Classification Method for Turnover While Sleeping Using Multi-Point Unconstrained Sensing Devices

K. Shiba, T. Kobayashi, T. Kaburagi, Y. Kurihara

***Abstract*—**Elderly population in the world is increasing, and consequently, their nursing burden is also increasing. In such situations, monitoring and evaluating their daily action facilitates efficient nursing care. Especially, we focus on an unconscious activity during sleep, i.e. turnover. Monitoring turnover during sleep is essential to evaluate various conditions related to sleep. Bedsores are considered as one of the monitoring conditions. Changing patient's posture every two hours is required for caregivers to prevent bedsore. Herein, we attempt to develop an unconstrained nocturnal monitoring system using a sensing device based on piezoelectric ceramics that can detect the vibrations owing to human body movement on the bed. In the proposed method, in order to construct a multi-points sensing, we placed two sensing devices under the right and left legs at the head-side of an ordinary bed. Using this equipment, when a subject lies on the bed, feature is calculated from the output voltages of the sensing devices. In order to evaluate our proposed method, we conducted an experiment with six healthy male subjects. Consequently, the period during which turnover occurs can be correctly classified as the turnover period with 100% accuracy.

***Keywords*—**Turnover, piezoelectric ceramics, multi-points sensing, unconstrained monitoring system.

I. Introduction

In recent years, the elderly population has increased in developed countries such as USA, Germany, and Japan. In 2030, it is expected that the world will have 1.4 billion elderly people who are at least 65 years old. Nursing care burden in such an aging society has been projected [1]. The automatic recognition and evaluation of an elderly person's daily action can result in efficient nursing care provided by the caregiver. In [2], Liu et al. reported the recognition of certain types of daily action, such as eating, resting, and sleeping. Among such actions, we focus on sleeping. During sleep, an elderly person performs unconscious actions, such as turnover. Monitoring such unconscious actions during sleep is essential to evaluate various conditions related to sleep. Bedsores are considered as one of the monitoring conditions. [3]. When an elderly person is sleeping on a bed without changing his/her posture, particular parts of his/her body are pressured and become sore. By monitoring unconscious activity during sleep, the condition of bedsores can be evaluated. In order to reduce the damage owing to bedsores, the caregiver should change the patient's posture if it does not change for two hours [4]. Therefore, an automatic classification to determine whether the patient turns over on the bed is essential.

A movie camera has been employed to monitor the subjects' posture during sleep [5]. However, capturing images using a camera while the subject is sleeping may invade his/her privacy. By adapting to such a circumstance, [6]–[9] demonstrated a posture recognition system using various types of devices. Devices are classified into two types: wearable devices and non-wearable devices. A wireless transceiver [6] and electrocardiogram [7] are examples of wearable devices. Although they can realize a high degree of posture recognition, patients have to wear them, which could lead to discomfort. A leaking coaxial cable [8] and force sensing register sensor [9] are examples of non-wearable devices. These devices are mounted on the bed where the patient lies; consistently, the posture can be estimated without constraints to a patient's body.

Accordingly, in this paper, we propose an unconstrained sensing method that can classify an arbitrary period during sleep into turnover period or other movement period. Piezoelectric ceramics, which do not require recharging, are proposed as a sensing device.

II. Proposed Method

Figs. 1 and 2 show the proposed method using the piezoelectric ceramics proposed in our previous study [10]. Two piezoelectric ceramics are prepared and placed under the right and left head-side legs of an ordinary bed. Accordingly, we develop a method to detect a subject's turnover over a certain period. Our proposed method is divided into two phases: a learning phase, as shown in Fig. 1 (section A), and a training phase, as shown in Fig. 2 (section B).

A. Learning Phase

In the learning phase, we select a threshold index to detect turnover by using two piezoelectric ceramics. Both devices output a signal corresponding to the subject's motion. Let $x_R(t)$ and $x_L(t)$ represent the analog signals from the right-side device and left-side device, respectively.

First, $x_R(t)$ and $x_L(t)$ are converted into digital signals $x_R(k)$ and $x_L(k)$. Subsequently, we subtract $x_L(k)$ from $x_R(k)$, which is referred to as $x_D(k)$. Further, the cumulative summation of $x_D(k)$ is calculated as $C(k)$. Subtracting the minimum of $C(k)$ from the maximum of $C(k)$, the feature C_M is obtained with one data.

