Intelligent Chair Sensor Classification of Sitting Posture.

Conference Paper *in* Communications in Computer and Information Science · September 2013

DOI: 10.1007/978-3-642-41013-0_19

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Intelligent Chair Sensor

Classification of Sitting Posture

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Abstract. In order to build an intelligent chair capable of posture detection and correction we developed a prototype that gathers the pressure map of the chair's seat pad and backrest and classifies the user posture and changes its conformation. We gathered the pressure maps for eleven standardized postures in order to perform the automatic posture classification, using neural networks. First we tried to find the best parameters for the neural network classification of our data, obtaining an overall classification of around 80% for eleven postures. Those neural networks were exported to a mobile application in order to do real-time classification of those postures. Results showed a real-time classification of around 70% for eleven standardized postures, but we improved the overall classification score to 93.4% when we reduced the posture identification to eight postures, even when this classification was done with unfamiliar users to the posture identification system.

Keywords: Sensing chair, Pressure-distribution sensors, Sitting posture, Posture Classification, Posture correction, Neural Networks

1 Introduction

Changes in transportation, communications, workplace and entertainment in the last century led to a sedentary lifestyle, forcing the population to spend longs periods of time in a sitting position [1, 2]. While seated, most of the bodyweight is transferred to the ischial tuberosities and to the thigh and the gluteal muscles. The rest of the weight is distributed to the ground through the feet and to the backrest and armrest when they are available [3]. Adopting a lumbar flexion position for long periods of time, leads to a decrease of the lumbar lordosis [4], which has been linked to back and neck pain due to the anatomical changes of the spine and the degeneration of the intervertebral

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discs and joints. Adopting a bad posture while seated can worsen these health problems [5].

The long term goal of this project is to build an intelligent chair that can detect the sitting posture and effectively correct an incorrect posture adoption in order to minimize the health issues that were previously described. In order to correct a bad posture we developed a first prototype with 8 pressure cells (4 in the seat pad and 4 in the backrest) which are able to change their conformation by inflation or deflation and can increase the user discomfort when a bad posture is adopted, encouraging the user to change to a correct position. We can also produce slight changes in the chair conformation over a period of time, which can help to evenly distribute the applied pressure on contact zones, reducing the fatigue and discomfort of the user due to the pressure relief on compressed tissues.

In order to do posture classification, we gather the pressure inside each bladder, which is then used as an input for the classification of eleven different postures using neural networks. Neural Networks were chosen as the classification method, since after creating and training the Neural Network we can easily export the weights and bias and apply to other applications. In our case we exported them to a mobile and portable application in order to build a system capable of real-time classification and correction of the user posture.

2 Related Work

The adoption of an incorrect posture in a sitting position over long periods of time can lead to neck and back pains [4, 5], which have a huge impact in the cost of work-related illness. Estimates show that, only in the USA, 50$ billion dollars are spent every year for the treatment of back pain [6].

There are a wide number of clinical views of ‘correct’ or ‘incorrect’ postures, but until recent years there were little quantitative studies to define those postures. Recent studies have been trying to determine whether the so called ‘good’ postures actually provide a clinical advantage [7].

To solve the problem of incorrect posture adoption for long periods of time in a sitting position, several investigation groups have been working with pressure sensors placed in chairs. These pressure sensors were able to detect the user posture, using the acquired pressure maps and various Classification Algorithms.

Various studies equipped with the same sensor sheets (one for the seat pad and one for the backrest) were able to distinguish various postures [8, 9, 10]. Slivovsky et al. (2000) and Tan et al. (2001) used Principal Component Analyses (PCA) for posture detection for human-machine interactions obtaining an overall classification accuracy of 96% and 79% for familiar and unfamiliar users, respectively [8, 9]. Zhu et al. (2003) used the same data acquisition methods from the previous two studies to investigate which classification algorithms would be the best for static posture classification. The authors found that among k-Nearest Neighbor, PCA, Linear Discriminant Analysis and Sliced Inverse Regression (SIR), both PCA and SIR outperformed the other methods [10].

