Smart Cushion Based on Pressure Sensor Array for Human Sitting Posture Recognition

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***Abstract*—A smart cushion based on a pressure sensor array is designed and manufactured to recognize human sitting posture. The smart cushion collects pressure images for convolutional neural network training to recognize 5 human sitting postures. In a series of experiments, a total of 16,300 pressure images were collected by 5 subjects to perform recognition tasks. By collecting pressure images multiple times to optimize the time independence of the data set, and the accuracy achieved 0.978. While ensuring comfortness, this smart cushion takes into account both the high accuracy of sitting posture recognition and the development prospects of visualization applications.**

Keywords—smart cushion; pressure sensor array; sitting posture; convolutional neural network

I. Introduction

Human sitting posture recognition is an important technique to provide smart life for sedentary people, such as the elderly, students, and drivers. Sitting posture recognition can effectively prevent diseases [1, 2], correct sitting posture [3, 4] and improve driving safety [5, 6]. For the task of human sitting posture recognition, researchers have proposed different solutions such as computer vision [7], wearable sensors [8], and pressure sensors [9]. Computer vision solutions were excluded due to privacy concerns. Wearable sensors are not suitable for daily environments due to their troublesome and uncomfortable features, especially in the elderly-led demand. Seat with pressure sensor does not have the above problems and has a variety of solutions, which has attracted intensive research interests [10, 11].

Different human behaviors can produce different sitting postures, resulting in different pressure distributions on a seat. Compared with independent pressure sensors, pressure sensor array can be spread all over the seat to collect complete human buttocks pressure distribution information, which is proven to have higher accuracy, visual solutions and capable of handling complex tasks [12-14]. However, we have noticed that commercial pressure sensor arrays are used in most related studies. These commercial pressure sensor arrays are not only expensive, but also very rigid, which makes them uncomfortable for daily usage. In this paper, piezoresistive material of Velostat is used as the core to build the pressure sensor array. Its flexible, soft and low-cost characteristics make the finished smart cushion almost free of foreign body sensation.

In our previous work [15], we studied the resistance sensitivity and quasi-static response of the Velostat material, discussed the crosstalk interference in the sensor array, established the signal processing subsystem and three experimental setups, and used a convolutional neural network (CNN) ResNet-PI to recognize 10 objects and reached an accuracy of 0.9854. In this paper, we applied the techniques developed previously and designed a smart cushion based on the pressure sensor array to collect and recognize pressure images of different subjects in different sitting postures. The CNN ResNet-PI was used to recognize pressure images of human sitting postures. Two simple recognition tasks were designed and tested: sitting postures recognition (SPR) and human identification (HI), and achieved an accuracy of 0.9973 and 1.0, respectively. After testing the ability of the smart cushion to recognize sitting postures at different times, a more advanced recognition task, time independent SPR, was proposed and designed. After we collected data multiple times to optimize the data set diversity, the accuracy achieved 0.978. Compared with the original data set, the accuracy of the optimized time independent data set increased by 11.61%. The experiment results prove that the designed smart cushion has time independency, repeatability, and reliability.

II. Methodology

A. Fabrication of Smart Cushion

Inheriting the principles of previous research [15], the flexible, soft and low-cost Velostat material is used as a piezoresistor in our smart cushions. Conductive threads made of stainless steel fibers form 27 rows and 27 columns above and below Velostat, respectively, and are connected to the signal processing subsystem. Considering multiple usage scenarios, DuPont jumpers were chosen to connect the conductive threads and the signal processing subsystem printed circuit board. Each intersection of the 27 rows and 27 columns of conductive threads is each sensor element and also a pixel on the generated pressure image. Acrylic adhesive is used to fix Velostat, conductive threads and protective layer. 100% cotton cloth was chosen as the protective layer because of its firmness, comfort and low cost. This sitting posture collection system, including the smart cushion fabrication and signal processing subsystem, costs around 45 dollars in total, which confirms the commercial development prospects of the smart seat we designed.

