Sleep Posture Classification with Multi-Stream CNN Using Vertical Distance Map

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***Abstract*—Sleep posture is closely related to sleep quality. Moreover, several studies reveal that an incorrect sleep position can result in physical pain. A non-invasive image-based method was proposed for identifying ten sleep postures with high accuracy. The positions of the legs and arms was considered and more complex but common sleep postures was classified, such as fatal left, yearner left, log left, fatal right, yearner right, log right, soldier down, faller down, soldier up, faller up. Input of depth images were preprocessed and a deep multi-stream convolutional neural network was adopted for classification. The work is available for natural scenarios in which people sleep with blanket or quilt covering. Finally, 22 subjects were participated for recording depth images of 10 types of sleep postures, and efficiency of the network was also evaluated.**

Keywords—Sleep Posture Classification; Depth Image; Multi-Stream CNN

I. Introduction

Sleep quality is closely related to health and life quality of people. Poor sleep can contribute to several diseases. Achieving high-quality and refreshing sleep has been an important topic in the field of healthcare research.

Numerous studies in the literature have shown that sleep positions are related to sleep quality. Agargun et al. [1] studied correlation among sleep positions, dream characteristics and sleep quality. They found that people who sleep on their left side tend to experience more nightmares compared to those who sleep on their right side. Therefore, dreams and sleep quality may be affected by body posture.

The influence of sleep positions on health has been highlighted in many studies. Supine sleep posture is strongly associated with obstructive sleep apnea syndrome [2][3]. In addition, it was found that a lateral position can attenuate the severity of central sleep apnea [4]. Moreover, the lateral position is observed to be more effective in removal of waste products including Aβ during sleep [5].

These studies demonstrate the importance of analyzing sleep positions. In previous studies, many researchers have used pressure mats to identify sleeping postures, but cost of the mat with high-resolution pressure sensors is high. For the reason, it is also not suitable for daily use. Another non-invasive technology, image processing, usually requires conditions of bright lights and no occlusions. Hence, in this study, a method for identifying sleep postures based on depth images was proposed. The problem of illumination and recognize sleep postures were also considered in the condition with blanket or quilt covering.

Sleep posture type was also considered in the study. Sleep Assessment and Advisory Service (SAAS) clusters sleep postures into six types: fetus, log, yearner, soldier, freefaller, and starfish. Most studies only focused on the identification of three sleep postures, including supine, left side, and right side [6 to 7]. However, the positions of legs and arms are also important factors for achieving comfortable sleep. According to the Clinical Journal of Pain, incorrect sleep positions held for a considerably long duration can result in spinal alignment problems. Moreover, several studies reveal that an incorrect sleep position can result in physical pain. For example, placing legs in an awkward position during sleeping may cause leg cramps. Sleeping with hands up position also add continual pressure on the back causing shoulder pains. Therefore, the positions of legs and arms were considered and more complex but common sleep postures were classified, such as fatal left, yearner left, log left, fatal right, yearner right, log right, soldier down, faller down, soldier up, faller up [8][14]. The 10 types of sleep postures are shown on Figure 1.

In the study, a non-invasive image-based method was proposed for identifying 10 sleep postures with high accuracy. The work is available for natural scenarios in which people sleep with blanket or quilt covering. Input of depth images were preprocessed and a deep multi-stream convolutional neural network was adopted for classification the 10 types of sleep postures.

II. Related Work

Numerous technologies have been applied for recognition and classification of sleep positions. A common technology, wearable device, is used to monitor and detect sleep positions. Yoon et al. [9] analyzed the features of 3-axis accelerometer signals to estimate sleep postures. A patch-type sensor was attached on the left side chest of subjects during the experiment. Borazio and Van Laerhoven [10] used a wrist-worn sensor to record 3D accelerations for monitoring sleep in a long duration.

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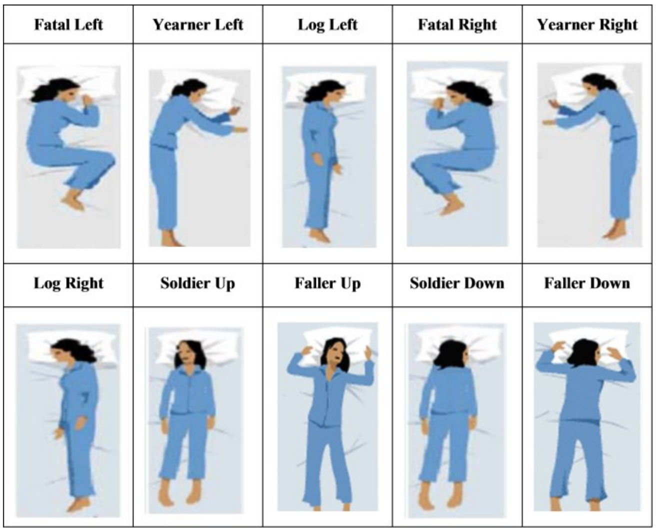

Fig 1.10 types of sleep postures [8].