When the state of learning data represents turnover, C_M is denoted as C_T, whereas when the state of learning data represents a different state, C_M is denoted as C_O.The dataset is sorted in the descending order, $C_{T,i}$ and $C_{O,i}$. For example, $C_{T,n}$

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represents the n^{th} greatest C_T.

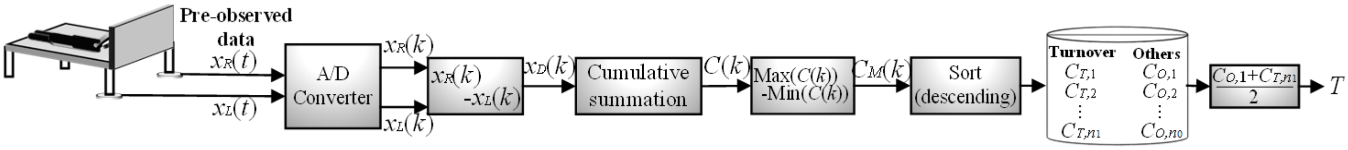

Fig. 1 Learning phase of our proposed system. The state-known dataset, which includes the turnover period and other movement periods, is measured in advance. By using a pre-observed dataset, the threshold classifies the state-unknown data into turnover period or other movement period

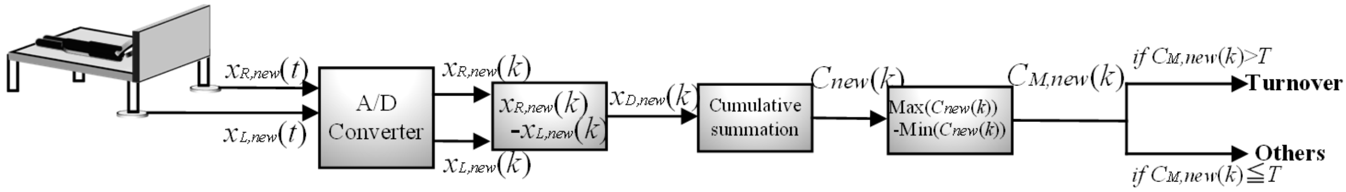

Fig. 2 Estimation phase of our proposed system. Using the T established in the learning phase, the measurement data are classified into turnover or other movement

Using $C_{O,i}$ and $C_{T,i}$ calculated from the pre-observed data, the threshold is defined as expressed in (1). Let n_1 and n_0 denote the number of turnover data and other movement data in the pre-observed dataset.

$$T = \frac{C_{O,1}+C_{T,n_1}}{2} \tag{1}$$

B. Estimation Phase

In the estimation phase, $x_{R,new}(t)$ and $x_{L,new}(t)$, where its state is unknown, is classified based on whether turnover is included in the data. In order to obtain the feature $C_{M,new}$, same procedures explained in the learning phase will be calculated. If $C_{M,new}$ is more than T obtained in the learning phase, the system indicates that the subject has turned over in the measurement period. In the other cases, turnover does not occur.

III. Experiment

In order to evaluate our proposed method, we conduct an experiment with six subjects.

A. Experimental System

Fig. 3 shows the experimental system. We developed the sensing devices shown in Fig. 3. The sensing devices are placed under the left- and right-side legs at the head-side of the bed. The output voltage from both the sensing devices is A/D converted with a sampling interval Δt = 0.01 s. In this experiment, the subjects are six healthy males ranging in age from 21 to 25 years. The experiment is carried out after obtaining informed consent.

B. Experimental Procedure

Each subject lies at the center of the bed as the starting position, and his/her posture is supine. The subjects are asked to perform the following actions: (a) turnover and (b) rest. Figs. 4 (a) and (b) show the movement of the subjects for the actions turnover and rest, respectively. For action condition (a), the subjects are asked to turn over every 5 s. Therefore, the posture sequentially changes as supine, right lateral position, supine, left lateral position, and supine. For action condition (b), the subject maintains a rest state without any turnover. Accordingly, the subject maintains a supine position for 30 s.

Each condition of data is measured 10 times for each subject. In total, 60 turnover data and 60 rest data are obtained.

