Conference Paper

Smart Chair for Monitoring of Sitting Behavior

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Abstract

Sitting is a common behavior of human body in daily life. It is found that poor sitting postures can link to pains and other complications for people in literature. In order to avoid the adverse effects of poor sitting behavior, we have developed a highly practical design of smart chair system in this paper, which is able to monitor the sitting behavior of human body accurately and non-invasively. The pressure patterns of eight standardized sitting postures of human subjects were acquired and transmitted to the computer for the automatic sitting posture recognition with the application of artificial neural network classifier. The experimental results showed that it can recognize eight sitting postures of human subjects with high accuracy. The sitting posture monitoring in the developed smart chair system can help or promote people to achieve and maintain healthy sitting behavior, and prevent or reduce the chronic disease caused by poor sitting behavior. These promising results suggested that the presented system is feasible for sitting behavior monitoring, which can find applications in many areas including healthcare services, human-computer interactions and intelligent environment.

Keywords: Sitting behavior, smart chair, classification

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1 Introduction

Sitting is one of the most commonly adopted postures of human being in daily life. People spend a long time on sitting in an office chair, car seat or lounge chair. The sitting behavior analysis becomes an important research topic recently in a variety of domains, such as biomedical engineering, public healthcare service and facility design. It has been suggested that poor sitting behaviour can cause a threat to human body by linking to various pains and other complications [1, 2]. Previous studies have showed that some common sitting postures of human body can lead to lumbar flexion and higher compressive forces in lumbar joints [2, 3].

In order to avoid the adverse effects of poor sitting behavior, the real-time monitoring of sitting posture has received particular attention and was used as a promising method in recent years. Research studies have been conducted using the pressure distribution measurement sheets placed on the seat pan and backrest to provide high resolution pressure data for posture recognition [4, 5]. Tan [4] used principal component analysis to solve the problem of sitting posture classification. Zhu [5] investigated the classification algorithms and found that Fisher-Rao's discriminant analysis can be applied for the application of sitting posture classification. Mutlu [6] proposed a low-cost solution with reduced sensors to detect sitting postures by a near optimal sensor placement strategy with a classifier based on logistic regression. Xu [7] designed a textile-based sensing system for sitting posture monitoring and proposed an optimized strategy to compensate the signal to improve the classification accuracy.

Most of the research studies in literature showed great concern for static sitting postures. The long term goal of our project is to develop a monitoring system for both static and dynamic sitting postures with an interactive ergonomic chair. As a preliminary study, this paper focused on building a smart chair system for the classification of eight static standardized sitting postures using artificial neural network (ANN), which can be easily implemented for further improvement. The smart chair can be used for the monitoring of user's sitting postures and promote the user to improve sitting behavior.

2 Methodology

2.1 Hardware Setup

The smart chair system developed in this study was constituted by pressure sensor array, data acquisition module and computational terminal. A 52 by 44 piezo-resistive sensor array shown in Figure 1 was used, with a thickness of 0.25mm, which is thin and flexible enough for the non-invasive application in this study. The sensor array was composed of two layers of polyester films, with the horizontal silver electrode strips and the other vertical on one layer. This orthogonal zebra pattern resulted in a network of silver strips with a resistive unit at each crossing of the sensor array. The resistive unit (circuit shown in Figure 1) is sensitive to pressure, with a resistance of more than 2MΩ at zero load and around 5KΩ at full load. For simplicity and efficiency, not all these 2288 sensing units were adopted, but 64 (8 by 8) evenly distributed sensing units in the sensor array were selected in this study to measure the pressure pattern at the body-seat interface, with each sensing unit around 4.5mm apart from the other.

2.2 Data Collection

In this paper, we focused on only static sitting postures, meaning the human body posture reaches an equilibrium state. For the experiments, subjects were asked to preform eight standardized sitting posture as shown in Figure 2 in each trial with the knee angle