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Mutlu et al (2007) and Zheng and Morrell (2010) reduced drastically the number of pressure sensors for posture identification. The first group determined the near optimal placement of 19 FSR (Force Sensitive Resistors) sensors obtaining an overall classification accuracy of 78%, improving the classification to 87% when the number of sensors was increased to 31 [11]. The second group adapted a chair with just 7 FSR and 6 vibrotactile actuators, in order to direct the subject towards or away from a certain position through haptic feedback. They obtained an overall classification of 86.4% on the same 10 postures using the mean squared error between the pressure measurements and their reference for each posture, showing also the effectiveness of haptic feedback on posture guidance [12]. A smart chair equipped with 6 sensors (4 in the seat and 2 in the backrest) was used to study how feedback can influence the sitting behavior of office workers. They showed that there was an average increase in basic posture in groups that received feedback [13].

3 Materials and Methods

3.1 Equipment

We built this prototype with the aim of producing an office chair capable of detecting the user posture and also correct bad posture adoption over long periods of time.

Considering a low cost and commercially available solution we produced a low resolution matrix of pressure sensors, which are able to change their conformation by inflation and deflation. Strategically sensor placement was required in order to achieve good performance results. Previous literature identified two types of strategies: a pure mathematical and statistical approach [11] and an anatomical approach [12]. Based on the second method we placed the pressure sensors in order to cover the most important and distinguishable areas of the body for detecting a seated posture, such as the ischial tuberosities, the thigh region, the lumbar region of the spine and the scapula. These are also the areas where most of the bodyweight is distributed [3].

The distribution of pressure cells is illustrated in figure 1. Both the seat pad and backrest were divided into a matrix of 2-by-2 pressures cells.

Fig. 1. (A) Distribution of the pressure cells in the chair. In the seat pad we accounted for the ischial tuberosities (Sensors 1 and 2) and the thigh region (Sensors 3 and 4). For the backrest we accounted for the scapular region (Sensors 5 and 6) and finally for the lumbar region (Sensors 7 and 8). Frontal (B) and lateral (C) view of the chair with the padding foam.

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We used the original padding foam of the chair, placing it above the pressure cells to maintain the anatomical cut of the seat pad and backrest as shown in figures 1-B and 1-C. Cell size was chosen in order to minimize the gaps between cells (large gaps would be uncomfortable for the users), while also covering the areas described above. We used a Honeywell 24PC Series piezoelectric gauge pressure sensor to measure internal cell pressure. Cells in the seat pad were rated to 15 psi, with a sensitivity of 15mV/psi while the cells in the backrest were rated to 5 psi with a sensitivity of 21 mV/psi.

3.2 Experiments

Two experiments were done with different datasets. The first experiment (A) served for data acquisition in order to create the Seated Posture Classification Algorithms while the second experiment (B) was done to test the Classification in real-time using a mobile application. The dataset for both experiments is presented in table 1. Half of the subjects (15) participated in both experiments, so in experiment B we also tested with the classification to unfamiliar users, since the other half did not participate in A.

Table 1. The dataset for experiments A and B. Here (M/F) corresponds to (Male/Female).

Dataset	No. of subjects (M/F)	Age (years) [a]	Weight (Kg) [a]	Height (cm) [a]
A	30 (15/15)	20.9±2.4	67.8±13.3	172.0±8.1
B	30 (15/15)	20.5±2.0	68.9±12.4	172.3±8.7

[a] Values for Average±Standard Deviation

Before conducting the experiments, we needed to define the specific time of inflation for each pressure cell, in order for them to have enough air to sense the pressure of the subject in the sitting position, but not enough to cause discomfort to the users. After some tests (data not shown), we decided to use a value of 4 seconds for inflating pressure cells represented by 1, 2, 3, 4, 7, 8 and 5 seconds for the inflation of pressure cells number 5 and 6 for every subject during both experiments.