Fig. 1(a) shows the designed human sitting posture collection system. When the human body sits on the smart cushion, Velostat receives different pressure distributions and produces different resistance distributions. The signal processing subsystem scans the 27×27 pressure sensor array row by column, and uses the analog pins (8-bit ADC) of Arduino Nano to generate a 27×27 readout matrix. The host computer receives this readout matrix and saves as a pressure image for CNN training and recognition. In order to ensure that the initial conditions of the experiment remain unchanged, when performing data collection, the relative position of the seat and the smart cushion have been kept unchanged. For this reason, we use tape to fix the smart cushion and the PCB on the laboratory chair seat and backrest, as shown in Fig. 1(b) and Fig. 1(c), respectively. The pressure sensor array made by Velostat is made in the middle of the smart cushion, leaving room around for conductive threads. According to experience and previous literature, the smart cushion is placed in the area where the human body contacts the seat and generates the most significant pressure, as shown in Fig. 1(d).

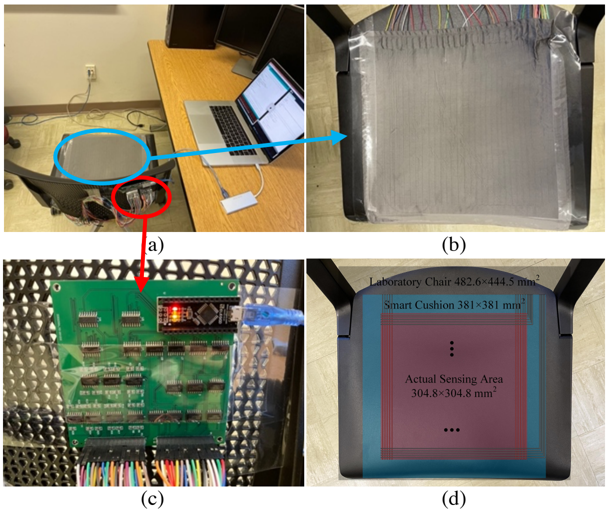

Fig. 1. Human sitting posture collection system, (a) the overall sitting posture collection system includes smart cushion, signal processing subsystem PCB and a host computer, (b) the smart cushion fixed on the laboratory chair seat, (c) the signal processing subsystem PCB fixed behind the laboratory chair backrest, (d) schematic diagram of the smart cushion structure.

B. *Host Computer*

As the center, the host computer has the functions of displaying and saving pressure images in real time, training CNN models and predicting human sitting posture. The Arduino and Processing sketch in the host computer display the readout matrix of the smart cushion in real-time and save as the image format locally. In order to save time, ensure enough samples, and avoid a large number of duplicate images in the data set, the sampling rate is set to 2 (samples/second). To reduce the manufacturing differences, crosstalk and electrical noise of the smart cushion, the unloaded pressure images for 1 hour were collected in advance to initialize the readout matrix of the smart cushion. The CNN ResNet-PI based on TensorFlow is trained and used to recognize pressure images.

C. *Human Sitting Postures*

In our experiment, based on daily life experience and relative literature, we set up 5 sitting postures: (a) normal, (b) lean forward, (c) lay back, (d) leg crossover, (e) upright, as shown in Fig. 2. "Lean forward" represents thinking in daily activities, and the body's center of gravity moves forward. "Lay back" stands for rest and the center of gravity of human moves backward. "Leg crossover" represents a relaxed and lively left and right cross-legged posture. "Upright" represents a sitting posture that is usually tense and attentive such as listening to a lecture. At this time, only half of the buttocks are on the chair, and the position of the caudal vertebra will move forward. The "upright" sitting posture deliberately changes the position of the caudal vertebrae to meet the possible SPR tasks in daily life.

