System for Posture Evaluation and Correction
Development of a Second Prototype for an Intelligent Chair

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Abstract: The sitting position has become one of the most common postures in developed countries. However, assuming a poor sitting posture leads to several health problems, namely back, shoulder and neck pain. In a previous work, an intelligent chair was developed and was shown to classify and correct the seating position. This work describes improvements on this intelligent chair prototype culminating with the development of a new prototype. The improvements of this new prototype are presented, resulting in new studies for posture identification. Pressure maps for 12 sitting postures were gathered in order to automatically detect user's posture through a neural network algorithm, obtaining an overall posture classification of around 81%.

1 INTRODUCTION

Nowadays, due to the rapid technological development, automation and computerization of the workplace, sitting has become the most common posture in developed countries (Maria et al. 2007; Chau et al. 2010; Hartvigsen et al. 2000; Graf et al. 1995). When a sitting position is adopted, most of the bodyweight is supported by the ischial tuberosities, 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 (Pynt et al. 2001). Furthermore, assuming a poor posture can lead to back and neck pain due to the anatomical changes of the spine and the degeneration of the intervertebral discs and joints (Lis et al. 2007; Graf et al. 1995). This fact has a huge impact in the cost of work-related illness (Waters 2004). Good posture is defined as the state of balance between musculoskeletal structures that prevents the appearance of lesions or their progressive deformation, and its adoption should prevent compensatory movements and evenly distribute the weight (Pynt et al. 2001).

Through the years, several investigations have been made to solve the problem of incorrect sitting posture. Most of these researches are focused on automatically detecting and classifying of the test subject based on pressure maps given by pressure sensors placed in chairs. Tan et al. (2001) used a chair as an interface for human-computer interactions. They used two Tekscan® sensor sheets, with 42-by-48 sensing units for real time capturing of contact information between the chair and its occupant in both seat pad and backrest. The use of pattern recognition technics to develop a static posture classification algorithm, such Principal Component Analyses (PCA), achieved an overall classification of 96% and 79% for familiar and unfamiliar users, respectively. Using the same sensing system, Mota & Picard (2003) managed to classify 9 static postures in real time, achieving an accuracy of 87.9% when tested with postures from new subjects. Zhu et al. (2003) compared several classification algorithms regarding their static posture classification capabilities and found that PCA and Sliced Inverse Regression (SIR) outperformed, in terms of overall posture detection,

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the k-Nearest Neighbour and Linear Discriminant Analysis.

Andreoni et al. (2002) combined a motion capture optoelectronic system and suitable pressure sensor matrices to measure a car driver's posture parameters.

With the aim of reducing the number of pressure sensors for posture identification Mutlu et al. (2007) and Zheng & Morrell (2010) made another approach. The first group studied a way to reduce the number of sensors to 19, obtaining an overall classification accuracy of 78%, improving the classification when the number of sensors was increased to 31, to 87%. The second group developed a system with only 7 sensors and 6 vibrotactile actuators, designed to posture guidance through haptic feedback. With a classification algorithm based on the mean squared error between the pressure measurements and the reference pressure for each static posture, an overall accuracy of 86.4% was achieved when distinguishing among 10 postures. This study also showed that is possible posture guidance trough haptic feedback.

Daian et al. (2007) developed a simple system where they used a chair equipped with force sensors, one in the seat pad and other in the backrest. The first one detects if someone is sitting and the other informs about the adequateness of the sitting position. The feedback to the subject, regarding posture and time, is given trough a computer program that identifies 3 different situations: the person is not sitting, the person is sitting in an adequate position, and the person is sitting in an inadequate position. These 3 situations were determined comparing the pressure values received from the sensor with preset threshold values. The threshold values were determined through repeated measurements values in the same way that the sensors' positions on the chair were determined. If an inadequate posture was taken for more than 20 seconds or the user was sitting for more than a 20, 40 and 60 minutes a feedback to the user is given. The feedback to the user is provided by a warning agent placed on the desk next to the computer display. Its warning should be understood as the need to do a break.

Other approaches that do not need the use of classification algorithms and interfaces with pressure sensors can be taking in consideration. One of that's approaches can be the use of software like WorkPace (Blangsted et al. 2004). This kind of software is intended to educate users about muscle fatigue and recovery. It recommends regular exercises and stretching, displays alerts when breaks are recommended, monitors the exposure and intensity of computer use, and provides feedback.