Before undergoing any experiment, subjects were asked to empty their pockets and to adjust the stool height so that the knee angle was at 90º (angle between the thigh and the leg) and to keep their hands on their thighs.

Experiment A was comprised of two tests, the first involved showing a presentation of the postures P1 to P11, each for a duration of 20 seconds, asking the subject to mimic those postures without leaving the chair. The second consisted in showing the same presentation, with every posture being repeated three times, but after every 20 seconds we asked the subject to walk out of the chair, take a few steps and sit back.

The eleven postures used in experiment A are represented in figure 2 and were based on previous works [8, 11, 12], since they include the most common posture found in office environments. We added the posture P5 - “Leaning back with no lum-

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bar support" (also reported as a posture that some office workers might adopt [14]) to the previous 10 postures.

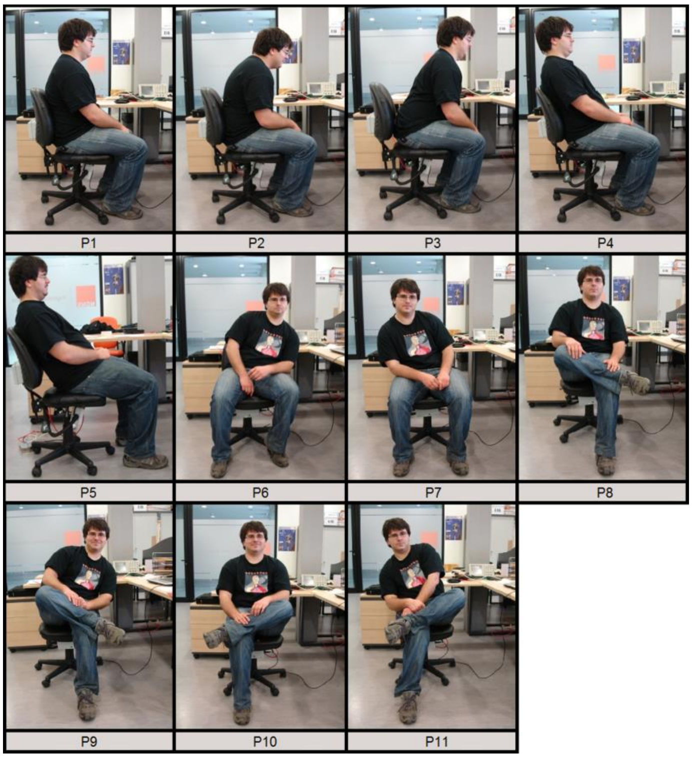

Fig. 2. Seated postures used in the experiments and their respective Class label: (P1) Seated upright, (P2) Slouching, (P3) Leaning forward, (P4) Leaning back, (P5) Leaning back with no lumbar support, (P6) Leaning left, (P7) Leaning right, (P8) Right leg crossed, (P9) Right leg crossed, leaning left, (P10) Left leg crossed, (P11) Left leg crossed, leaning right.

Not all of the data acquired was used for the classification, because when a user changes his posture, the pressure maps will oscillate (Transient zone) until they stabilize (Stable zone), as shown in figure 3. Here we focus our study on the Stable zone (figure 3) of the pressure maps and therefore, approximately 13 out of the 20 seconds were used. Since our sampling rate is 18.4 Hz, we were able to extract 240 data-points out of the 13 seconds, which were divided in groups of 40 points.

The average of those groups was used to create 6 pressure maps for posture classification, giving a total of 720 maps for each posture (30 subjects * 4 repetitions * 6 pressure maps) and a total of 7920 maps (720 * 11 postures). For each user, 12 seconds of data points from the Stable Zone (see figure 3) were previously acquired in posture P1 in order to define a baseline pressure. All the 7920 maps were normalized to an input interval of [-1, 1] for the Artificial Neural Networks (ANNs). For the creation of the ANNs we used the MATLAB® Neural Network Toolbox™ and then exported the ANN to a mobile application for experiment B.

