on the bed of the care recipient, as shown in section IV-A. The machine learning algorithm used to train the classifier uses Random Forest (RF), a kind of ensemble learning [9]. RF is an algorithm that constructs a plurality of decision trees trained to classify a specific class with high accuracy and takes a majority decision of the decision tree to classify newly input data to a prepared class. RF has a learning phase and a predict phase. In the learning phase of this paper, we attach posture labels to body pressure features acquired by the body pressure sensor in advance and use these as training data to construct a set of decision trees that classify the posture from body pressure features. After that, in the classification phase, each decision tree classifies the position of the care recipient using newly acquired body pressure features as explanatory variables, and outputs the most frequent identification result. In this way, by predicting the care recipient's posture related to getting out of the bed in real time, it can prevent bedside accidents by detecting when a care recipient needs to go to the bathroom on their own.

v. Experiment

It was verified by this experiment whether the posture of the care recipient could be classified from the body pressure features obtained by the body pressure sensor. The details and results of this experiment are shown below.

A. Outline of The Experiment

In this experiment, we performed an intervention in which the subject's posture on the bed was specified in advance. At that time, the body pressure of the subject was acquired by a body pressure sensor. And, we verify whether the body pressure features shown in section IV-C are effective for classifying the posture of the 16 types of care recipients on the bed shown in section IV-A. The subjects were university students and graduate students between the ages of 22 and 23, 3 males and 2 females, for a total of 5 subjects. In order to acquire the subject's body pressure, we installed SR Soft Vision (a sheet type pressure distribution measuring device manufactured by Sumitomo Riko Co, Ltd.) on the bed, and acquired the subject's body pressure every 200ms. The pressure-sensitive range of SR Soft Vision is 1800×700 mm, and the body pressure is measured in the range of 15 to 110mmHg by 25×64 sensors arranged

at 2.8cm intervals. The body pressure of the subject's whole body acquired every 200ms is divided into three parts, and the average of the center of gravity of the back, hips, and legs every 1000ms, the average of the velocity and acceleration at the center of gravity shown in section IV-C, and the variance-covariance matrix of the position of the center of gravity was calculated. Figure 3 shows the experimental environment and the body pressure acquired during the supine position.



Figure 3. Environment of experiment

In order to acquire the body pressure in the 16 positions shown in section IV-A, the subjects performed the posture changes of the following patterns 1 and 3 three times each. The arrows between the stable states of patterns 1 and 2 are transient states. The subject stayed in each stable state for 10 seconds and changed his or her posture to the next posture. In a general hospital, the left or right side of the bed is closed by a wall, so the exit direction is limited to the right side from the viewpoint of the subject.

- ★ Pattern 1: supine position → right lateral position → prone position → right lateral position → supine position → long sitting position → edge sitting position
- ★ Pattern 2: supine position → left lateral position → prone position → left lateral position → supine position → long sitting position → edge sitting position

We can acquire the body pressure of all 16 postures shown in section IV-A by subject turning over patterns 1 and 2. Before the experiment, subjects practiced turning over patterns 1 and 2. In addition, when the subject turned over, we instructed the next posture after 10 seconds in a stable state.

B. Classification Results

In the intervention experiment, A classifier was constructed using RF, which is supervised learning. For comparison of the classification results, a classifier using Support Vector Machine (SVM) was constructed [10]. As the SVM parameters, those with optimal results were selected within the range of ($0 \leq C \leq 300, 0.00001 \leq \text{gamma} \leq 1$). General classification results were calculated by 5-fold cross validation. In this paper, we do not consider the posture of the subject before going to bed because the purpose is to predict the getting out of the bed of the care recipient. According to doctors' opinions, most care recipients sleep in the supine position at bedtime. Therefore, the data section used for classifying the subject's posture was from a few seconds after the subject was in the supine position on the bed until the subject completely got out of the bed.

The explanatory variables were the 21 types of body pressure features shown in section IV-C, and the objective

variables were the 16 types of postures shown in section IV-A. Table II shows the RF confusion matrix. Table III shows the results of RF and SVM classification. The Macro Average of the classification results is the average of the precision, recall, and F-Value are classification accuracy calculated for each class. Weighted Average is weighted by the ratio of the number of data records of each class. Precision, Recall, and F-value are calculated and averaged. And, the accuracy rate is an index indicating the rate at which the true value matches all the classification results. Therefore, Recall and Precision are not considered.

Table II. Confusion matrix of RF

From the confusion matrix, it was possible to classify all stable states with high accuracy by estimating the posture of the care recipient using 21 types of body pressure features as explanatory variables. There were many misclassifications in the transient state, especially in the prone position. In addition, it was possible to identify the body position from the supine position to the long sitting position related to leaving the bed with high accuracy.

