The Sitting and lying Posture Recognition via Pressure Information based on Unconstrained Flexible Pressure Sensor

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ABSTRACT

For detecting sleeping and sitting postures, a system based on unrestrained flexible pressure sensor is designed and proposed. The large-area capacitive pressure sensor, which composited by 64-row and 32-column, is designed to capture posture pressure signals. A total of 30 participants were recruited for 10 postures data acquisition, and the acquired images were normalized and bilinearly interpolated. The processed data images were randomly grouped by 80% of the training set and 20% of the test set. And the deep learning neural network (YOLOv5) was used for training. The final recognition accuracy was 99.3%. Accurate division in the posture categories of sleeping and sitting postures is achieved, which is important for realizing posture monitoring.

CCS CONCEPTS

• **Hardware** → Communication hardware, interfaces and storage; Sensor applications and deployments.

KEYWORDS

Flexible pressure sensor, Unconstrained, Sitting and lying postures recognition, Neural network, YOLOv5 algorithm

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1 INTRODUCTION

The research of monitoring the health status of the elderly is becoming more and more prominent with the aging of society [1]. The quality of sleep is a particularly important part of the health monitoring process, so it is necessary to develop a system that can monitor the human posture in bed and record the data. In this paper, a set of unrestrained sleeping and sitting recognition system is developed to facilitate the detection of the sleeping and sitting posture.

In recent years, researchers have developed a variety of posture detection methods, which are broadly classified into bound and unbound types.

Most of the restraint detection uses wearable devices to monitor human posture by installing sensors on the wrist [2, 3] and torso [4–6] to record human posture position signals. This posture monitoring method can cause physiological discomfort, such as the sensor requires battery power and additional signal output device. This inevitably increases the weight of the tester, and it is difficult to ensure that the sensor is not a burden on the tester when lying or sitting [7].

Unconstrained posture detection can be further subdivided into non-contact and indirect contact detection postures. For example, non-contact type detection methods using microwave Doppler bio-radar, camera, etc. As well as indirect detection methods such as bed posture detection by human pressure distribution.

Non-contact detection methods mainly use ultrasound, visible light or infrared signals for detection. Among them, microwave Doppler bio-radar [8–11], ultra-wideband (UWB) [12] radar and other methods can be used to detect sleeping posture without contact. It has the advantages of easy installation and robustness to the clothing worn by the subject. However, it is vulnerable to environmental vibration and electromagnetic noise. Although the method using camera can achieve the detection of sleep posture in an unconstrained way in principle. But the camera parameter setting and positioning adjustment is more complex, and the detection is easily affected by factors such as bedding, and there is also the risk of privacy leakage of the subject. And it is difficult to track changes in position and posture during sleep, which limits its usefulness and has not gained popularity [13].

Indirect contact detection is mainly performed using the pressure fluctuation distribution of the bed and mattress. In indirect contact detection, measuring pressure distribution is mainly achieved by setting pressure sensors in or on the mattress and other devices that can recognize human pressure signals. Hsiao RS et al, used a combination of piezoresistive sensors (FSR) and infrared sensors to collect upper and lower body sleeping positions separately and used a fuzzy c-mean clustering algorithm for combined identification [14]. Chen et al, embedded 5×5 radio frequency identification (RFID) tags in a mattress, using RFID electromagnetic waves cannot penetrate human tissue, the tags covered by human tissue will not be read by the reader this characteristic, to identify the pressure distribution and use CNN algorithm to achieve sleep posture recognition and body movement detection [15]. Liu et al, applied a piezoelectric sensor to a mattress to obtain human posture data, extracted feature parameters by cubic discrete wavelet transform, and used a plain Bayesian learning phase to predict human posture [16].