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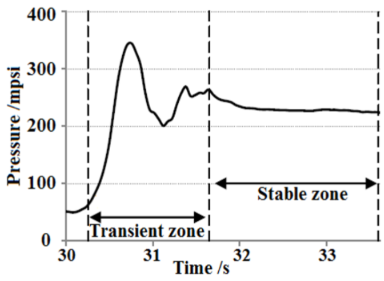

Fig. 3. Pressure measurement from pressure cell 1, when a subject went from posture P7 to P8, showing the Transient zone and the Stable zone.

In experiment B we also showed a presentation with the postures in a specific order: (P1 → P3 → P4 → P1 → P6 → P7 → P1 → P8 → P10 → P1 → P5 → P1), where each posture lasted 15 seconds.

In this experiment, each posture was classified every 2 seconds, using the average of all the data-points acquired during that time. Before starting the classification 12 seconds of data-points were also gathered in order to set a baseline for each user. Half of the subjects from experiment B did not participate in experiment A, allowing us to test how the classification in real time acted for people that were first time visitors, and were not part of the training database.

4 Results

4.1 Results for experiment A

Initially, we tested various parameter combinations such as number of neurons, number of layers, transfer function and network training function. In table 2 we present all considered combinations of parameters and the ANN returned the best overall classification. We also tried different combinations of transfer functions depending on the number of layers. For this test we used a “leave-1-out” program that would use 29 subjects to create the network, and then the last subject was used to test the network. Using the average of all the 30 “leave-1-out” processes, we were able to choose the best parameters for our ANNs. Here we only present the data from the best ANN.

Table 2. Parameter combination for the Neural Networks and the parameters that gave the best overall classification scores. Here, LM correspond to Levenberg-Marquardt algorithm, SCG to Scaled Conjugate Gradient algorithm and RP to Resilient Backpropagation algorithm.

Parameters	Combination	Best
Nº of Neurons	10, 15, 20, 25, 30, 35,40	15
Nº of Layers	1,2,3	1
Transfer function	Tansig and Logsig	Only Tansig
Network training function	LM, SCG, RP	RP

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With the best parameterization, we used the best parameters obtained in Table 2 to train a new ANN to gather the weights and bias of the ANN in order to export them to a mobile application for real time posture classification. For this we divided the entire dataset (7920 pressure maps) in 60% for the ANN training, 20% for the validation and the rest for the ANN testing. A simple feedforward network with one-way connections from input to the output layers was able to fit our multidimensional mapping problem with a good overall classification score and can be very simply implemented in other systems without needing the MATLAB® Neural Network Toolbox™, since we can obtain the weights and bias of the ANN and export them to other systems.

TRAIN Confusion Matrix

1	375	50	9	8	0	2	0	8	0	5	3	85.1
2	11	253	67	11	0	0	13	0	4	3	0	69.9
3	4	83	316	27	3	3	0	1	0	0	0	72.3
4	15	38	25	314	26	3	0	2	0	7	0	73.0
5	0	4	7	32	391	3	0	0	0	0	0	89.5
6	7	0	4	3	0	411	3	0	31	6	0	88.4
7	3	0	0	0	1	0	355	4	0	0	57	84.5
8	0	5	0	13	0	0	5	421	20	0	0	90.7
9	0	0	0	6	0	21	0	9	386	0	0	91.5
10	3	3	4	5	6	4	0	0	0	400	22	89.5
11	0	0	0	0	0	0	46	4	0	18	340	83.3
	89.7	58.0	73.1	74.9	91.6	91.9	84.1	93.8	87.5	91.1	80.6	83.4
	1	2	3	4	5	6	7	8	9	10	11	