In previous works (Martins et al. 2014; Lucena et al. 2012), a chair prototype was built with the objective of correcting and preventing poor posture. In this first prototype the pressure cell concept was introduced and its capabilities of differentiating 11 different posture using 8 air bladders distributed in a matrix of 2 by 2 in the backrest and in the seat pad. These air bladders were able to obtain pressure maps and change their conformation (the amount of air inside the bladders) by inflation and deflation. Our main hypothesis is that by increasing discomfort when a poor posture is adopted, the user will be encouraged to change his position. That discomfort will be made by inflating and deflating the air bladders. We can also induce changes in the chair conformation over a period of time, which can help to eventually distribute the applied pressure on contact zones, reducing user fatigue and discomfort due to the pressure relief on compressed tissues. In order to classify 11 different postures, the pressure maps were used as input for an Artificial Neural Network (ANN). The ANN were exported to a mobile application and have been able to execute postural classification in real-time. Results show that, for 11 postures, in real-time classification the overall score was 70%, but when the number of positions decreases to 8, the overall classification score was 93%. Two correction algorithms were integrated in the mobile application in order to test if the user is seated for long periods of time and also if he or she is seated in an incorrect posture. In both situations the chair's conformation automatically changes, inducing the user to adopt a more correct posture. Despite significant achievements of this previous work, some improvements are needed to develop a better intelligent chair capable of real-time classification and correction of sitting posture. For that reason, the aim of this paper is present a new prototype with improved features.

2 EQUIPMENT DEVELOPMENT

As in Martins et al. (2014) work, the aim of this project was to adapt a regular office chair for sitting posture detection and correction. Taking into account the limitations in the previous prototype, we propose to build a new improved one. With this intent, several changes were made regarding the design and control of the air bladders.

In order to posture guidance and correction, is required an interface capable of measure the applied pressure and change the chair´s conformation. For that purpose air bladders were developed that are able to inflate and deflate. One of the limitations existing in the old prototype was the fact that the air bladders were made manually using off the shelf materials such as water bags used in back packs. The problem with this approach lies in the fact that the air bladders were not all identical, creating a problem at the time of system calibration and control. Therefore, for the new prototype, new air bladders were design. The new air bladders were design by NGNS Ingenious Solutions and industrially built by Aero Tec Laboratories Inc. This way we can guarantee all pressure cells have the same dimensions and correctly fit the chair. In Figure 1 it is possible to see the design of the air bladders and how each one is distributed into a matrix of 2 by 2.

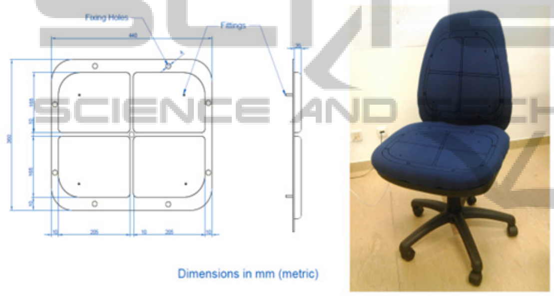

Figure 1: On the left is shown the design of the new air bladders and on the right their position on the chair.

Two matrices containing the bladders were placed under the original padding foam of the chair in order to maintain the anatomical cut of the seat pad and the back rest, totaling 8 air bladders. While building the previous prototype, the calculated pressure inside the bladders were shown to not be significantly altered by using the original padding foam of the chair.

Air bladders placement was strategically chosen. According to previous literature, there are two types of approaches: a pure mathematical and statistical approach (Mutlu et al. 2007) and an anatomical approach (Zheng & Morrell 2010). Based on the second method we placed the air bladders in order to cover the most important and distinguishable areas of the body for detecting a seated posture, such as the ischial tuberosities, the posterior thigh region, the lumbar region of the spine and the scapula. These are also the areas where most of the bodyweight is distributed (Pynt et al. 2001).

In the previous prototype, all instrumentation responsible for the control and measure of pressure in the bladders was centralized in two places, one for the backrest and other to the seat pad. In this new prototype we approach the problem in a modular way. Each one of the eight bladders is connected through a rubber pipe to its control module. In case of malfunction in a control module, it can easily be replaced without compromising the others.

