Optimization of Sitting Posture Classification based on Anthropometric Data

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Abstract: An intelligent chair prototype was developed in order to detect and correct the adoption of bad sitting postures during long periods of time. A pneumatic system was enclosed in the chair (4 air bladders inside the seat pad and 4 in the backrest) to classify 12 standardized sitting postures, with a classification score of 80.9%. Recently we used algorithmic optimization applied to the existing classification algorithm (based on Neural Networks) to split users (using Classification Trees) by their sex and used two different previously trained Neural Networks (Male and Female) to get an improved classification of 89.0% when the user was identified and 87.1% for unidentified users. In this work we aim to investigate the usage of the anthropometric information (height and weight) to further optimize our classification process. Here we use four Machine Learning Techniques (Neural Networks, Support Vector Machines, Classification Trees and Naive Bayes) to automatically split the users in 2 classes (above and below the specific anthropometric median value). Results showed that Classification Trees worked best on automatically separating the body characteristics (i.e. Height) with a global optimization of 88.3%. During the classification process, if the user is identified, we skip the splitting step, and this optimization increases to 90.2%.

1 INTRODUCTION

There has been a growing interest in developing intelligent chairs capable of detecting a person's sitting posture and alerting that person to improve his or her sitting posture. Numerous researchers applied sheets of surface-mounted pressure sensors placed as if in a 2D array or used statistical techniques to find the best way to place singular force-sensitive resistors (Zhu et al., 2003; Tan et al., 2001; Zheng and Morrell, 2010; Mutlu et al., 2007; Daian et al., 2007; Goossens et al., 2012). Other groups implemented sensing textiles in the chair (Forlizzi et al., 2005). Most of these chairs alert the users by using vibrotactile motors or by computer pop-ups (Haller et al., n.d.; Schrempf et al., 2011; Zheng and Morrell, 2010). Another group used 36 intelligent pneumatic actuators over sensing plates to detect and guide the sitting posture (Faudzi et al., 2010).

These intelligent chairs, which have shown the capability of monitoring physiological parameters (e.g. heart rate) (Griffiths and Saponas, 2014) or monitor everyday activities, are starting to be implemented in real homes for year-long tests (Palumbo et al., 2014) and they are needed because our society spends long periods of time in the workplace and even at home in the sitting position. This sedentary lifestyle has been associated with an increased risk of cardiovascular and musculoskeletal diseases, although some studies have not been able to prove direct and causal correlation between sitting time and those disorders (Chau et al., 2010; Hartvigsen et al., 2000; Owen et al., 2010; Owen et al., 2014; Roffey et al., 2010). Musculoskeletal disorders were recognized as one of main causes of work-related disability and loss of productivity in industrialized countries (Ramdan et al., 2014; Punnett and Wegman, 2004), so there is a necessity for monitoring and prevention of those health

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dysfunctions.

When an individual is sitting, most of the bodyweight is supported by the ischial tuberosities, the thigh and gluteal muscles, while the rest is transferred by the feet and armrests when they are present (Pynt et al., 2001). During extended periods of sitting, there is a decrease of the lumbar lordosis, which has been implicated in increasing the physical risk factors related to back, neck and shoulder pain (Ariëns et al., 2001; Juul-Kristensen et al., 2004), due to anatomical changes and degeneration of intervertebral disks and joints, especially the lumbar disks (Adams and Hutton, 1986; Kingma et al., 2000; Billy et al., 2014). If a person is sitting in a so called 'bad posture' (for example sitting in a leaned back position without lumbar support, see Figure 3 for other examples), the risk of musculoskeletal disorders increases (Lis et al., 2007)

The increase in these health disorders supports the necessity for their monitoring and prevention, leading to the development of chair prototypes that identify several sitting positions and then alert or correct the adoption of bad postures over extended periods. Our first prototype had 4 air bladders placed in the seat pad and 4 in the backrest, with pressure sensors that measured the internal pressure of the bladder. We used Artificial Neural Networks (ANN) to classify 11 standard sitting postures, with 70% accuracy, and we were able to do a real-time classification of 8 postures, with 90% accuracy. This prototype had had a rudimentary correction algorithm based on Boolean logic (Martins et al., 2014; Martins et al., 2013).

The second prototype was built in order to overcome the gaps identified in the first prototype, mainly the introduction of a vacuum pump to control efficiently the air inside the bladders, the design of industrially constructed air bladders and the reorganization of the communication protocols (Pereira et al., 2015). We then revised our classification and correction algorithms and introduced Fuzzy Logic to the existing ANN algorithms, which was able to integrate time spent in each posture (recognized by the ANN) and was able to identify intermediate postures, other than the 12 standard ones and correct them based on fuzzy logic actuators (Ribeiro et al., 2015). This work precedes our previous implementation of algorithmic optimization, applied to the second prototype in order to improve posture classification performance, based on the sex of the users (Ribeiro et al., 2015). It continues the trend of classification optimization by using the anthropometric information of the users (height and weight) to surpass the previous classification Accuracy, by testing various classification methods to split the users. This study was also driven by the discovery that our previous classification algorithms (with leave-one-out strategy to train with 49 users and test with the last one) had some difficulties in the classification of users with weights between 60 and 73 Kg and heights between 173 and 190 cm (highlighted in the red square in Figure 1).