TEST Confusion Matrix

1	140	16	2	4	0	0	0	2	0	3	1	83.3
2	10	82	29	3	0	0	4	0	1	0	0	63.6
3	4	25	85	6	5	2	0	1	0	0	0	66.4
4	4	11	13	118	13	0	0	0	0	4	0	72.4
5	0	1	1	10	131	1	0	0	0	0	0	91.0
6	4	0	2	1	0	115	2	0	11	4	0	82.7
7	2	0	0	0	2	0	124	2	0	0	15	85.5
8	0	1	0	1	0	0	1	129	5	0	0	94.2
9	0	0	0	2	0	9	0	7	125	0	0	87.4
10	4	0	1	2	1	0	0	0	0	121	5	90.3
11	0	0	0	0	0	0	17	2	0	10	125	81.2
	83.3	60.3	63.9	80.3	86.2	90.6	83.8	90.2	88.0	85.2	85.6	81.8
	1	2	3	4	5	6	7	8	9	10	11	

Fig. 4. Confusion Matrices for experiment A. Rows indicates the Output Class and Columns indicates the Target Class. The Class labels correspond to the respective postures from figure 1. The gray boxes give the percentages of correct classification in relation to the respective class and the blue box represents the overall classification score.

We obtained an overall classification of 83.4% and 81.8%, respectively for the training and testing of all postures. As confirmed in previous studies, postures P2, P3 and P4 had the lowest classification scores. [11]. In these postures, the torso shifts in the anteroposterior axis while the lower part of the body remains still. Therefore, the classification of these postures greatly rely on the backrest's pressure cells, opposed to postures such as P5 or P6, featuring lateral movement and affecting all pressure cells.

4.2 Results for experiment B

Our next objective was to export the ANN to a mobile application in order to classify the user position in real-time. Our first test with the eleven postures had very low scores for real-time classification, especially for position P1. With this in mind, we decided to test again with just 4 postures (P1 to P4) using the data-points from experiment A, but creating an ANN with just four outputs instead of the original eleven. In this test, we still observed that the classification of P1 was much worse than expected

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(beneath 25%), so in order to identify the problem, we observed the acquired pressure maps, during experiment A, for each posture. In figure 5, we present the normalized pressure data from each Sensor and how it varies for Posture P1, P2, P3 and P4. The normalized pressure data is calculated by subtracting the experimental data from each posture with the baseline that was obtained before doing the experiments.

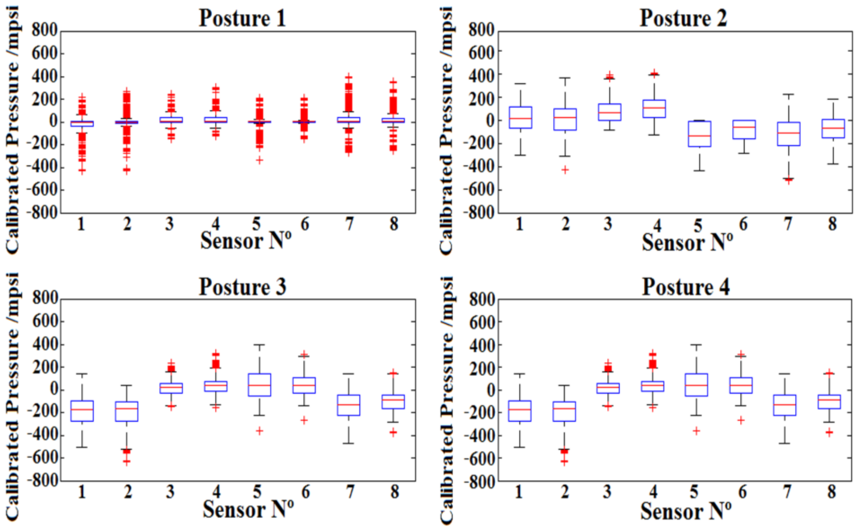

Fig. 5. Difference between the pressures measured in each sensor for postures P1, P2, P3 and P4 and the baseline pressure.

As expected, the pressure maps for Posture 1 in Figure 5 tend to cluster around 0 mpsi because the data-points for the baseline were also acquired while the user maintained the P1 posture. This causes a problem to the real-time classification, because any deviations larger than 50 mpsi (which can happen during the transition from one posture to another) in any sensor makes the ANN to classify incorrectly the Posture P1.

