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SleePS: Sleep Position Tracking System for Screening Sleep Quality by Wristbands

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***Abstract*— Sleep plays an important role in recovering physical and mental functions. Sleep position is known to affect sleep quality, hence, managing sleep position is beneficial for patients suffering from sleep disorders. For a long-term sleep management, we propose a sleep position tracking system using two wristbands. From the data collected from the wristbands, the system detects sleep positions and their changes. We define a sleep position motion model that consists of seven transitions between three sleep positions. Then, we propose pre-processing methods to overcome difficulties in analyzing sleep motion data, i.e., discontinuity, uncertainty, and time-variability. We tested experimental data in state-of-art pre-trained convolution neural networks by transfer learning. The accuracy of our proposed system was 96.03% and 88.02% in pilot experiment and on-site sleep experiment, respectively. Our experimental results demonstrate that the proposed system effectively and accurately keeps track of sleep positions without causing any inconvenience to users, and hence, serves as a key building block for cost-effective 24/7 sleep monitoring solutions**

I. INTRODUCTION

Sleep occupies one-third of our life and plays an important role in overall health by recovering physical and mental functions, so it is crucial to have sound sleep [1] [2]. Many of us sometimes feel tired all day long due to overworking on previous day or symptom of flu. Continued lack of sleep causes health problems, and sometimes sleep shortage is caused by sleep disorders. The common sleep disorders include sleep apnea, narcolepsy, restless legs and insomnia [3]. These sleep disorders are diagnosed by Polysomnography (PSG) [4], which is a golden standard diagnosis tool providing high accuracy of diagnosis. Nevertheless, a sleeper should wear cumbersome wired sensors such as electroencephalography (EEG), electrooculography (EOG), electromyography (EMG), and respiratory monitoring sensors, which result in inconvenient sleep. Although the PSG provides an accurate diagnosis of sleep disorders, sleep experiment is expensive and sometimes is difficult due to limited time and space of a sleep laboratory. Therefore, a portable PSG has been developed to solve the cost and complexity problems in the conventional PSG [5]. Due to recent advances in sensing technologies, many smartwatches or wristband-based sleep trackers provide sleep monitoring as a basic function. They provide quantitative information about sleep patterns and duration of sleep cycles, but clinical validation is needed [6]. Depending on purpose and severity of sleep disorders, an appropriate sleep analysis tool is required.

Sleep position is one of important factors in sleep studies since it is related to sleep qualities [7]. Especially, sleep disorder patients suffering from sleep disorders should be managed by avoiding bad sleep position to improve their health. Supine position is increasing a tendency of sleep apnea [8]. A positional therapy avoiding the supine position is effective to snoring or mild sleep apnea patients [9] [10]. Another sleep disorder related to the sleep position is pressure ulcer. It causes localized injury to the skin and underlying soft tissue due to lack of movement [11].

For tracking sleep positions, there are three conventional approaches. First, a depth camera sensor captures sleep postures and classifies sleep positions. Grimm et al [12] made depth images of bed and classified sleep position using deep learning. Body joint information from Kinect sensor is used for tracking sleep positions [13]. However blanket, pillow or other stuffs hiding vision of camera will decrease a classification performance. Second, multiple pressure sensors on a bed provide a pressure map and have a high classification accuracy [14][15]. Furthermore, a sensor fusion such as multi-modal RGB-Depth-Pressure sensors provides sophisticated segmented body parts [16]. These approaches have advantages such as a non-contact sensing and high classification accuracy. Lastly, the chestband-based approach uses an accelerometer sensor with a chest strap, and the simple processing algorithm is an advantage [17]. It is commonly used for a sleep positional therapy [18][19]. These three conventional approaches have issues such as privacy, installation requirement, and inconvenience to breath, respectively. Therefore, we employed a wristband approach since it has advantages in that it is easy to wear and cost-effective, which compensate aforementioned disadvantages of conventional approaches.