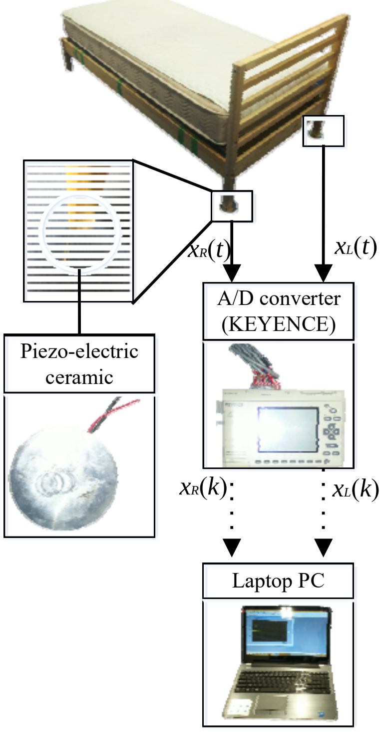

Fig. 3 Experimental system. Devices are placed under each leg at the head-side of the bed. Data are sent to an A/D converter and converted from continuous time to discrete time. Finally, these discrete time-series data are collected as a csv file in a laptop PC

C. Evaluation

The leave-one-subject-out method is applied for evaluation. The evaluation point is the ability of the system to classify whether the subjects turn over or not. The classification result is of four types: a true positive when the system correctly classifies turnover condition; a true negative when the system correctly classifies rest condition; a false positive when the system incorrectly classifies rest condition as turnover condition; a false negative when the system incorrectly classifies turnover condition as rest condition. The number of occurrences of each case is counted, and the accuracy, sensitivity, and specificity are calculated. Sensitivity represents the rate at which turnover can be classified correctly. Specificity represents the rate at which rest can be classified correctly.

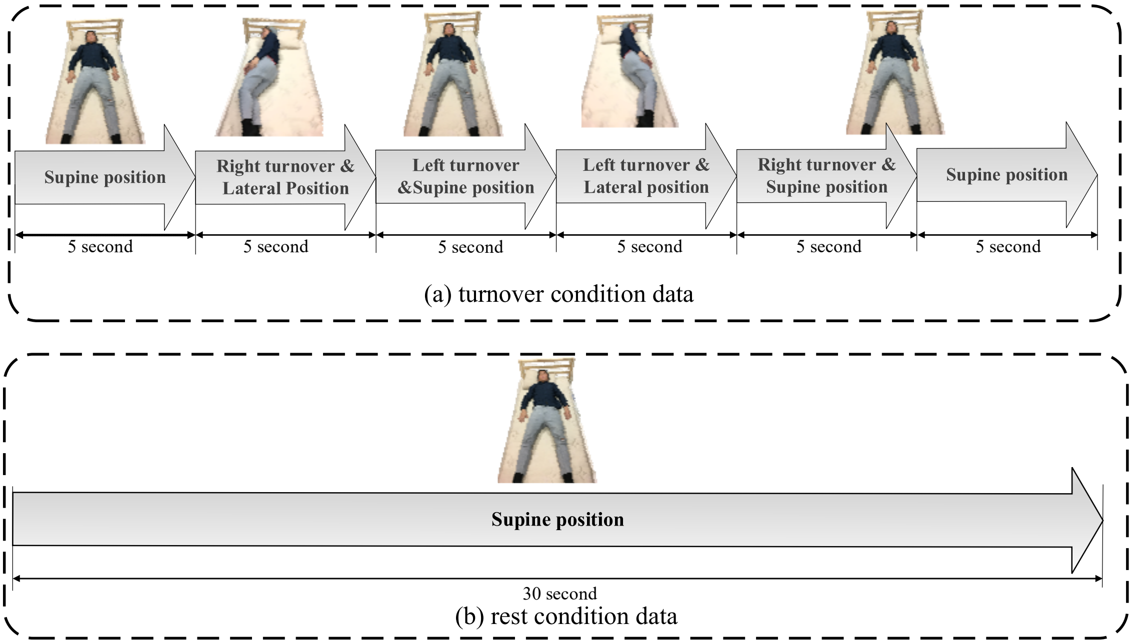

Fig. 4 Schedule of each action condition: (a) the turnover condition, (b) the rest condition