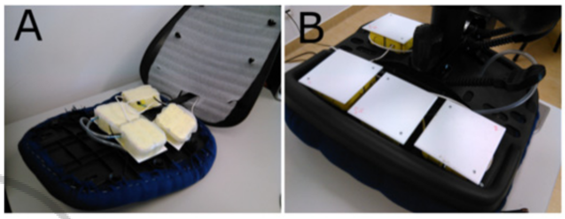

Figure 2: A – Placement of the control modules in the back rest; B – Placement of the control modules in the seat pad.

The control module is, in itself, an improvement. Previously, each bladder would be connected to an air pump and a solenoid valve. Air would flow out of the bladders when the valve would open and through gravity's action, meaning there was no effective control when decreasing pressure. Since the system's goal is to correct the user's sitting posture, it was understood that it would be an asset to have a better control over the amount of air that leaves the air bladders. For that reason, a vacuum pump was added to each control module. In each control module we can also find a piezoelectric gauge pressure sensor to measure the internal pressure of the bladder. The piezoelectric gauge pressure sensors used were the Honeywell 26PC Series rated to 5 psi with a sensitive of 10 mV/psi. The placement of the control modules in the chair can be seen in Figure 2.

In Martins et al. (2014), control and processing of the pressure maps from the chair was essentially made by the use of a smartphone. To achieve independence from the use of a smartphone, a single-board computer, the Raspberry Pi, was used to control the chair's instrumentation through an I^2C connection. A Bluetooth interface was added to the RPi in order to connect it to the outside world, enabling one to retrieve data and statistics through a smartphone.

3 CLASSIFICATION OF SITTING POSTURE

To create a Seated Posture Classification Algorithm, one experiment for data acquisition was conducted with the dataset presented in Table 1.

Figure 3: Seated postures used in the experiments and their respective class label: (P1) seated upright, (P2) leaning forward, (P3) leaning back, (P4) leaning back with no lumbar support, (P5) leaning left, (P6) leaning right, (P7) right leg crossed, (P8) right leg crossed, leaning left, (P9) left leg crossed, (P10) left leg crossed, leaning right, (P11) left leg over right, (P12) right leg over left.

Before the experiment starts, it was necessary to inflate the air bladders in order for them to have enough air to accurately obtain the pressures maps. It is important to say that the time of inflation must be carefully chosen because is essential that the air inside the air bladders doesn't be enough to cause discomfort to the users. For that reason, after some tests, we decided to use a value of 5 seconds for inflation. Before undergoing any experiment, subjects were asked to empty their pockets and to adjust the stool height so that the knee angle (angle between the thigh and the leg) was at 90º and to keep their hands on their thighs.

The experiment was comprised of two tests, the first test involved showing a presentation of the postures from P1 to P12 (for a duration of 20 seconds each), asking the subject to mimic those postures without leaving the chair.

The second consisted in showing the same presentation, with every posture being repeated two times, but after every 20 seconds we asked the subject to walk out of the chair, take a few steps and sit back. The twelve postures chosen were based on previous works and are represented in Figure 3 (Zhu et al. 2003; Forlizzi et al. 2005; Tan et al. 2001; Zheng & Morrell 2010; Mutlu et al. 2007; Vergara & Page 2000).

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 4. Here, we focus our study on the Stable zone of the pressure maps and therefore, 12.5 out of the 20 seconds were used. Since our sampling rate is 8 Hz, we were able to extract 100 data-points out of the 12.5 seconds, which were divided in groups of 20 points. The average of those groups was used to create 5 pressure maps for posture classification, giving a total of 1080 maps for each posture (72 subjects x 3 repetitions x 5 pressures maps) and a total of 12960 maps (1080 x 12 postures). All the 12960 maps were normalized to an input interval of [-1, 1] for the ANNs. For the creation of the ANNs we used the MATLAB® Neural Network Toolbox™.

Table 1: Data of the participants in the experiment, namely, Sex, Age, Weight and Height. Note: a Values for Average ± Standard Deviation and (M/F) corresponds to (Male/Female).

No. of subjects (M/F)	Age (years)[a]	Weight (Kg)[a]	Height (cm)[a]
72 (37/35)	26,6±9,3	67,7±12,7	170,8±9,4

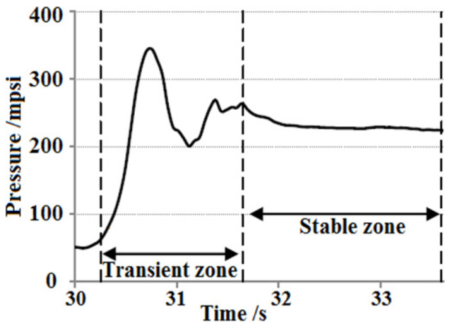

Figure 4: Pressure measurement from one air bladder, when a subject went from posture P7 to P8, showing the transient zone and the stable zone.