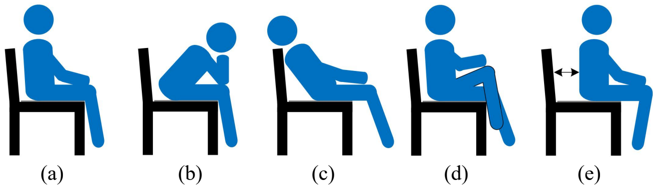

Fig. 2. Schematic diagram of 5 sitting postures in human daily activities, (a) normal, (b) lean forward, (c) lay back, (d) leg crossover, (e) upright.

The subjects are 4 males and 1 female, and their physical information is shown in TABLE I. It can be seen that the huge differences between subjects ensure the robust performance of smart cushions among different people.

TABLE I. SUBJECT'S PHYSICAL INFORMATION

	Min	Max	Mean	Standard Deviation	Variance
Age (y. o.)	22	27	24.6	2.51	6.3
Weight (kg)	70	100	78.4	12.62	159.3
Height (cm)	168	183	178.4	6.77	45.8

III. EXPERIMENTS AND RESULTS

In our experiment, human sitting posture data collection followed the experimental setups in the previous research [15]. After the subjects sit down and then adjust their posture, they start to collect 10 seconds of data continuously. After every 10 seconds of continuous data collection, the subjects need to stand for at least 5 seconds. At the same time, subjects need to release at least 100 seconds in the middle of each sitting posture category to make the smart cushion release to its initial state.

A. *SPR and HI Classifications*

We collected 200 (samples/subject/posture) pressure images, a total of 5000 pressure images data sets of human sitting for simple recognition tasks. In SPR task, the different subjects are mixed respectively; while in the HI task, the different sitting postures are mixed respectively. Fig. 3 shows the classification results of two simple recognition tasks, the accuracy of SPR and HI tasks are 0.9973 and 1.0 respectively. In the simple recognition tasks, the excellent pressure distribution ability of the smart cushion can collect the spatial pressure distribution on the seat, so that the simple recognition tasks have high accuracy.

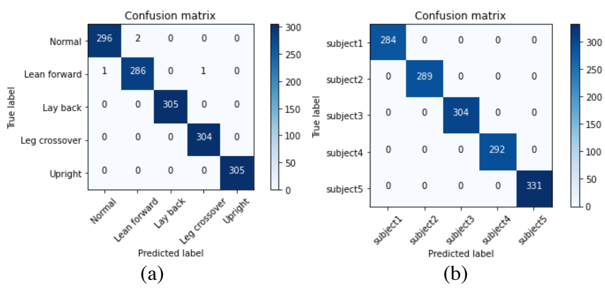

Fig. 3. Results of simple recognition tasks, (a) confusion matrix of SPR task, (b) confusion matrix of HI task.

B. *Time Independent SPR*

Although the human sitting posture collection system perform great in the simple recognition tasks, we have noticed that the performance of this trained ResNet-PI model doesn't perform well when developing real-time application. We believe that the main reason is the subject's muscle memory when the sitting postures are collected, which leads to the singularity of the sitting posture in the data set, as well as the sitting posture when the real-time application is developed a few days later is quite different from the original data set. The secondary reasons include changes in the subject's weight, laboratory temperature, initial state of the smart cushion, electrical resistance of the smart cushion after long hours of work, etc.

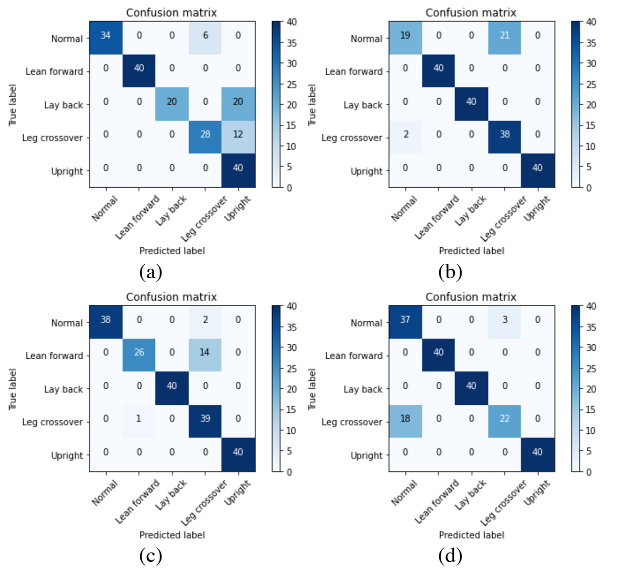

Fig. 4. Results of second validation at different times, confusion matrix of (a) 0.5 hour, (b) 1 hour, (c) 12 hours, (d) 24 hours interval.