An HMM-based method was applied for analyzing posture changes and myoclonic twitches. However, wearable device usually cause uncomfortable sleep, and that may affect sleep quality of people. It is also not convenient for using in sleep condition.

Pressure mattress was also widely used for sleep posture recognition. Jason et al. [11] monitored sleep postures using a pressure-sensitive bed sheet, and features of pressure images were extracted for identifying sleep postures using three sparse classifiers. Ostadabbas [7] used GMM-based clustering approach to classify sleep positions from pressure image data. The shortage of pressure mattress is the cost of high-resolution pressure-sensor array, and it is not popular used in common people.

Computer vision technique has the advantages of non-invasive and inexpensive in sleep posture recognition. Nakajima et al. [12] used a CCD video camera and an optical flow method was adopted for evaluating posture changes and respiratory rate. However, classification of sleep postures was not considered. Lee et al. [13] developed a sleep monitoring system using Microsoft Kinect. However, the system was not able to detect joint information using Kinect when people sleep with quilt or blanket covering. Torres et al. [14] used both camera and pressure mat to extract features from RGBD data for classifying sleep postures. The histogram of oriented gradients and geometric moments features were used for training SVM (and LDA) classifiers, and achieved 80% accuracy under dark and occlusion situations. Grimm et al. [15] used bed-aligned maps generating from depth images, and a small convolutional neural network was applied for classifying sleep postures, and that achieved 94% accuracy. However, they only focused on simple posture types: empty, right side, left side and supine, and did not consider other complex posture types, such as fatal, yearner, log, soldier and faller.

III. PROPOSED METHODS

A. *System Setup*

Microsoft Kinect with a depth sensor and an RGB camera that has 8-bit VGA resolution (640 × 480 pixels) for RGB images and 11-bit VGA resolution (640 ×480 pixels) for depth images was utilized to detect 10 types of sleep postures. The camera captures RGB and depth images simultaneously at a frame rate of 30 fps. The device was placed at a horizontal distance of 50 cm and vertical distance of 55 cm above the bed, and the field of view can cover the bed and entire body of a subject (Figure 2).

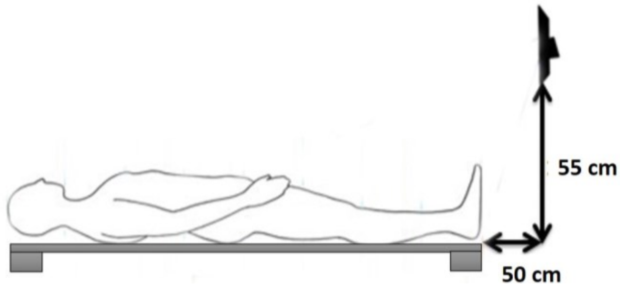

Fig 2. An illustration of devide setting in the experiment [8].

B. *Vertical Distance Map*

The ROI of bed area was extracted from images showing on Figure 3. The world coordinate of each point was calculated from the projective coordinate of each point. The 3D point cloud was obtained after coordinate transform, and the bed plane was formulated to a defined region. Then, the vertical distance of each point on the subject from the bed plane can be estimated. Finally, a new map was generated, called “vertical distance map” (Figure 4). In the study, image pyramids was applied to down-sample the vertical distance map from 304 × 320 to 40 × 40 pixels.

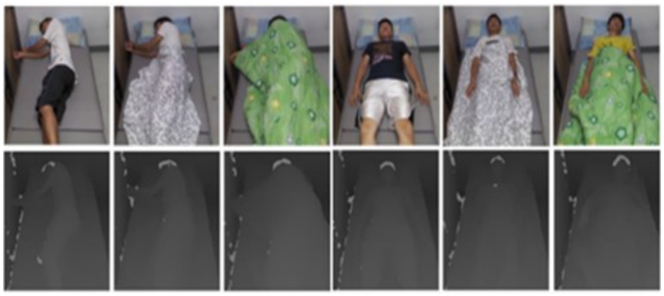

Fig 3. Examples of RGB images and depth images. First row is ROI of RGB images shwoing a subject in three sleep conditions(no covering, blanket covering and quilt covering), and second row is that of depth image [8].