2 METHODS

2.1 Flexible sensor design

The self-designed large-area flexible sensors to extract human posture pressure distribution data are applied in the present study. The sensor is designed as a three-layer structure with upper and lower electrode layers and ionic gel layer, as shown in Figure 1. The sensor adopts an array structure, with the upper and lower electrode layers designed with 64 horizontal and 32 vertical parallel electrode strips interlaced vertically, and the middle ion gel layer as a dielectric layer to form a capacitive sensing unit. The sensor has a total of 64×32 capacitive sensing units. When pressure is applied, the upper and lower electrode layers and the middle ionic gel layer come into contact with each other, resulting in a change in the contact area and thus a change in the capacitance of the sensing unit in the corresponding area. The pressure data is obtained through the change in capacitance.

Through testing, the capacitance sensitivity of the sensor used in this paper is about 135.9 (nF/cm^2)/kPa, and the perceivable pressure range is 0~50 kPa, and the relationship between the two is shown in the literature [17].

2.2 Data acquisition system design

This paper independently developed a data signal transmission system with pressure sensors, which consists of a data acquisition card, a host computer system and a flexible pressure sensor. The detection area size of the sensor is 2000 mm × 1000 mm, with 2048

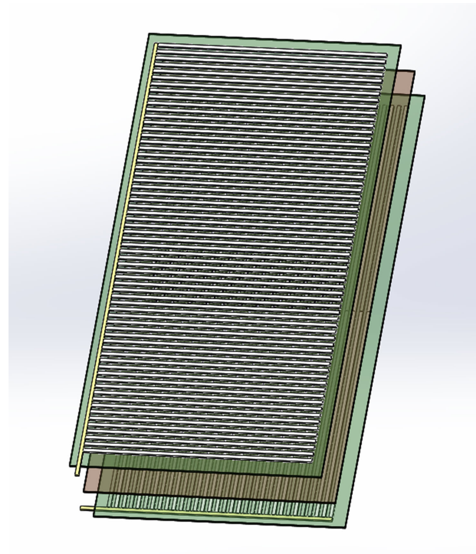

Figure 1: Schematic diagram of flexible pressure sensor structure.

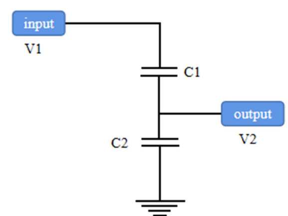

Figure 2: Voltage divider circuit.

detection units, which can obtain the data of human sitting and lying postures.

The data acquisition card consists of four parts: voltage divider circuit, amplification and filtering, data processing, and serial communication. The set fixed capacitor unit and the sampling capacitor form a voltage divider circuit to map the change of the capacitance value of the sensing unit to the output voltage value,

$$V_2/V_1 = C_1/(C_1 + C_2)\ , \tag{1}$$

where, the V_1 is the value of the Alternating Current (AC) voltage connected externally to the sensor, typically 3-5 V, the V_2 is the value of the voltage output by the sensor to the acquisition card, the C_1 is the capacitance value set by the voltage divider circuit (fixed value), and the C_2 is the sensor capacitance unit capacitance value, as shown in Figure 2.

When the transmitted voltage signal is received at the acquisition end, it is amplified and filtered. The voltage output from the sensor is converted into a digital quantity by the 8-bit Analog signals Digital signals (AD) module that comes with the Advanced RISC Machine (ARM) architecture Micro Control Unit (MCU), filtered and sorted by software. Finally, the data is transferred to the host