Table III. Classification result by RF and SVM

RF

Accuracy	0.813		
	Precision	Recall	F-value
Macro Average	0.722	0.69	0.722
Weighted Average	0.812	0.813	0.806

SVM(C=240, Gamma=0.0001)

Accuracy	0.813		
	Precision	Recall	F-value
Macro Average	0.722	0.69	0.722
Weighted Average	0.812	0.813	0.806

Estimation of the posture of the care recipient using body pressure features was better with RF than with SVM. From the RF results, The F-value was about 0.72 in the Macro Average and about 0.81 in the Weighted Average. Accuracy of RF is 0.813, which is a higher result than the correct answer rate of 0.0625 in the case of random classification. These results indicate that 21 types of body pressure features are useful for classification in estimating 16 types of postures.

VI. Discussion

A. Consideration of Experimental Results and Applicability

In Section V-A, the experiment was performed to estimate the posture on the bed from the subject's body pressure measured by the body pressure sensor. From the results in Tables II and III, we showed that the F value can be classified at 0.7 or more by classifying the subject's posture by RF using the 21 types of body pressure features shown in section IV-C as explanatory variables.

It was suggested that by measuring the body pressure of the care recipient on the bed using a body pressure sensor, the getting out of the bed of the care recipient can be estimated in real time. Therefore, by detecting getting out of the bed in the long sitting position of the care recipient, it is possible to stop the care recipient and notify the caregiver, it can prevent accidents of care recipients.

Also, by maintaining the transition sequence of the posture of the care recipient on the bed, it is possible to confirm the posture of the care recipient and how long it has been staying. This system can encourage the caregiver to change the posture of the care recipient appropriately and reduce the risk of bedsores of the care recipient.

B. Important variables for Classification

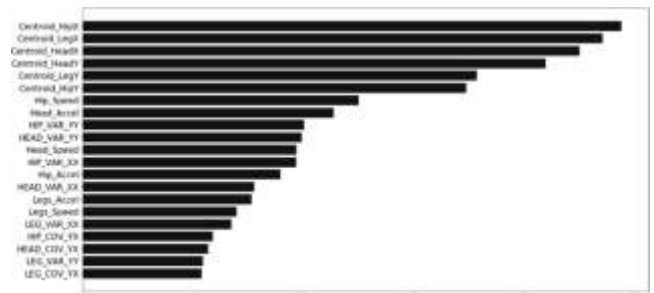


Figure 4. Important variables for classification

The six most important variables are the position of the center of gravity of each part, and the X coordinate is particularly important. This means that the position of the center of gravity of the body pressure sensor in the short side direction is important for estimating the posture of the subject. The reason why the X coordinate of the position of the center of gravity is important is that the speed and acceleration of each part are very small when the subject is in a stable state. It is considered that the center of gravity is biased in the direction of the body by the arms and legs.

The important variables after 7 are the velocity of the center of gravity of the waist and the acceleration of the back. It is considered that the reason why the waist and back movement is important is that when the subject turns over from the supine position, the subject moves quickly without applying any physical force. when turning over from the prone position, the subject moves slowly with force. On the other hand, when the subject is getting the bed, the subject moves with applying force and moves quickly.

The results in Table II indicate that there were many misclassifications of the transient state related to the prone position, and that there was no feature variable in the body pressure features that clearly distinguished the prone position from the supine position. Therefore, in order to classify the transient state related to the prone position in more detail, it is necessary to consider not only the X and Y coordinates of the position of the center of gravity but also the depth and spread of the body pressure in the Z axis direction. By measuring the three-dimensional body pressure features, it is possible to grasp the movement and position of the body parts such as the arms and thighs of the subject in more detail, and the classification accuracy is improved.

VII. Conclusion

In this paper, we proposed a system for predicting the getting out of the care recipient in the bed. Through experiments, we verified whether the posture of the care recipient on the bed can be identified. The body pressure of the care recipient measured by the body pressure sensor was divided into three parts, and the body pressure features of each part were calculated. Using body pressure features as explanatory variables, 16 types of posture on the bed of the care recipient were classified by machine learning. as a result, It was suggested that by measuring the body pressure of the care recipient on the bed using a body pressure sensor, the getting out of the bed of the care recipient can be estimated in real time.

In the future, we will conduct experiments to measure the body pressure of care recipients for a long time. And it will be possible to detect the getting out of bed of a care recipient more quickly by considering the transition sequence of the posture. In addition, the body pressure feature is analyzed in consideration of three dimensions.

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