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Intelligent Chair Sensor – Classification and Correction 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 measures a pressure map of the chair's seat pad and backrest and classifies the user posture. The posture classification was done using neural networks that were trained for 5 standardized postures achieving an overall classification of around 98%. Those neural networks were exported to a mobile application in order to do real-time classification of those postures. Using the same mobile application we devised two correction algorithms that were implemented in order to create an intelligent chair capable of posture detection and correction. The posture correction is forced through the change of the conformation of the chair's seat and backrest by changing the pressure of eight pneumatic bladders.**

Keywords—**Sensing chair, Pressure-distribution sensors, Sitting posture, Posture Classification, Posture Correction.**

I. INTRODUCTION AND RELATED WORK

Changes in the society workforce in the last decades has forced the adult population to spend long periods of time in a sitting position in the workplace that coupled with a sedentary lifestyle at home is associated to health problems, such as back and neck injuries [1]. While a person is seated, most of their bodyweight is transferred to the ischial tuberosities, to the thigh and the gluteal muscles. The rest of the bodyweight is distributed to the ground through the feet and to the backrest and armrest of the chair when they are available [2]. The adoption of a lumbar flexion position for long periods of time, can lead to a decrease of the lumbar lordosis [3], causing anatomical changes to the spine and degenerate the intervertebral discs and joints, disorders that have been linked to back and neck pain.

There are a wide number of clinical views of 'correct' or 'incorrect' postures, but until recently there were little quantitative studies to define those postures. Recent studies have shown that not only adopting a seating position over long periods cause health problems, but also the adoption of an incorrect posture can also worsen the health problems [4, 5]. Other groups are trying to determine whether the so called 'good' postures actually provide a clinical advantage [6].

Several investigation groups have been working with pressure sensors placed in chairs in order to solve the problem of an incorrect posture adoption for long periods of time in the seated position. These pressure sensors were able to detect the user posture, using the acquired pressure maps and various Classification Algorithms. Various studies equipped with the sensor sheets with 2016 sensors (one for the seat pad and one for the backrest) were able to distinguish various postures [7, 8, 9]. 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 [7, 8]. The same data acquisition as the previous studies were used by Zhu et al. (2003) to investigate which classification algorithms would be work 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 two methods [9]. One group, also using the same sensor sheets, studied the relationship between patterns of postural behaviors and interest states in children. [10] They were able to classify nine postures in real time achieving an overall accuracy of 87.6% with new subjects, while using Hidden Markov Models to study the interest levels [10].

Mutlu et al (2007) and Zheng and Morrell (2010) even reduced more drastically the number of pressure sensors for posture identification. The first group determined the near optimal placement of 19 FSR (Force Sensitive Resistors) sensors and were able to obtain an overall classification 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 were able to obtain an overall classification of 86.4% on those same ten postures using the mean squared error between the pressure measurements and their reference, showing also the effectiveness of haptic feedback on posture guidance [12].

The long term goal of this project is to build an intelligent chair capable of detecting the sitting posture and effectively correct an incorrect posture adoption over long periods of time in order to minimize the previously described health issues associated with the anatomical changes to the spine. In order to correct an incorrect posture we a first prototype with 8 air bladders (4 in the seat pad and 4 in the

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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 are also able to 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. The pressure values inside each bladder can be used as an input to our classifier in order to analyze and detect the seating posture of a user in real-time.

This papers focus on the classification of five different postures and the correction algorithms implemented to correct the adoption of incorrect postures for long time periods.

II. METHODS AND MATERIALS

A. Equipment

This prototype was built with the aim of producing an office chair capable of detecting the user posture and also correcting an incorrect posture adoption over long periods of time, but also considering a low cost and commercially available solution that could fit the office furniture market. To accomplish this we placed a low resolution matrix of 8 air bladders inside the chair (4 in the seat pad and 4 in the backrest) coupled with pressure sensors that measure the pressure inside each bladder. The system is also comprised by an air pump and a vacuum pump for each bladder to change their conformation by inflation and deflation.