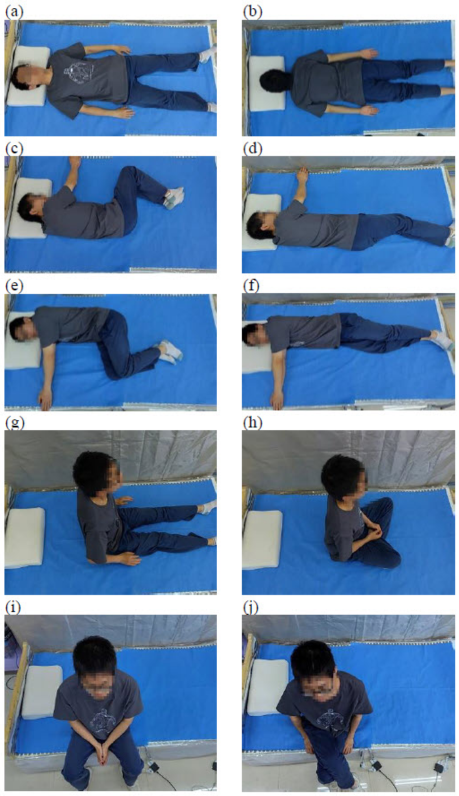

Figure 3: Examples of posture data sampling. (a) frontal lying down, (b) lying down, (c) bent leg left side lying down, (d) left side lying down, (e) bent leg right side lying down, (f) right side lying down, (g) sitting position with extended legs on the bed, (h) sitting position on the bed side, (i) sitting position with two legs on the bed side, (j) sitting position with crossed legs on the bed.

computer for storage, processing and display by frame through serial communication.

The upper computer system arranges the received data frames in a sequential order. The voltage values are converted to the same coordinates as the corresponding pressure values to ensure that the posture image displayed by the host computer corresponds to the actual human posture. In order to make the image more intuitive and specific, reflecting the different pressure levels, the corresponding voltage data values are converted to the 0~255 range for easy conversion into RGB image form. The data is also converted into a 64×32 matrix to correspond to the sensor capacitance cell distribution.

2.3 Data Acquisition

Ethical principles and the Declaration of Helsinki were observed during data collection in this experiment, and subjects were free of physical defects and completed data collection under the guidance of the testers. Data were collected from 30 subjects (25 males and 5 females), age (26±8.1), height (171±7.3) cm, weight (61±16.6) kg,

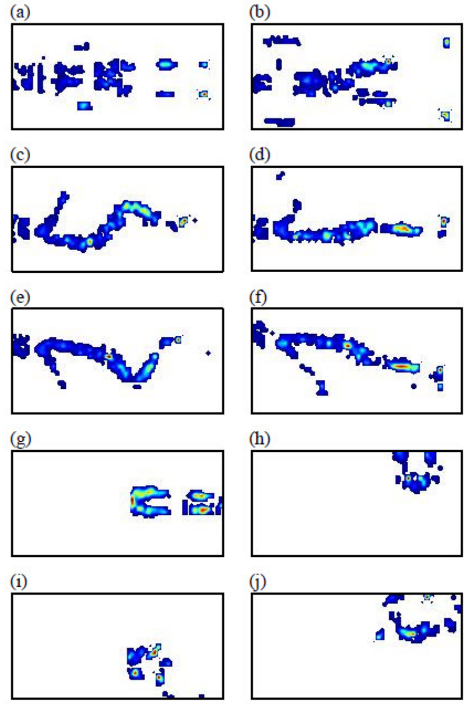

Figure 4: Examples of pre-processing result diagram. (a) frontal lying down, (b) lying down, (c) bent leg left side lying down, (d) left side lying down, (e) bent leg right side lying down, (f) right side lying down, (g) sitting position with extended legs on the bed, (h) sitting position on the bed side, (i) sitting position with two legs on the bed side, (j) sitting position with crossed legs on the bed.

and body mass index of (25.1±7.7) kg/m^2. In totaling 9000 sets of data, 10 postures were collected. The ten postures were frontal lying, lying down, bent leg left side lying down, left side lying down, bent leg right side lying down, right side lying down, sitting on the bed with extended legs, sitting on the side of the bed, sitting on the bed with legs crossed, and sitting on the side of the bed with legs crossed. An example of data posture collection is shown in Figure 3.