To solve this problem we created 2 different ANNs, one specifically designed to classify P1, and one to target the other Postures. To choose between each ANN we defined a Threshold for each sensor. The goal of this Threshold was to include the maximum of P1 data-points (from experiment A), while excluding the other Postures. We tested several value combinations and were able to obtain 2 different Thresholds.

The first (Threshold 1) included 86% of P1, but also included 32 % of P4 (other postures were all below 5%), while the second (Threshold 2) included 84% of P1and 24% of P4. Due to these values we also included P4 in the first ANN. The Threshold 1 and 2 values for sensors 1, 2, 7, 8, were 250mpsi and 225 mpsi, respectively. For sensors 3,4,5,6 the values were 180 and 150 mpsi, respectively for Threshold 1 and 2. The presentation order for this experiment was devised in order to test P1 after other postures. In figure 6 we present a flowchart of the real-time classification of those 8 postures.

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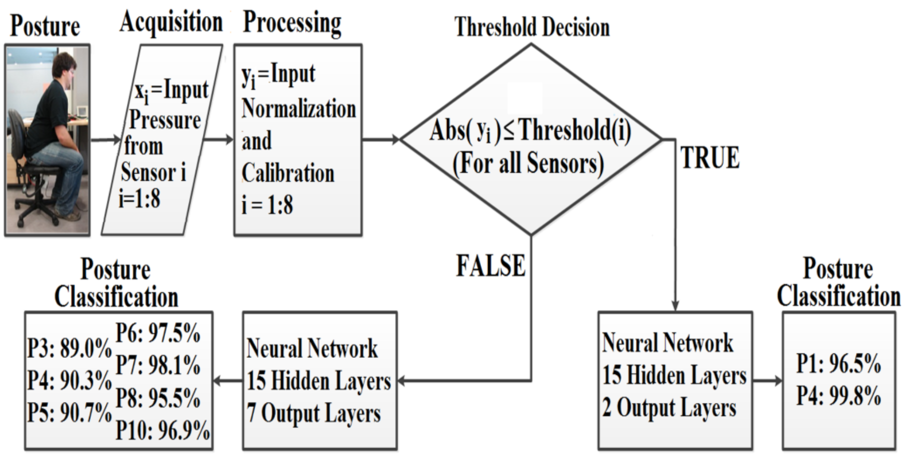

Fig. 6. Flowchart representing the real-time classification for experiment B. The Posture Classification boxes have the classification scores of the respective ANN.

The classification values using each Threshold are presented in table 3. We were able to achieve an overall score of 93.4% (increasing the previous real-time classification without the Thresholds) for those eight postures using Threshold 1, altough P1 still has a lower classification score than the others.

Table 3. Classification for each posture of experiment B.

Position	Classification using Threshold 1	Classification using Threshold 2
P1	74.0%	62.0%
P3	93.3%	91.7%
P4	88.3%	91.7%
P5	100.0%	100.0%
P6	98.3%	98.3%
P7	98.3%	98.3%
P8	95.0%	98.3%
P10	100.0%	100.0%

5 Conclusions and Future Work

A chair prototype with pressure cells in the seat pad and backrest was developed to detect the posture and correct bad posture adoption over long periods of time. Pressure maps of eleven postures were gathered in order to classify each posture using ANNs. First we studied the best parameters of the ANNs for the classification of our data-points and then, using the best parameters, we created an ANN and exported it to mobile application and execute the postural classification in real-time.

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Results showed that for the eleven postures, real-time classification the overall classification of each posture was around 70% but when we reduced the classification to eight postures, we were able to obtain an overall score of 93.4 %.

Our next aim is to continue studying classification algorithms in order to improve them (mainly for classification of P1 and the other 3 postures) and to start studying the posture correction algorithms. We will do clinical trials to evaluate those correction models but also to validate our classification algorithms, which we will use to build an intelligent chair capable of posture correction, which will help in the reduction of health problems related to back pain.

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