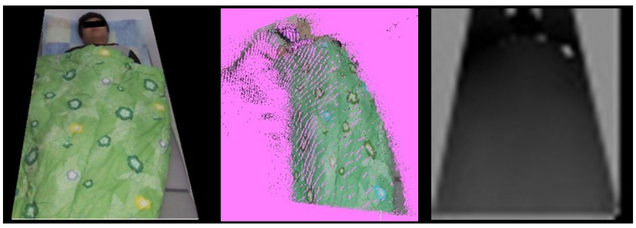

Fig 4. Example of ROI of rgb image(right),3D point cloud (center) and vertical distance map(right).

C. *Convolutional Neural Network Architecture*

The structure of our network is three-stream 2D convolutional, 2D max-pooling and fully connected layers, followed by one softmax layer showing on Figure 5. The main characteristic in our network is combination of three 2D CNNs and one max-pooling layer. Total three sets of combination in the network. For the purpose of obtaining more comprehensive information concealed in image data, different sizes of kernel (3×3, 5×5 and 7×7) was applied. Features of three-stream CNNs was concatenated and ended with a softmax layer.

The hidden layers in model 1 are three 2D convolutional layers which learned 64 kernels of size 3×3 with stride of 1. The inexpensive Rectified Linear Unit (ReLU) activation function was applied for generating the layer. The first feature map was created from Conv1 with 64 filters of size 38×38, followed by 2×2 max-pool Pool1, and generating 64 filters of size 19×19. The second feature map was created from Conv2 with 128 filters of size 17×17, followed by 2×2 max-pool Pool1, and generating 64 filters of size 8×8. The third feature map was constructed from Conv3 with 256 filters of size 6×6, followed by 2×2 max-pool Pool1, and generating 64 filters of size 3×3.

The next two sets of combination were programming as first step but with kernels of size 5×5 and size 7×7. For the reason, different resolution feature maps were generated to perform classification precisely. Therefore, all the features of three-stream maps were concatenated into one dimensional vector of size 1024. Finally, the fully connected layer of size 128 was followed by a softmax layer to generate the number of classes in the work (10 types of sleep postures).

The objective of multiple-stream CNNs is to generate thorough description, and to enhance abilities of feature maps. Thus, an accurate model is available via multiple-stream CNNs with various kernel sizes.

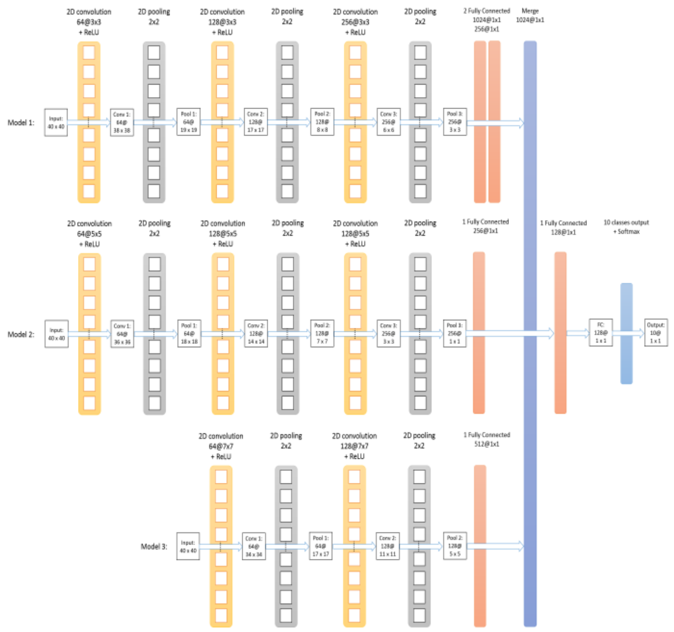

Fig 5. The network architecture of sleep position classification.