Strategically bladder 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]. We placed the bladders, based on the second method, 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 while a user is seated [2]. The distribution of pressure cells is illustrated in figure 1-A, where both the seat pad and backrest were divided into a matrix of 2-by-2 pressure sensing bladders. 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. Honeywell 24PC Series piezoelectric gauge pressure sensor were used to measure the pressure inside each bladder. Since most of the bodyweight while seated is transferred to the ischial tuberosities, the thigh and the gluteal muscles, meaning that the seat pad will sense more pressure than the backrest, so the pressure sensors in the seat pad where chosen to be rated up to 15 psi, with a sensitivity of 15mV/psi while they were rated to 5 psi with a sensitivity of 21 mV/psi for the sensors in the backrest.

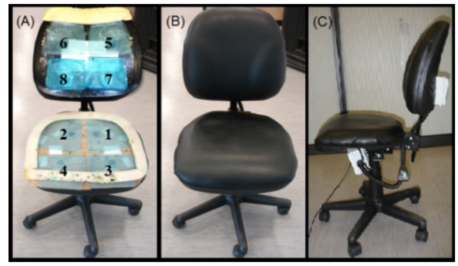

Fig. 1 (A) Distribution of the pressure cells in the chair. In the seat pad we accounted for the ischial tuberosities (Sensors 1 and 2) and the thigh region (Sensors 3 and 4). For the backrest we accounted for the scapular region (Sensors 5 and 6) and finally for the lumbar region (Sensors 7 and 8).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

The bladder 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 but also to be incorporated in standard office chair.

B. Experiments

The tests were done on 30 subjects (15 male and 15 female) with an average age of 20.9 years, average weight of 67.8 Kg and an average Height of 172.0 cm.

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 used a value of 4 seconds for inflating pressure cells represented by 1, 2, 3, 4, 7, 8 and 5 seconds to inflate pressure bladder number 5 and 6 for every subject during both experiments, which is the time chosen for the calibration process.

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. The five postures for the classification algorithms are represented in figure 2 and were based on previous works [7, 11, 12], since they include the most common postures in literature and are classified as P1, P2, P3, P4 and P5 respectively. To obtain the experimental data for the classification algorithms, we carried out two tests, first we showed a presentation of the postures P1 to P5, 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, but every posture was repeated three times, but after every 20 seconds the subject was asked to walk out of the chair, take a few steps and sit back.

Fig. 2 Seated postures used in the experiments: (P1) Seated upright, (P2) Leaning forward, (P3) Leaning back, (P4) Leaning left, (P5) 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 until they stabilize. In this study we focus on the Stable zone of the pressure maps and therefore, approximately 13 out of the 20 seconds were used, and since our sampling rate is 18.4 Hz, we were able to extract 240 data-points out of the 13 seconds, which were then divided into 6 pressure maps of 40 data points, giving a total of 720 maps for each posture (30 subjects * 4 repetitions * 6 pressure maps) and a total of 3600 maps (720 * 5 postures).

For each subject, we acquired an additional 12 seconds of data points in posture P1 in order to define a baseline pressure. All the 3600 maps were normalized to an input interval of [-1; 1] to create the Artificial Neural Networks (ANNs) using the MATLAB® Neural Network Toolbox™.

III. RESULTS

We tested various parameter combinations such as number of neurons, number of layers, transfer function and network training function for the classification algorithms based on ANN. In table 1 we present all considered combinations of parameters and the specific 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-person-out" program that would use 29 subjects to train the ANN, and then the last subject was used to test the network. This process was done 30 times, in order to calculate the average classification of each ANN, in order to choose the best parameters. 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® NN Toolbox™, since we can export the weights and bias of the ANN to other systems, such as mobile devices, capable of classification in real-time.

Table 1 Parameter combination for the Neural Networks and the parameters that gave the best overall classification scores. Here, LM corresponds 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	15
Nº of Layers	1,2,3	1
Transfer function	Tansig and Logsig	Only Tansig
Network training function	LM, SCG, RP	RP

In Table 2 we present a confusion matrix for both the test and training data of the neural network that gave the best overall classification of the eleven postures.