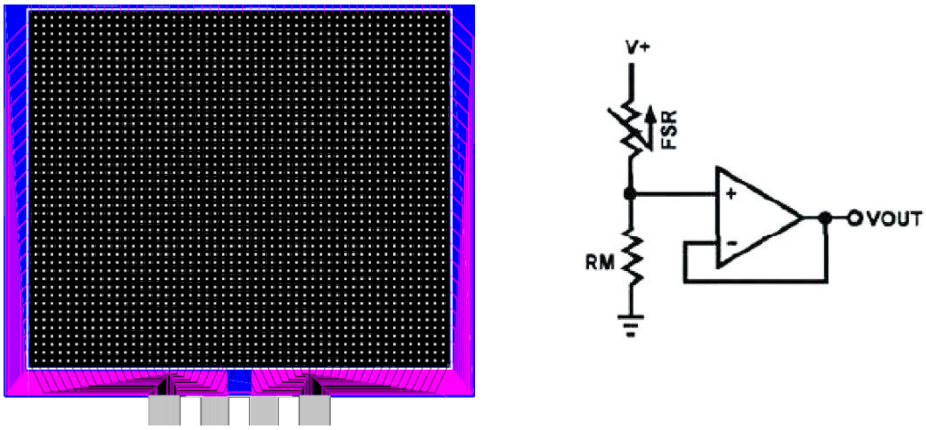

Figure 1: PRESSURE SENSOR ARRAY (LEFT) AND CIRCUIT FOR THE SENSING UNIT (RIGHT).

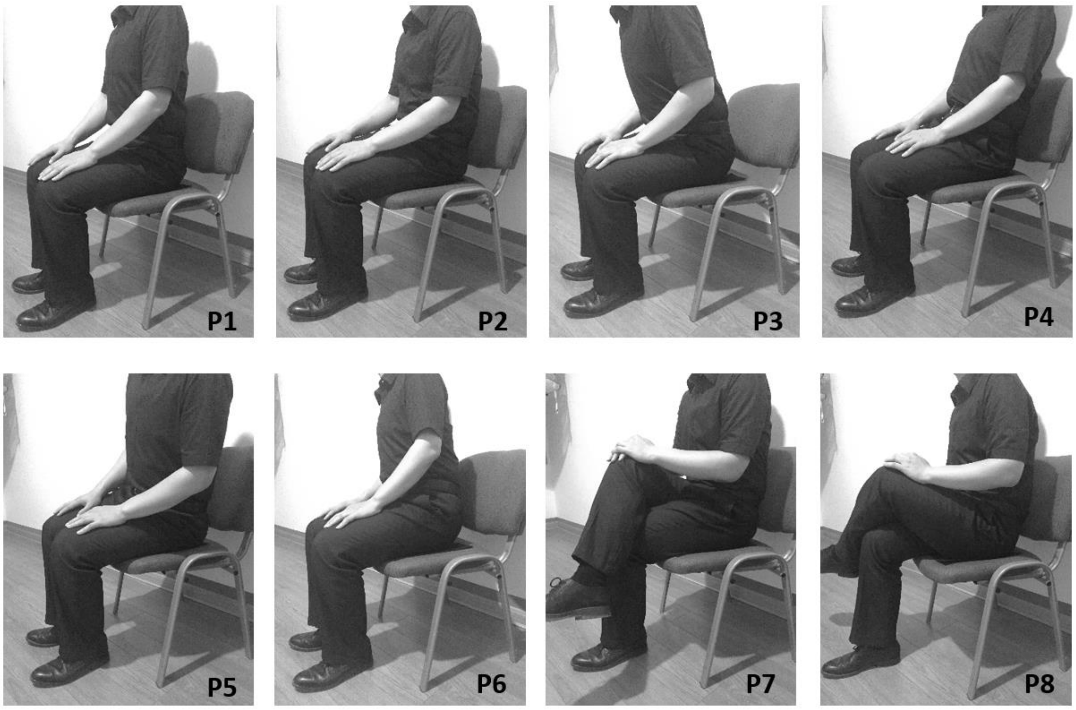

Figure 2: EIGHT SITTING POSTURES : UPRIGHT SITTING (P1); SLUMPED SITTING (P2); LEANING FORWARD (P3); LEANING BACKWARD (P4); LEANING LEFT (P5); LEANING RIGHT (P6); RIGHT LEG CROSSED (P7); LEFT LEG CROSSED (P8).

at 90 degrees and hands putting on thighs, including upright sitting, slumped sitting, leaning forward, leaning backward, leaning left, leaning right, right leg crossed and left leg crossed. Each posture lasted 5 seconds. The pressure data of 5 trials for each subject were acquired after experiments. For better visualization, the pressure patterns of eight sitting postures on log-10 scale for z axis are shown in Figure 3.