IV. Experimental Results and Discussions

A. *Experimental Setup*

Sleep positions of subjects were recorded in the lab for evaluating the accuracy of sleep posture classification. 10 types of sleep positions were investigated, including left side in fetal position, left side in yearner position, left side in log position; right side in fetal position, right side in yearner position, right side in log position; soldier in hand-up position, soldier in hand-down position; faller in hand-up position, and faller in hand-down position. The investigations were conducted under three conditions: (1) without covering, (2) blanket covering, and (3) quilt covering. 22 subjects participated in the experiment, and 16 subjects were male and 6 subjects were female, ranging in the age of 20 to 37 years. Each subject performed each type of sleep posture in the three sleep conditions.

B. *Evaluation*

The performance of the network architecture on sleep-posture image data was evaluated. There are 600 (60×10 classes of sleep posture) samples of each subject. Total 13200 samples (600×22 subjects = 13200 samples) of 22 participants were recorded for evaluating robustness of the proposed model. 5-fold cross validation was used for suitable weights while training model, and leave one out strategy was adopted for ensuring the high accuracy in testing data without overfitting. Subsequently, evaluation results in the three sleep conditions are as follows:

- Without covering condition

  Firstly, the results in the without covering condition are evaluated. The characteristics of sleep patterns are recognizable with obvious body shape without occlusion. In Figure 6 shows the major shapes of the 10 types of sleep postures with high accuracy (93.2% accuracy).

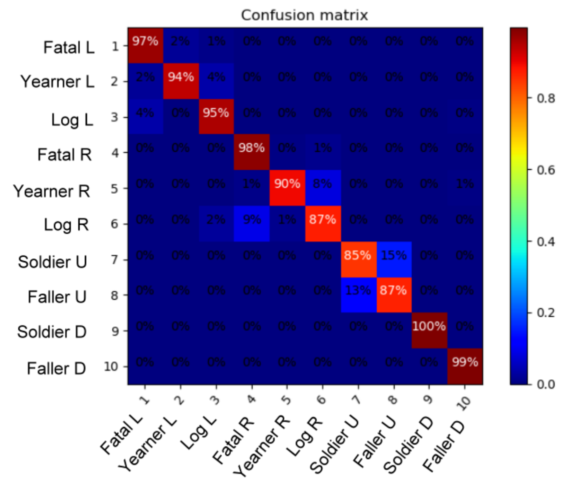

Fig 6. Confusion matrix of without covering condition (93.2% accuracy).

- Blanket covering condition

  The results of blanket covering condition are evaluated. The characteristics of sleep patterns with recognizable property are with clear shapes under blanket covering. The major shapes of the 10 types of sleep postures with high accuracy (90.9% accuracy) showing on Figure 7.

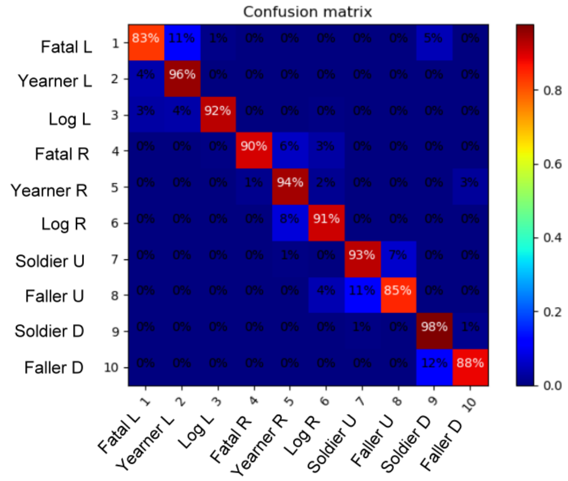

Fig 7. Confusion matrix of blanket covering condition (90.9% accuracy).

- Quilt covering condition

  Finally, the results of quilt covering condition are evaluated. The major shapes of the 10 types of sleep postures with high accuracy (88.6% accuracy) showing on Figure 8.

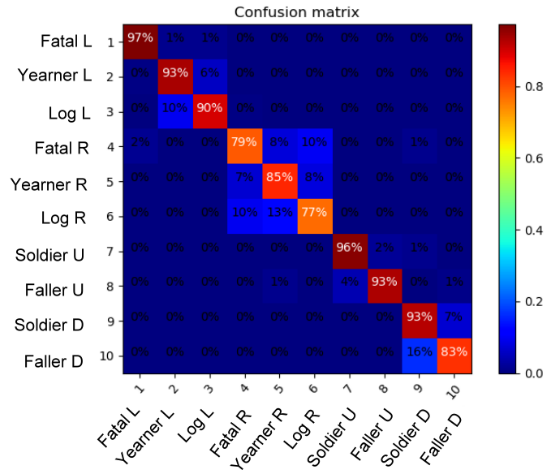

Fig 8. Confusion matrix of quilt covering condition (88.6% accuracy).