We propose a Sleep Position tracking System (SleePS) consisting of only two wearable wristbands for managing sleep qualities, which is designed for a long-term sleep monitoring. In developing the SleePS, we address following challenges. First, sleep motion shows *discontinuity*. We sometimes scratch our bodies discontinuously during sleep, which acts as measurement noise for classifying sleep positions. Second, sleep motion has *uncertainty*. Not every sleep motion indicates meaningful sleep positions due to unconscious sleep motion characteristics. Some sleep motion may indicate different sleep positions since our hand can move freely. Lastly, sleep motion has *time-variability* in

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the sense that the duration of sleep motions can vary in a wide range. To compensate aforementioned challenges, we designed a Sleep Position (*SP*) motion model and proposed pre-processing methods.

The novelty of this work lies in the pre-processing methods which help to overcome the challenges in analyzing sleep motion data. In addition, we evaluated our sleep position model using state-of-art deep learning models such as Alexnet and VGG16. We demonstrated that our system can track sleep positions with 98.03% accuracy in the pilot experiment and with 88.02% accuracy in the on-site sleep experiment. Our SleePS may be considered as a supplement to existing sleep diagnosis solutions such as PSG, serving as a cost-effective 24/7 monitoring tool for sleep disorders and other sleep-related applications.

The rest of the paper is organized as follows. Section II provides *SP* motion model and the proposed system. Section III presents the results of experiments. Finally, the paper concludes in Section IV.

II. Proposed System

In this section, we propose a *SP* motion model and introduce the pre-processing methods. The processed motion data are used in deep learning models as input data. Before introducing the sleep position motion model, we analyzed sleep motion characteristics according to sleep positions. We investigated the motion data by checking times when sleep positions were altered. Largely, there are four different sleep positions: *Up*, *Left*, *Right*, and *Down*. Table I shows that *Up* sleep position occurred with 78.88% frequency. The other positions such as *Left*, *Right*, and *Down* comprise 10.36%, 10.56%, and 0.20%, respectively. The sleep time characteristic, i.e. duration, also shows similar results. *Down* sleep position rarely occurs. Therefore, we eliminate the down sleep position from our system. We design the sleep motion change model using the three sleep positions (i.e., *Up*, *Left*, and *Right*) and name it as the *SP* motion model.

TABLE I
SLEEP MOTION CHARACTERISTICS ACCORDING TO SLEEP POSITIONS

Sleep positions	Up	Left	Right	Down
Sleep time [hours] (percentage)	59.55 77.14%	7.97 10.32%	9.60 12.44%	0.08 0.10%
Motion frequency (percentage)	396 78.88%	52 10.36%	53 10.56%	1 0.20%

A. Sleep Position Motion Model

Unconscious sleep motion is observed during sleep while we are dreaming. We define seven elements in the *SP* motion model that are transitions among the three sleep positions as shown in Fig. 1. When a motion occurs, our SleePS classifies it as one of seven *SP* motions. As we noted, sleep motion has three characteristics such as *discontinuity*, *uncertainty*, and *time-variability*. Thus, pre-processing methods are required to better prepare the data for the next step of analysis. First, the *discontinuity* indicates that discontinuous sleep motions are observed especially due to sleep habits such as scratching body. Multiple motions are observed for a short time period. Even though they are separated based on time, they should be considered as one motion for tracking sleep positions. *SP* motion grouping is performed to combine consecutive motions into one motion. Second, the *uncertainty* means that our wrists can move anywhere freely, which may result in errors in detecting sleep positions correctly. When we observed wrist directions before and after a sleep motion, each sleep position (*Up*, *Left* or *Right*) showed different wrist directions. In other words, stationary motion data also can be helpful for finding the sleep positions. We use this insight in our system by a padding method. Lastly, *time-variability* indicates that *SP* motion time is diverse. There are big variations of time length of the *SP* motions. But, making fixed data size is important as a normalization process. Pre-trained neural network models in Convolution Neural Network (CNN) require an a fixed input size. Therefore, we properly transformed the size of our input data for the neural network by using the re-sizing method. Detailed processing procedures are discussed in the next sections.