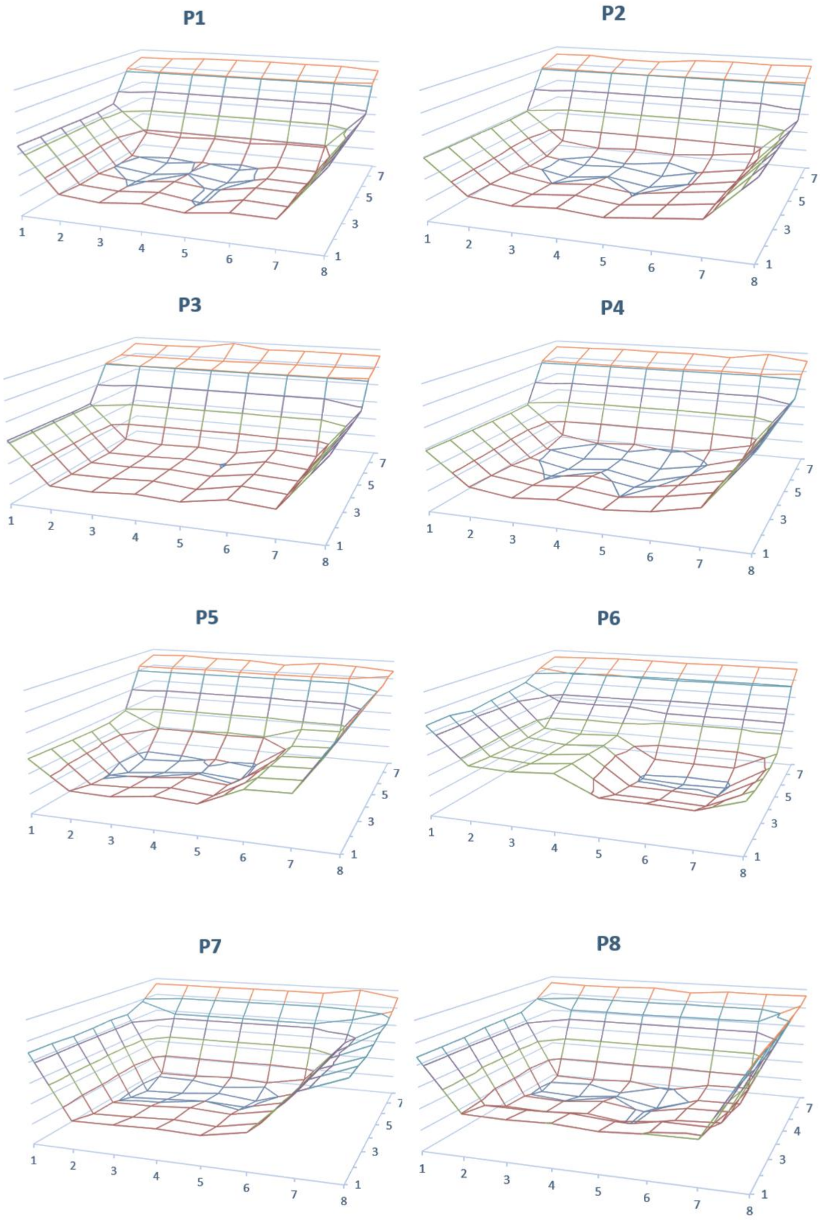

Figure 3: PRESSURE PATTERNS OF EIGHT SITTING POSTURES ON LOG -10 SCALE FOR Z AXIS.

2.3 Posture Recognition

Inspired by biological neural networks, ANN is a useful tool which can be applied to approximate unknown functions based on known inputs. The architecture of ANN is shown in Figure 4, where $u = \{u_1, u_2, ..., u_M\}$, $h = \{h_1, h_2, ..., h_L\}$ and $y = \{y_1, y_2, ..., y_N\}$ represent the data of the input layer, the neurons in the hidden layer and the approximated data at the output layer respectively and M, L and N represent the number of input data, hidden neurons and approximated outputs respectively. In this paper, ANN classifier was implemented using MATLAB to recognize and classify the postures. The advantages of ANN classifier include, but are not limited to: high classification accuracy;

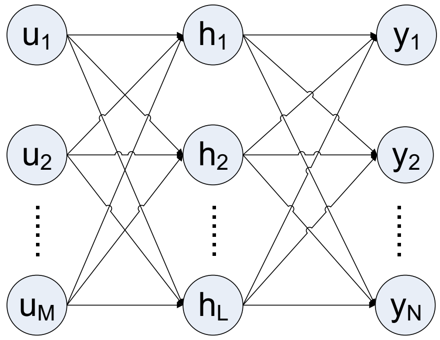

Figure 4: ARCHITECTURE OF ANN.

powerful capacity for parallel distributed processing, distributed storage and learning; strong robustness, fault tolerance to noise and nonlinear approximation ability.