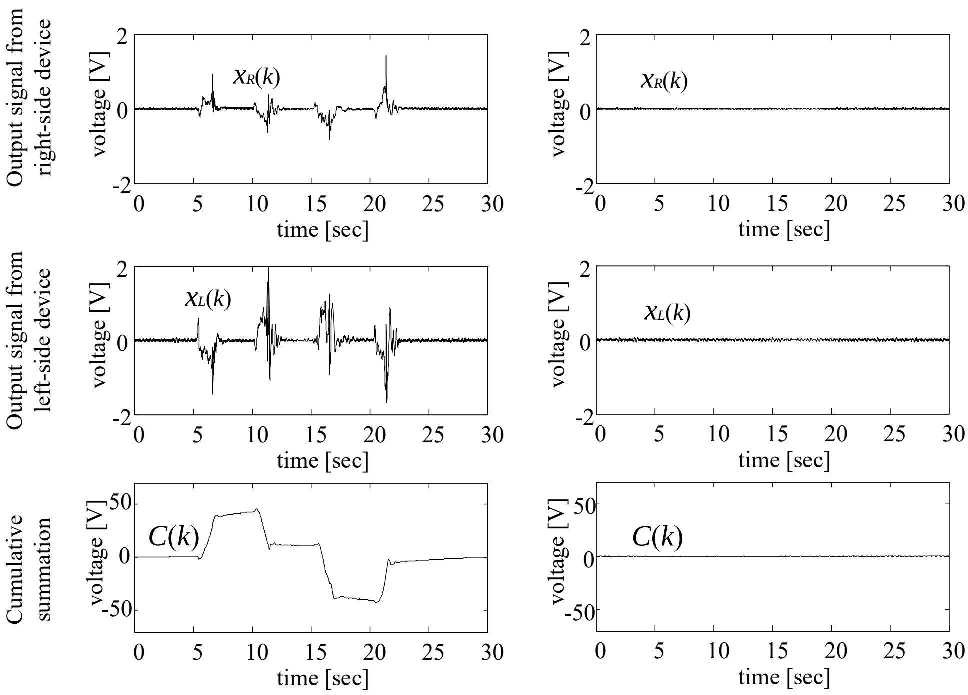

Fig. 5 Typical example data: (a) the data corresponding to turnover period, (b) the data corresponding to rest period

IV. Experimental Result

A. Examples of Data

Fig. 5 shows each type of measurement data. Fig. 5 (a) shows the measurement data corresponding to turnover. Fig. 5 (b) shows the measurement data corresponding to rest. The upper chart and middle chart in Figs. 5 (a) and (b) represent the output signals from the right-side sensing device $x_R(t)$, and the left-side sensing device $x_L(t)$, respectively. Cumulative summation $C(k)$, which is the integration of the difference between $x_R(k)$ and $x_L(k)$, is shown in the bottom chart in each figure.

As shown in the turnover state data in Fig. 5 (a), both piezoelectric ceramic signals roughly show horizontal symmetry. When a subject changes his/her posture, the feature changes significantly. If the subject's posture is the right lateral position, the cumulative summation $C(k)$ is converged to a higher positive value than the other cases. On the contrary, if the subject's posture is the left lateral position, the cumulative summation $C(k)$ is converged to a higher negative value than the other cases. If the subject lies at the center of the bed, the feature is converged to 0.

As shown in the rest state data in Fig. 5 (b), both piezoelectric ceramic data and cumulative summation are flat-shaped.

B. Estimation Result

Table I shows the result of classification into turnover period and rest period. Each period can be classified perfectly. The accuracy, sensitivity, and specificity are reported to be 100%.

TABLE I
Classification Result Wherein the Gray Parts Represent Incorrect Cases

		True State	
		Turnover	Rest
Classification State	Turnover	60	0
	Rest	0	60

Accuracy = 100.00%
Sensitivity = 100.00%.
Specificity = 100.00%.

V. Discussion

The system can detect a subject's turnover with 100%. Since the devices are placed at the right- and left-sides, the data corresponding to turnover on both sides are characterized quantitatively as shown in Fig. 5 (a).

As observed between 6 and 11 s, 17 and 21 s, and 22 and 30 s in the cumulative summation of Fig. 5 (a), $C(k)$ changed slightly although the subject did not move. This is because the amplitudes of $x_R(k)$ and $x_L(k)$ are different as shown in Fig. 5 (a). In order to prevent the amplitude difference between $x_R(k)$ and $x_L(k)$, the calibration of the piezoelectric ceramic amplitude is required.

VI. Conclusion

In this paper, we proposed a method that can classify a subject's turnover on a bed with 100% for each time point. Our piezoelectric ceramic shows a differential characteristic at the multi-point observations. This differential characteristic is useful for detecting turnover and recognizing a subject's posture.

In this study, we only focused on turnover. However, monitoring a subject's posture and changes in posture may be essential to prevent bedsores. The classification of a subject's posture into supine position, prone position, and lateral position for each time period is required. As classification states, supine, right lateral position, and left lateral position are considered. Further types of data and real nocturnal data are required to develop such a system.

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