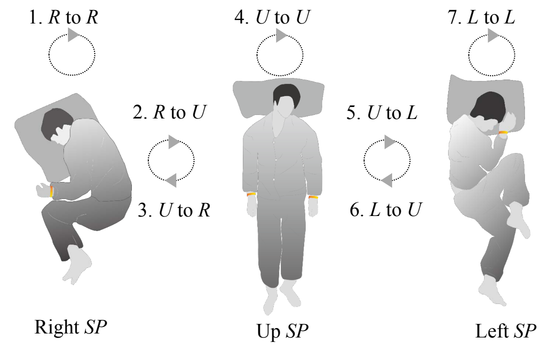

Fig. 1. Seven elements in *SP* motion model: *U*, *L*, *R* and *SP* stands for Up, Left, Right and Sleep Position, respectively.

B. System Setup

SleePS uses two wristbands to classify sleep positions. Microsoft Kinect sensor is used as a ground truth as shown in Fig. 2-(c). Depth images from the Kinect sensor and motion data from an inertial measurement unit (IMU) sensors and wrists motion data are recorded in the same Laptop. After the sleep experiment, the time of sleep position changes is manually checked for labeling. Fig. 2 shows the system setup. Fig. 2-(a) shows components of sensor set. The wristbands use an inertial measurement unit (IMU) that contains 3-axis accelerometer, 3-axis gyroscope and 3-axis magnetometer sensors for collecting sleep data. The IMU sensor we use is an AHRS EBIMU24GV module from E2BOX Company in Korea having a sampling rate of 100Hz, an accelerometer sensor range of $\pm$2g, and a gyroscope range of $\pm$2000dps. The sensed data from IMU sensors are sent to Laptop through 2.4GHz wireless communications as shown in Fig. 2-(c). Participants wear two IMU sensors that are placed according to a pre-defined orientation such that a y-axis in the sensor coordinate system points to the fingertip while a

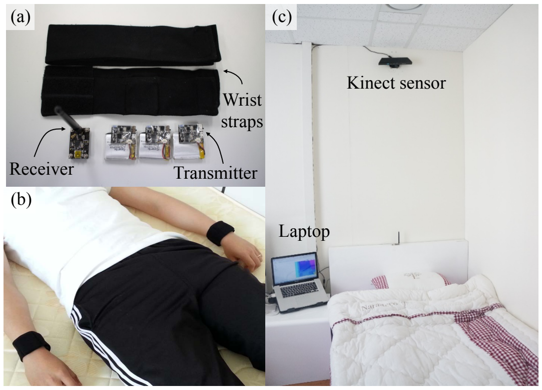

Fig. 2. System setup, (a) Sensor sets and wrist straps (b) Participant wearing wrist sensors (c) Experimental room

Algorithm 1: Sleep Position Motion Grouping

Result: *SP* motion duration: $Time_{start}$, $Time_{end}$
Interval = 1 minute;
while *incoming new SP motion* **do**
  if $Time^{new}_{start}$-$Time^{old}_{end}$ < *Interval* **then**
    $Time_{end}$ = $Time^{new}_{end}$;
    $Time_{start}$ = $Time^{old}_{start}$;
  else
    $Time_{end}$ = $Time^{old}_{end}$;
    $Time_{start}$ = $Time^{old}_{start}$;
  end
end

z-axis points downward direction in the back of a hand as shown in Fig. 2-(b).

C. Pre-processing for Sleep Position Motion

Sleep motion data is pre-processed for a deep learning. Pre-process consists of four steps: *SP* motion grouping, padding, labeling, and re-sizing. Fig. 3 shows a design of input data. Input data size is 4x[$3T_{NS}$]x3 as shown in Fig. 3-(a), where T_{NS} denotes the duration of non-stationary. The data are processed by *SP* motion grouping and padding. Fig. 3-(b) shows RGB images of seven *SP* motions after re-sizing.