Table 2 Confusion Matrix for posture classification. Rows indicate the Output Class and Columns indicates the Target Class. The Target 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. The blue box represents the overall classification score.

Output Class	P1	P2	P3	P4	P5	(%)
P1	713	0	11	7	1	97.5%
P2	7	710	10	2	3	97.0%
P3	0	10	689	0	0	98.6%
P4	0	0	10	713	10	97.3%
P5	0	0	0	0	706	100%
(%)	99.0%	98.6%	95.7%	99.0%	98.1	98.1%

Target Class

Using the same mobile application we devised two correction algorithms in order to create a full application capable of posture detection and correction. This process starts with the seating of a user and its identification. If it is a known user the calibration profile is applied, otherwise a new calibration process is done with the protocol previously described and then we start the classification process, distinguishing between the five standardized postures. At the moment we implemented 2 correction algorithms.

The first tests if the user has been seated for more than X minutes. The variable X can vary for different persons, but should be between 90 and 180 minutes. The algorithm changes the conformation of the bladders to cause a discomfort to the user, alerting them to stand up in order to prevent that users stay too seated for long periods of time. The second algorithm was devised in order to prevent that a user stay seated in incorrect postures for periods of time that may cause health problems. This algorithm acts after Y minutes, a variable that should vary between 5 and 15 minutes, based on the ISO standards for working standards [13]. Specific bladders are inflated for correcting different posture adoption, as for example to correct posture P2 we just need to inflate bladders 1 to 4 (see figure 1) while to correct posture P3 we will need to also inflate bladders 5 to 8, but change less the conformation of bladders 1 to 4. The full process workflow is presented in figure 3.

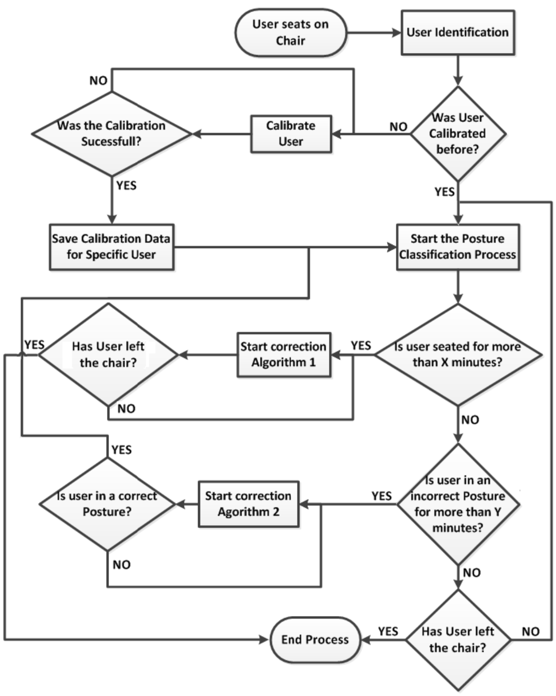

Fig. 3 Workflow of the both the Classification and Correction Processes

IV. CONCLUSIONS AND FUTURE WORK

A chair prototype with air bladders 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 five postures were gathered in order to classify each posture using ANNs. First we studied the best parameters of the ANNs for the posture classification and then we used them to create an ANN and export it to a mobile application. Results showed that for the five postures, the overall classification of each posture was around 98%. Two correction algorithms were integrated in the mobile applications in order to test if the user is seated for long periods of time and also if is seated in an incorrect posture. In any of the situations, the conformation of the chair automatically changes, so the user can adopt a correct posture.

Our next aim is to continue studying the classification algorithms in order to start classifying more postures and the correction algorithms to understand if they are being effective or if we need other correction processes. We will do clinical trials to evaluate the correction models but also to validate our classification algorithms, in order to build an intelligent chair capable of posture correction, reducing the health problems related to back and neck pain.

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