We tested one of the subjects at different times. After the subject collected the original data set to train the CNN model, there was an interval of 0.5 hour, 1 hour, 12 hours and 24 hours, and then the sitting posture was collected again for second validation data set. Fig. 4 shows the second validation results performed by the subject at different times. The accuracy of the secondary verification data collected at these 4 times are 0.81, 0.885, 0.915 and 0.895, respectively.

To obtain a time independent CNN model suitable for real-time applications, human sitting postures are collected multiple times to generate an optimized data set. We collected 4 data sets at different times in two days, with an interval of 6 hours between each data set to obtain diverse samples. These 4 data sets are all collected by the same subject with 500 (samples/data set/posture), a total of 10,000 human sitting posture images data set for CNN training.

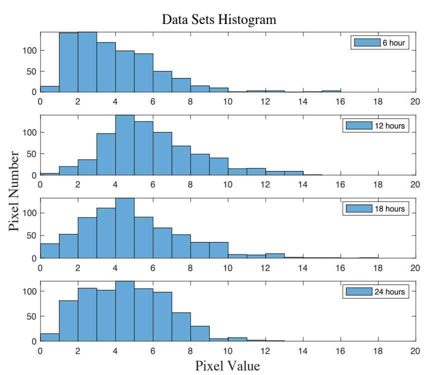

Fig. 5. Histogram of "normal" sitting posture in 4 data sets

The histogram of the "normal" sitting posture in these 4 data sets are shown in Fig. 5 to illustrate the difference. Then on the 3rd day, 100 (samples/posture) were collected, a total of 500 sitting posture images secondary validation data set was used to test the time independency of the smart cushion.

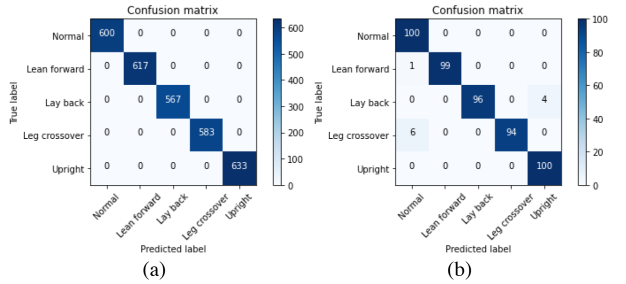

Fig. 6. Results of advanced recognition task, (a) confusion matrix of original data set, (b) confusion matrix of second validation data set.

Fig. 6(a) shows that the original data set collected at multiple times has a confusion matrix with an accuracy of 1.0. Fig. 6(b) shows that the secondary validation data set has a confusion matrix with an accuracy of 0.978. It can be seen that this model has better time independency than the model is trained on the data set collected only once. Fig. 7 shows the pressure image of the subject's "normal" sitting posture, and the contours of the thighs and the areas of different pressure distribution can be clearly seen, which shows the prospect of this smart cushion in visualization applications.

Fig. 7. The pressure image of the subject's "normal" sitting posture after contrast enhancement, filtering and resizing.