1) SP motion grouping: *SP* motion grouping consists of two parts such as detecting and grouping. By grouping small consecutive motions, we can get one *SP* motion. First, we used Stance Hypothesis Optimal Detector (SHOD) [20] for the detector. This detector used both accelerometer and gyroscope sensors to capture a human body movement having acceleration and angular rate. The SHOD classifies both static and moving (non-stationary) sections. The SHOD computes V_n as follows:

$$V_n = \frac{1}{N}\sum_{i=1}^{N}\left(\|a_i - g\frac{\bar{a_n}}{\|\bar{a_n}\|}\|^2 + \|\omega_i\|^2\right) \tag{1}$$

where a_i and ω_i are an acceleration vector and an angular rate vector at an instance i. $\bar{a_n}$ and g are the mean of the acceleration of the frame at instant n and gravity, respectively. $N = 100$, which corresponds to 1 [sec] in case of 100 [Hz] sampling rate, is used to eliminate small fluctuations. The moving sections are then classified by using a threshold, γ [sec] as follows. it classifies as non-stationary if $V_n \geq \gamma$ and Stationary if $V_n < \gamma$, and γ is determined empirically. After extracting temporal sleep motion duration, one *SP* motion duration is determined by grouping method as shown in Algorithm 1. The grouping method combines consecutive motions into one *SP* motion, and the *SP* motion has more meaningful sleep position information. Algorithm 1. shows how to get one *SP* motion. If the SHOD detects a motion from any hands, the time stamp of the motion is added into *SP* motion grouping. And then, motions that occur within 1 minute interval are considered as one motion, and start and end time stamps for the motion are extracted as a result. Accelerometer and gyroscope sensor data are extracted from both hands with same time stamps, i.e., four sensor data are extracted as shown in Fig. 3-(a).

2) Padding: Sleep motion has no distinctive patterns, and sleep habits such as scratching or stretching may result in a false prediction. But possible moving directions of wrists are limited in each sleep position. Furthermore, wrist directions in stationary durations are also limited in each sleep position. Both non-static motion and static motion data have a clue for sleep positions. The key idea is that a wrist direction has information about sleep positions even if it is stationary. In stationary duration, there is no big difference in sensor values. Therefore, we simply utilize first and end sensor data in non-stationary duration, i.e., adding the first padding and end padding at the beginning and the ending points of non-stationary section. The padding size of the stationary duration is equal to that of the non-stationary duration to give same weights. This padding method will be evaluated in algorithm evaluation parts.

3) Labeling: For labeling sleep position for wrist motions, an anatomical structure is considered. Ground truth data for labeling are obtained as follows. We made labels of sleep positions manually by observing video recordings from the depth camera sensor. However, wrist movements and body movements are not synchronized due to the anatomical structure. Wrist movements can occurr faster than body movement and vise versa. Therefore, an extra checking time is needed for checking sleep positions. We set 1 minute as the checking time for labeling the sleep positions. Ground truth about seven *SP* motions are determined by observing times before and after 1 minute from *SP* motions.

4) Re-sizing: We used transfer learning which uses pre-trained models and re-trains some parts with new training data. Specifically, the transfer learning re-trains some parts of the pre-trained network, not the whole network, and it is

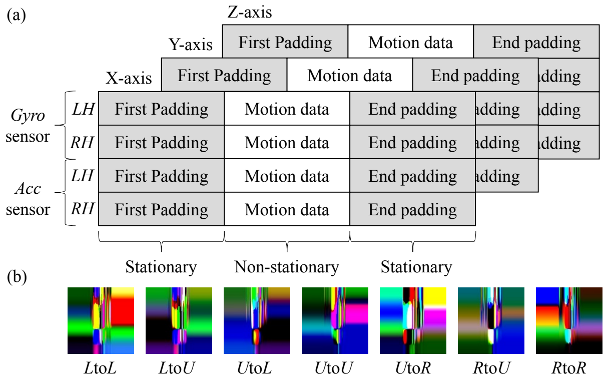

Fig. 3. Design of input data in Deep learning; (a) Input data structure (b) Example of input RGB image data after padding and re-sizing, where LH, RH, L, U, R, Gyro and Acc stand for Left Hand, Right Hand, Left, Up, Right, Gyroscope and Accelerometer, respectively

sometimes called fine-tuning. A huge network requires a lot of time for processing. However, the transfer learning saves time and can re-train the huge network with small amount of training data. The transfer learning requires fix-sized input data. Therefore, re-sizing is needed depending on deep learning models. The original size is [4x3T_{NS}x3] in our sensor data, but it should be enlarged or reduced depending on deep learning models by re-sizing. For example, the input size of Alexnet is [227x227x3]. Therefore, we converted our data to RGB images with size [227x227x3] as shown in Fig. 3-(b). The images are used for transfer learning and classification of *SP* motions as input data.