From the result, the average accuracy is 90.9%. Sleep posture recognition in heavy quilt condition have more difficulties than the other two conditions, because the sheathing influences the contour of vertical distance map. Hence, the layers of covering affect the classification results.

V. CONCLUSIONS

Unlike other approaches only consider a single scenario, the proposed method dealt with the real sleep environment including no covering, thick and heavy covering. The positions of legs and arms were considered, and 10 more complex sleep postures were classified. A simple multi-stream CNN with different kernel sizes was used for training on the same input samples, and that would learn more favorable feature representations.

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REFERENCES

[1] Agargun M.Y., Boysan M., Hanoglu L. Sleeping position dream emotions and subjective sleep quality. Sleep Hypnosis, 2004; 6(1): pp. 8-13.

[2] Penzel T., Möller M., Becker H.F., Knaack L., Peter J.H. Effect of sleep position and sleep stage on the collapsibility of the upper airways in patients with sleep apnea. Sleep, 2001; 24 (1): pp. 90-5.

[3] George C.F., Millar T.W., Kryger M.H. Sleep apnea and body position during sleep. Sleep, 1988 Feb;11(1): pp. 90-9.

[4] Szollosi I., Roebuck T., Thompson B., Naughton M.T. Lateral sleeping position reduces severity of central sleep apnea/Cheyne-Stokes respiration. Sleep, 2006; 29(8): pp. 1045-51.

[5] Hedok Lee, Lulu Xie, Mei Yu, Hongyi Kang, Tian Feng, Rashid Deane, Jean Logan, Maiken Nedergaard and Helene Benveniste. The effect of body posture on brain glymphatic transport. The Journal of Neuroscience, 5 August 2015,35(31):pp. 11034-11044.

[6] Hsia C.C., Liou K.J., Aung A.P.W., Foo V., Huang W., Biswas J. Analysis and comparison of sleeping posture classification methods using pressure sensitive bed system. In Engineering in Medicine and Biology Society (EMBC) 2009. Annual International Conference of the IEEE, pp. 6131-6134, Sept. 2009.

[7] Ostadabbas S., Pouyan M.B., Nourani M., Kehtarnavaz N. In-bed posture classification and limb identification. In 2014 IEEE Biomedical Circuits and Systems Conference (BioCAS), Lausanne, Switzerland, pp. 133-136, 2014.

[8] Lyn Chao-ling Chen and Yi-ping Hung, On Detection and Browsing of Sleep Events, Doctorial Dissertation, National Taiwan University, Taiwan,2016.

[9] Yoon H.N., Hwang S., Jung D.W., Choi S., Joo K., Choi J., Lee Y., Jeong D., Park K.S. Estimation of sleep posture using a patch-type accelerometer based device. In Engineering in Medicine and Biology Society (EMBC) 2015. 37th Annual International Conference of the IEEE, pp. 4942-4945, 2015.

[10] Borazio M., Van Laerhoven K. Combining wearable and environmental sensing into an unobtrusive tool for long-term sleep studies. In 2nd ACM SIGHIT International Health Informatics Symposium (IHI 2012), Miami, Florida, USA (in Press,2012)

[11] Liu J.J., Xu W., Huang M., Alshurafa N., Sarrafzadeh M., A dense pressure sensitive bedsheet design for unobtrusive sleep posture monitoring. IEEE International Conference on Pervasive Computing and Communication (PerCom'13), San Diego, CA, USA, Mar. 2013.

[12] Nakajima K., Matsumoto K., Tamura T. Development of real-time image sequence analysis for evaluating posture change and respiratory rate of a subject in bed. Physiological Measurement, 2001; 22: pp. N21-N28.

[13] Lee J., Hong M., Ryu S. Sleep monitoring system using Kinect sensor. International Journal of Distributed Sensor Networks, 2015; 875371.

[14] Torres C., Fragoso V., Hammond S., Fried J., Manjunath B. Eye-CU: Sleep pose classification for healthcare using multimodal multiview data. Winter Conference on Applications of Computer Vision, 2016.

[15] Grimm T., Martinez M., Benz A., Stiefelhagen R. Sleep position classification from a depth camera using bed aligned maps. International Conference on Pattern Recognition, 2016.