IV. Conclusions

This paper discusses the collection and recognition of human sitting postures through smart cushion. After the smart cushion obtained an accuracy of approximately 1.0 for SPR and HI, the ability of the smart cushion to recognize sitting posture at different times was tested. After optimizing the data set by collecting data multiple times, time independence SPR accuracy achieved 0.978, which is 11.61% higher than the original data set. Although independent sensors have been able to complete the recognition task in many literatures, the pressure sensor array provides a choice of visualization and has attracted our attention. In a nursing community, after CNN recognizes a dangerous sitting posture, the nursing staff can observe the pressure image to verify it again to avoid misjudgment. Compared with existing techniques, our smart cushion highlights the performance in terms of flexibility, softness, comfort, low-cost and time independence, and demonstrates the potential for developing real-time visualization applications.

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REFERENCES

[1] W. Min, H. Cui, Q. Han, and F. Zou, "A scene recognition and semantic analysis approach to unhealthy sitting posture detection during screen-reading," *Sensors,* vol. 18, no. 9, p. 3119, September 2018.

[2] M.-O. Park and S.-H. Lee, "Effects of seating education and cushion management for adaptive sitting posture in spinal cord injury: Two case reports," *Medicine,* vol. 98, no. 4, January 2019.

[3] C. Ma, W. Li, R. Gravina, J. Du, Q. Li, and G. Fortino, "Smart cushion-based activity recognition: prompting users to maintain a healthy seated posture," *IEEE Systems, Man, and Cybernetics Magazine,* vol. 6, no. 4, pp. 6-14, October 2020.

[4] L. Feng, Z. Li, and C. Liu, "Are you sitting right?-sitting posture recognition using RF signals," in *2019 IEEE Pacific Rim Conference on Communications, Computers and Signal Processing (PACRIM)*, 2019, pp. 1-6.

[5] M. Ding, T. Suzuki, and T. Ogasawara, "Estimation of driver's posture using pressure distribution sensors in driving simulator and on-road experiment," in *2017 IEEE International Conference on Cyborg and Bionic Systems (CBS)*, 2017, pp. 215-220.

[6] O. Halabi, S. Fawal, E. Almughani, and L. Al-Homsi, "Driver activity recognition in virtual reality driving simulation," in *2017 8th International Conference on Information and Communication Systems (ICICS)*, 2017, pp. 111-115.

[7] J. C. T. Mallare *et al.*, "Sitting posture assessment using computer vision," in *2017IEEE 9th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM)*, 2017, pp. 1-5.

[8] A. Petropoulos, D. Sikeridis, and T. Antonakopoulos, "SPoMo: IMU-based real-time sitting posture monitoring," in *2017 IEEE 7th International Conference on Consumer Electronics-Berlin (ICCE-Berlin)*, 2017, pp. 5-9.

[9] C. Ma, W. Li, R. Gravina, and G. Fortino, "Posture detection based on smart cushion for wheelchair users," *Sensors,* vol. 17, no. 4, p. 719, April 2017.

[10] E. Fragkiadakis, K. V. Dalakleidi, and K. S. Nikita, "Design and development of a sitting posture recognition system," in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2019, pp. 3364-3367.

[11] Y. Zhu *et al.*, "A smart portable mat that can meausre sitting plantar pressure distribution with a high resolution," in *2019 IEEE 6th International Conference on Industrial Engineering and Applications (ICIEA)*, 2019, pp. 141-144.

[12] H. Ai, L. Zhang, Z. Yuan, and H. Huang, "iCushion: a pressure map algorithm for high accuracy human identification," in *2018 24th International Conference on Pattern Recognition (ICPR)*, 2018, pp. 3483-3488.

[13] S. Hongchang, Z. Zhijing, J. Xin, D. Sanpeng, J. Yongxiang, and Z. Zhongpeng, "Monitoring driving psychological fatigue through unconstrained heartbeat signal extraction by using pressure sensor array," *IEEE Access,* vol. 8, pp. 22193-22202, December 2019.

[14] J. Wang, B. Hafidh, H. Dong, and A. El Saddik, "Sitting posture recognition using a spiking neural network," *IEEE Sensors Journal,* vol. 21, no. 2, pp. 1779-1786, August 2020.

[15] L. Yuan, H. Qu, and J. Li, "Velostat sensor array for object recognition,"manuscript submitted for publication.