D. Classifiers

We used two well-known pre-trained neural networks such as Alexnet and VGG16. We re-trained the two networks with our sleep data by the transfer learning. The Alexnet won ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) in 2012, and the structure is composed of 25 layers including 5 convolution layers and 3 fully connected layers [21]. The VGG16 won ILSVRC 2014 and consists of 41 layers including 13 convolution layers and 3 fully connected layers [22]. Big difference between the Alexnet and VGG16 is a network size, i.e., the VGG16 consists of more layers than the Alexnet. In addition to the two models, we used a deep learning method using a linear Support Vector Machine (SVM). Deep learning is used for a feature extractor, and the extracted features are classified by the linear SVM. This method changes a softmax layer in deep learning model into the linear SVM layer. We used L2-SVM since the L2-SVM using features from layer 2 performs slightly better than L1-SVM [23]. We used the pre-trained neural networks such as Alexnet and VGG16 models that are available in the neural network toolkit in Matlab 2017a. We also used the Liniear SVM that is available in the machine learning toolkit in Matlab 2017a.

III. Experimental Results

A. Sleep Position Motion Dataset

For evaluation of proposed *SP* motion model, we performed the pilot experiment and on-site sleep experiment. The actual sleep data set are small. Hence, the pilot experiment is performed to generate additional *SP* motion data by mimicking the actual *SP* motions. The generated data are used for re-training the pre-trained neural network models. The on-site sleep experiment was performed in the smart-home testbed in DGIST, and we collected total 501 *SP* motions from 11 participants. For the on-site sleep experiment, a pillow and a blanket are used on a bed to make a similar sleep environment. Exceptional cases such as going toilet and texting a message are excluded in sleep motion analysis by observing video recording.

1) Pilot experiment: In the pilot experiment, 5 participants imitated seven *SP* motions more than 100 times per motion. Participants were asked to imitate them differently per motion. Total 1084 number of *SP* motions are collected. These *SP* motions are used for fine-tuning pre-trained neural networks such as Alexnet and VGG16. For evaluation, we performed 5-fold cross validation with ratio of 7:3 for the training data set and the test data set. The training data set and test data set are randomly selected among 1084 *SP* motions five times, and total 5420 *SP* motions are used for evaluating the classification performance.

2) On-site sleep experiment: 11 participants were recruited for one-night sleep experiment in our testbed. These participants selected one day, without drinking or overworking, for the sleep experiment. For evaluation, we used the one-verse-all cross validation. But, on-site *SP* motion data are too small to train deep learning models. Therefore, we also added pilot experiment datasets. For example, if the sleep data for one participant were used for a test data set, the data of all the other participants and all pilot experiment datasets are used for a training data set to train pre-trained neural network models.

B. Performance Evaluation

We evaluate deep learning models with transfer learning and L2-linear SVM that uses features from the deep learning. For the performance evaluation, we used the accuracy metric. The accuracy is defined as a correct classification rate in multiclass test datasets. Computer specifications are Xeon CPU E5-2670, Graphic card is NDVIA 1080 Ti. 32G ram, 256 SSD.

1) Algorithm Performance Evaluation: In this section, we evaluated the performances of seven *SP* motion classification by state-of-art deep leanings and the combination of deep learning and machine learning. In addition, we investigated effectiveness of padding method. Table II shows classification accuracy under the two experiments, i.e., pilot experiment and one-site sleep experiment. The pilot experiment showed that VGG16-L2SVM algorithm has the highest classification accuracy of 96.03%. On the other hand, VGG16 algorithm has the highest classification accuracy of 88.02% for the on-site sleep experiment. In more detail, the comparison of deep learning models such as AlexNet and VGG16 showed that the VGG16 classification performance is better than that of the Alexnet. The more layers, the better classification performance. Besides, L2-SVM showed slightly better performance except for VGG16. Although the machine learning can improve classification performance slightly, an architecture of deep learning to make features is more important. Lastly, the padding method showed better performance in all classifiers as we designed in the on-site sleep experiment, since actual *SP* motion has many noises due to sleep habits such as scratching and stretching. On the other hand, the padding method is not effective in the pilot experiment. Although participants were asked to perform *SP* motions randomly, they exhibited some patterns and distinguishable sleep motion patterns, making the padding method unnecessary.