2.4 Image pre-processing

Before formal training using YOLOv5, some processing of the dataset is also required to improve the training effect and facilitate image processing and presentation. The image data were converted to color RGB images and bilinear interpolation was performed to make the natural transition of the contour edges. The bilinear interpolation processed images were normalized and the results are shown in Figure 4. The effect of the difference in weight of the subjects on the stress images was eliminated to accelerate the convergence of the neural network learning.

After the preprocessing is completed, the data are manually labeled using LabelImg software to obtain the xml format label file. Since the file format required for yolov5 training is yolo (txt

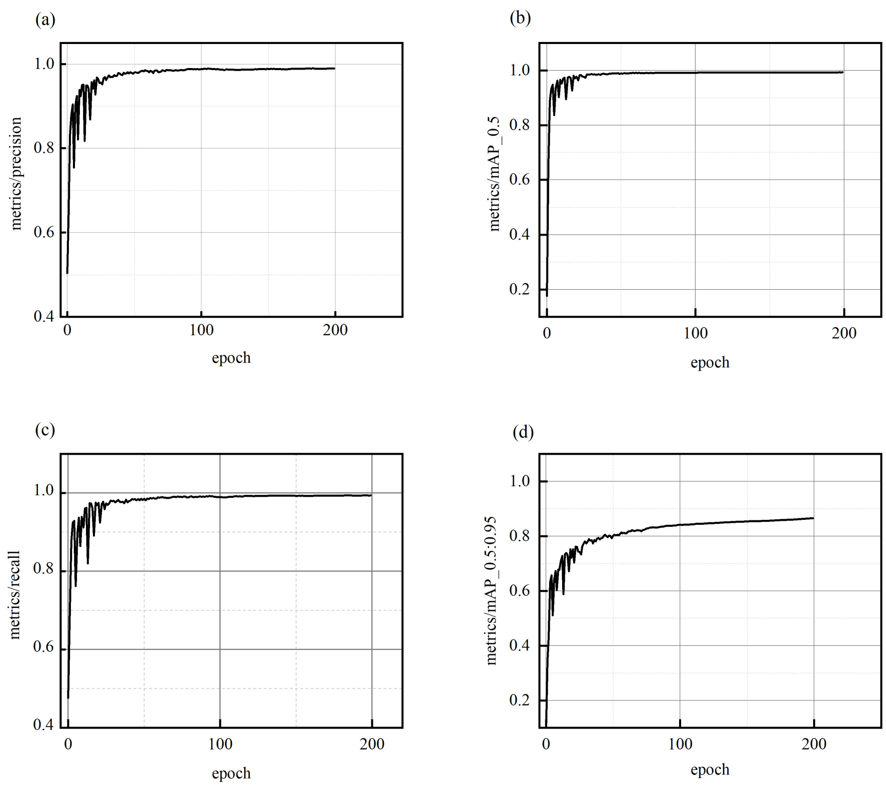

Figure 5: Training result graph. (a) precision and epoch, (b) the average *mAP* with threshold greater than 0.5, (c) recall and epoch, (d) the average *mAP* at different IoU thresholds (from 0.5 to 0.95, in steps of 0.05).

format), it is also necessary to convert the xml format label file to txt file using the program. The converted dataset is then divided into training and validation sets in a ratio of 8 : 2 for the next step of neural net training.

The hardware and software environment used in this experiment is NVIDIA GeForce GTX 1050 GPU with 8G RAM. The PyTorch framework is used to build a deep learning framework on Windows 10 system. During the training process, the training parameters are set as follows: the batch size is set to 16, and the total number of training rounds (epoch) is 200.

3 EXPERIMENTAL RESULTS

The Yolov5 training results are shown in Figure 5 below.

In this paper, *mAP* (mean Average Precision), accuracy *P* (Precision), and recall *R* (Recall) are chosen as the evaluation criteria of the model. These three data are used to measure the detection accuracy of the algorithm. The formula *TP* indicates the number of postures correctly recognized by the network, *FP* indicates the number of postures incorrectly recognized by the network, and *FN* indicates the number of postures not recognized by the network.