3 Results

In this paper, the pressure data of different postures was the input data and the classified positions were the output of the ANN classifier. To avoid the effects of different weights of subjects on the position classification results, the acquired pressure data of eight sitting postures were normalized prior to data processing. For each collected data set, the normalization process was conducted by taking the maximum and minimum data as 1 and -1 respectively and scaling the rest data proportionally. Thus the collected data were normalized to an interval of [-1,1] for pattern recognition.

After normalization, the ANN classifier was trained with the pressure data of known postures. 40 sets of collected pressure data of each position were used as the training sets of ANN classifier. In order to acquire the best overall classification accuracy, various parameters were tested in the first place to find out the optimal settings of the ANN, including the number of neurons in the hidden layer, the transfer function and the network training function. Based on the test results, 20 neurons in the hidden layer, logarithmic sigmoid (logsig) transfer function and scaled conjugate gradient (SCG) backpropagation network training function were adopted for the ANN classifier in this study. The training performance of the ANN classifier is shown in Figure 5, with mean square error (0.00989) less than the goal (0.01) after 166 epochs.

With the properly trained ANN classifier, another 40 sets of pressure data of each position was used for verification of the classifier. Table 1 shows the confusion matrix for experiments. With the optimal settings of neural network, the overall classification accuracy of eight sitting postures reached 92.2%. It was found that postures P1, P2 and P4 showed relatively lower classification rates than the other postures. The reason can be the pressure patterns of these postures are quite similar to each other due to the fact that the hip keeps relatively fixed in these postures. The classification rates of the other postures (P3, P5, P6, P7 and P8) were close or equal to 100%.

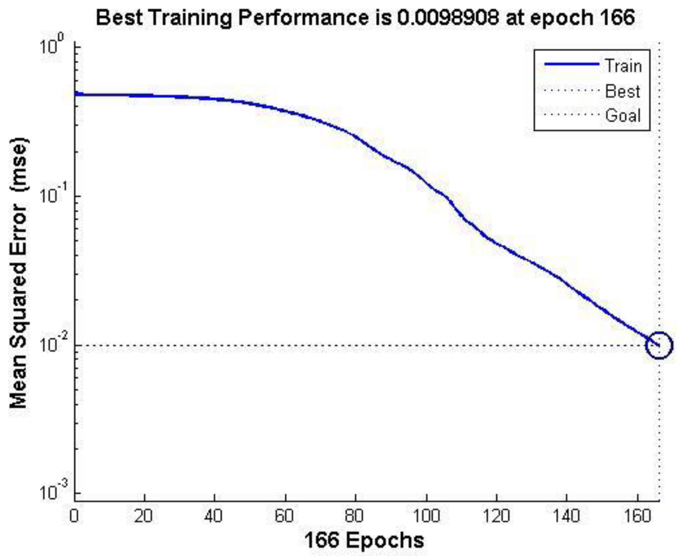

Figure 5: NEURAL NETWORK TRAINING PERFORMANCE.

Output Class / Target Class

	P1	P2	P3	P4	P5	P6	P7	P8	
P1	35	4	1	2	0	0	0	0	83.3%
P2	3	32	0	8	0	0	1	0	72.7%
P3	1	0	39	0	0	0	0	0	97.5%
P4	1	4	0	30	0	0	0	0	85.7%
P5	0	0	0	0	40	0	0	0	100.0%
P6	0	0	0	0	0	40	0	0	100.0%
P7	0	0	0	0	0	0	39	0	100.0%
P8	0	0	0	0	0	0	0	40	100.0%
	87.5%	80.0%	97.5%	75.0%	100.0%	100.0%	97.5%	100.0%	92.2%

Table 1: CONFUSION MATRIX.

4 Conclusion and Future Work

A smart chair system was built in this paper to detect sitting posture of human body. The experimental result showed that the overall classification rate of eight sitting postures is high using ANN classifier. The developed smart chair system is able to monitor the sitting behavior of human body and help in advocating better sitting habits of users. In the future, more subjects will be involved for experiments. Meanwhile, the influence of hip location on the pressure pattern recognition will be considered in future to further improve the classification rate of sitting postures.

Acknowledgements

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