TABLE II

CLASSIFICATION PERFORMANCE EVALUATION CONSIDERING PADDING METHOD IN PILOT EXPERIMENT AND ON-SITE SLEEP EXPERIMENT

Motion data	Classifiers	With padding	Without padding
Pilot experiment	AlexNet	95.52	95.83
	VGG16	95.89	96.00
	AlexNet-L2SVM	95.63	95.96
	VGG16-L2SVM	95.87	**96.03**
On-site sleep experiment	AlexNet	85.23	81.64
	VGG16	**88.02**	85.03
	AlexNet-L2SVM	86.03	82.44
	VGG16-L2SVM	86.83	85.83

2) Classification Performance Evaluation and Discussion: Table III and Table IV show confusion matrices of highest classifiers in pilot experiment and on-site sleep experiment, respectively. These tables show that the proposed *SP* model performs well. The padding method is effective in on-site sleep experiment since actual sleep environment has many unpredictable factors. Nevertheless, we achieved 88.02% accuracy in on-site sleep experiment. Other performance metrics such as recall and precision will be evaluated in future work after collecting more on-site sleep experiment data. Since the amount of *SP* motion collected from the on-site sleep experiment is small, and the data unbalanced, i.e., Up to Up *SP* motion occupies most of dataset.

Unconscious sleep motions do not have regular patterns, but we proposed the *SP* motion model for tracking sleep positions. The proposed four pre-processing methods are used for extracting the regular *SP* motion patterns, and we achieved high classification accuracy by deep learning techniques. For better evaluation of on-site sleep experiment, we will collect more sleep data and develop a personalized *SP* motion model to achieve higher accuracy in actual sleep environments. We preliminarily applied our proposed *SP* motion model to state-of-art reference deep learning models such as Alexnet and VGG16. We will find or develop better classifiers in future work.

TABLE III

PILOT EXPERIMENT: CONFUSION MATRIX OF VGG16-L2SVM WITHOUT PADDING. THE ACCURACY IS 96.03%

		Predicted						
		LtoL	LtoU	RtoR	RtoU	UtoL	UtoR	UtoU
Actual	LtoL	773	5	0	0	1	0	15
	LtoU	9	695	0	0	0	2	1
	RtoR	0	0	730	7	0	4	32
	RtoU	0	2	13	798	1	0	14
	UtoL	8	2	0	1	735	0	6
	UtoR	0	5	9	0	0	738	9
	UtoU	27	3	31	2	4	2	736

TABLE IV

ON-SITE SLEEP EXPERIMENT: CONFUSION MATRIX OF VGG16 WITH PADDING. THE ACCURACY IS 88.02%

		Predicted						
		LtoL	LtoU	RtoR	RtoU	UtoL	UtoR	UtoU
Actual	LtoL	22	4	0	0	6	0	3
	LtoU	2	12	0	0	0	0	1
	RtoR	0	0	20	4	0	8	3
	RtoU	0	0	2	15	0	1	3
	UtoL	3	0	0	0	14	0	2
	UtoR	0	0	1	0	0	14	4
	UtoU	2	0	3	2	0	6	344

IV. CONCLUSIONS

Sleep positions are related to sleep qualities, thus, managing sleep positions for sleep disorder patients is important to improve both mental and physical health. For screening and managing sleep quailities, we proposed SleePS, which is easy to wear and cost-effective, and practical in sleep environments. For this purpose, we propose seven element-*SP* motion model and four pre-processing methods. We apply our *SP* motion model to deep learning classifiers. Experimental results showed that the accuracy of the *SP* motion classification is 96.03% in the pilot experiment and 88.02% in the on-site sleep experiment. The SleePS can be used in commercial smart-watches or wristbands for long-term sleep monitoring, and may replace portable PSG if its medical validation is acquired. By adding additional wristbands, we can track sleep positions more accurately for better sleep management. We expect that the SleePS will be used in many applications such as portable polysomnography or sleep-quality screening.

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