4 RESULTS AND DISCUSSION

4.1 Improvements of the Prototype

With the new prototype ready, it is possible to compare it with its predecessor. Looking at Figure 5, it can be seen that the changes made to the chair's structure were virtually inexistent when compared to the previous model. In the previous one, great number of important adaptions was required in order to accommodate all the necessary components for the functioning of the classification system. This implies that this new prototype is closer to being an easily adaptable system, regardless of the used chair.

The introduction of a vacuum pump in the pneumatic module greatly improved the correction control, since, as it was already mentioned, it is now possible to effectively monitor the amount of air that leaves the bladders.

4.2 Seated Posture Classification Algorithm

For the parameterization of the ANN we used a combination of 1 layer, 40 neurons and resilient back propagation algorithm as the network training function. We trained a new ANN to gather the weights and bias in order to export them for real time posture classification. For this we divided the entire dataset in 60% for the ANN training, 15% for the validation and the rest for the ANN testing. The confusion matrix for all data is represented in Table 2 with the respective overall scores for each posture class and the overall classification score. We obtained an overall classification of 80.9%. This result is comparable with the overall classification in the work done by Martins et al. (2014). It is important to notice that for this new test two new positions were added, the P11 and the P12. As expected postures with lateral inclination (P5, P6, P8 and P9) weren't well distinguish between them. The same problem is verified in positions with the legs cross. To solve this situation, in a parallel work, we are developing other classification alghoritms to combine icnclination and leg crossing positions.

In the previous prototype (Martins et al. 2014), a problem with the classification of posture P1 was identified. The solution to solve that problem was to use decision trees with specific threshold values to divide into two neural networks (one specialized

Table 2: Confusion Matrix for posture classification of the training data, where rows indicate the Output Class and columns indicates the Target Class. The Target Class labels correspond to the respective postures from figure 3. The grey boxes in the main diagonal give the output classes that were correctly classified as the target class. The row and column in grey give the percentages of correct classification in relation to the respective class and the overall classification score.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	(%)	
P1	911	7	54	4	1	4	6	2	30	5	0	4	88.6	Output Class
P2	19	989	11	6	21	8	31	9	8	9	8	7	87.8	
P3	27	9	815	42	0	11	102	4	41	16	0	1	76.3	
P4	0	3	26	957	13	0	5	9	21	5	19	28	88.1	
P5	0	6	5	1	860	1	33	5	1	137	16	0	80.8	
P6	0	0	0	1	5	815	5	115	27	5	0	30	81.3	
P7	19	0	63	0	14	7	671	27	22	16	17	27	76.0	
P8	0	0	2	2	0	102	26	777	7	0	3	54	79.9	
P9	44	1	13	1	2	31	14	20	722	58	30	45	73.6	
P10	0	1	24	4	86	0	11	0	35	721	23	7	79.1	
P11	0	1	1	6	23	0	71	14	22	46	900	10	82.3	
P12	5	8	11	1	0	46	50	43	89	7	9	812	75.1	
(%)	88.9	96.5	79.5	93.4	83.9	79.5	65.5	75.8	70.4	70.3	87.8	79.2	**80.9**	
	Target Class													

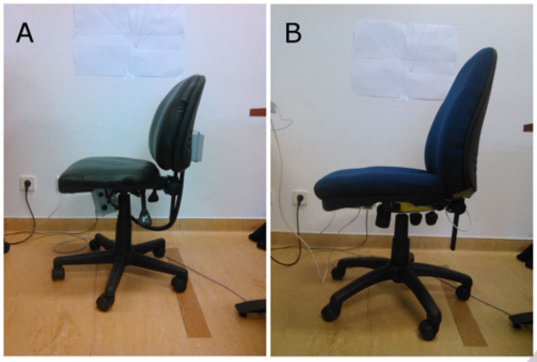

Figure 5: Representation of the old (A) and new (B) prototype.

identifying posture P1 and the other to classify the remaining postures). However, preleminary tests show that this new prototype will not need the division in two ANNs due to its higher structural stability, which caused classification problems in the previous prototype. In the future, real-time classification tests must be conducted to evaluate the accuaracy of this new Prototype.

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