Precision *P* (Precision) indicates the number of correctly identified by the algorithm as a percentage of what the algorithm judges to be correct. The formula is shown below:

$$P = \frac{TP}{TP + FP}. \tag{2}$$

Recall R (Recall) indicates the number of correctly identified by the algorithm as a percentage of the category. The formula is shown below:

$$R = \frac{TP}{TP + FN}. \tag{3}$$

Mean Average Precision *mAP*, the average of the mean precision of all categories in the dataset. The formula is shown below:

$$mAP = \frac{1}{m}\sum_{i=1}^{m} AP\,(m)\,. \tag{4}$$

After the training was completed, the performance metrics obtained on the test set are shown in Table 1.

At the end of the test, the effect on posture recognition is shown in Figure 6.

The confidence level of each of these posture recognition is above 90% and the recognition is good. Compared to unconstrained detection using other algorithms (fuzzy c-mean clustering algorithm [14], plain Bayesian algorithm [16], CNN algorithm [15], sparse classification algorithm [18], trunk centerline prediction algorithm [19]), this algorithm has higher human posture recognition variety and recognition accuracy. The detailed comparison is shown in Table 2.

Table 1: Test performance

	P	*R*	*mAP*
YOLOv5	0.997	0.991	0.993

Table 2: Comparison of algorithm recognition

Algorithm	Number of postures	Accuracy
Fuzzy c-mean clustering algorithm	3	91.6%
Plain Bayesian algorithm	4	97.9%
CNN algorithm	3	88.9%
Sparse classification algorithm	6	83.2%
Trunk centerline prediction algorithm	3	97.2%
Algorithm of present paper	10	99.3%

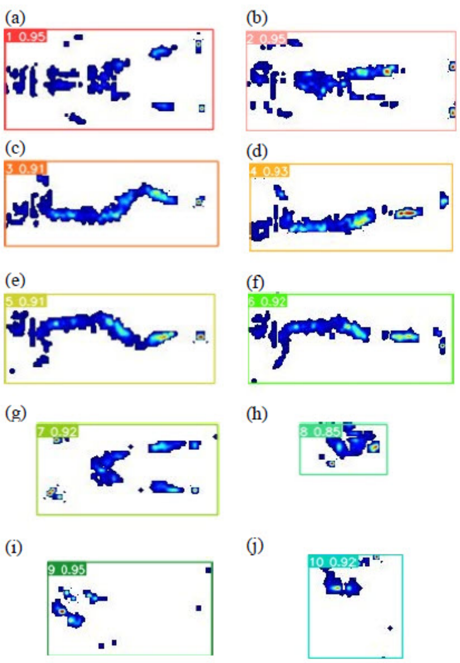

Figure 6: Examples of posture recognition effects. (a) frontal lying down, (b) lying down, (c) bent leg left side lying down, (d) left side lying down, (e) bent leg right side lying down, (f) right side lying down, (g) sitting position with extended legs on the bed, (h) sitting position on the bed side, (i) sitting position with two legs on the bed side, (j) sitting position with crossed legs on the bed.

4 SUMMARY

This system combines the unconstrained flexible pressure sensor with deep learning neural network to realize the recognition of human bed posture. It eliminates the concern of user's privacy being violated or better improves the user's restraint status. Its 99.3% recognition accuracy rate is much higher than other unconstrained monitoring system platforms, and it achieves precise division in the distinction of posture categories of sleeping and sitting postures, which is important for realizing sleep posture monitoring.

The experimental platform of this system lays the foundation for realizing dynamic posture recognition in home-based sleep monitoring system. And this system will possess a broad application prospect in the field of unmanned intelligent nursing. In the future research, the number of experimental samples will be expanded to improve the follow-up experimental studies. And the study of real-time monitoring of sleep posture and sleep quality detection will be conducted based on this system.

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