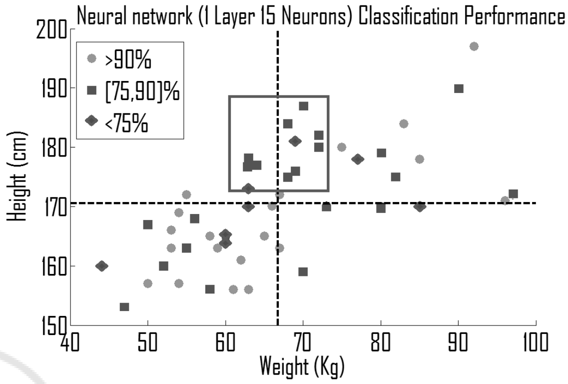

Figure 1: (A) Classification Performance for each participant regarding their Anthropometric Data (Height and Weight), based on a Neural Net-work with 3 Layers and 15 Neurons.

2 EXPERIMENTS AND METHODS

2.1 Equipment – Sensors and Pneumatic Actuators

For this work we use the second prototype that was previously built, with 8 industrially made polyurethane bladders, and with new features that were improved from the first prototype, as previously mentioned (Pereira et al., 2015). The main objective was that the bladders covered and distinguished the anatomical areas involved in the weight transfer during the seated posture (Pynt et al., 2001), such as the scapula, the ischial tuberosities, the posterior thigh region, the lumbar spine (Martins et al., 2014). The air bladders (see Figure 2-A for configuration) were placed inside the original padding foam (as can be observed in Figure 2-B, the chair maintains the original integrity) (Pereira et al., 2015). All the sensors and the pneumatic circuits were integrated in eight small boxes that were inserted in the backrest and connected to the lower part of the seat pad, which makes all the electronics and pneumatic circuit invisible to the user (Pereira et al., 2015).

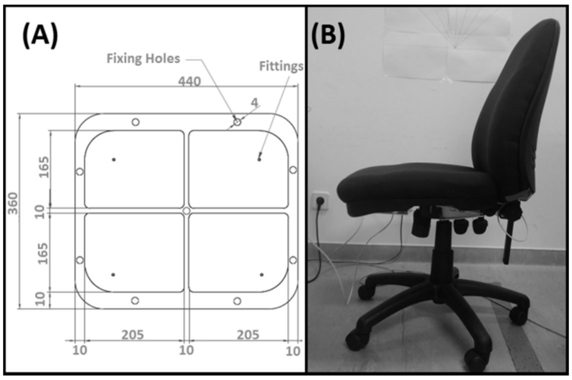

Figure 2: (A) Air bladder schematic (B) External aspect of the chair prototype.

2.2 Experimental Design - Participants and Procedure

The same dataset is used as in the previous optimization work (Ribeiro et al., 2015) (see Table 1 for the participants information). We split the users based on their weight and height (see dashed lines in Figure 1). Just as in the previous work protocol, we use a value of 5 sec for bladder inflation and also asked the subjects to empty their pockets and adjust the stool to their popliteal height and to keep their hands on their thighs (Ribeiro et al., 2015).

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).

Participants Information	Value	Median
Number of Subjects (M/F)	50 (25/25)	-
Age (years) [a]	26,4±9,5	-
Weight (Kg) [a]	66,8±12,8	67
Height (cm) [a]	170,5±9,8	171

Our experiment consists of two tests, the first involved showing a presentation of the postures P1 to P12 (see Figure 2), each for a duration of 20 seconds, asking the subject to mimic those postures without leaving the chair. In the second we used the same presentation, repeating every posture two times, but after every 20 seconds we ask the subject to leave the chair, take a few steps and sit back. The twelve postures (P1 to P12 – see Figure 2) used in this experiment represent the most common sitting postures found in office settings (Vergara and Page, 2000; Mutlu et al., 2007; Zheng and Morrell, 2010; Martins et al., 2014).

Figure 3: Seated postures classes: (P1) seated upright, leaning (P2) forward (P3) back (P4) back with no lumbar support (P5) left (P6) right (P7) right leg crossed (P8) right leg crossed, left lean (P9) left leg crossed (P10) left leg crossed, right lean (P11) left leg over right (P12) right leg over left.

Not all of the 20 sec of acquisition were used (as in previous experiments), due to the existence of a Transition zone, where the sensor values are not stable (Martins et al., 2014; Ribeiro et al., 2015; Pereira et al., 2015). We extracted 100 data-points, corresponding to 12.5 sec with a sampling of 8 Hz. Pressure maps were done, by averaging 20 acquisitions, obtaining 5 maps so out of the 100 data-points, for a total of 9000 (50 subjects * 3 repetitions * 5 pressure maps * 12 postures)..

This (P1) pressure is used as a baseline by subtracting its average from the entire data-points (9000 maps). After the calibration, the maps are normalized to an interval of [-1, 1] to use as inputs for the Posture Classification Algorithm based on Artificial Neural Networks (ANNs), based on the average pressure values of the P1 posture of each subject (Pereira et al., 2015; Martins et al., 2014). To create ANNs we use the MATLAB® Neural Network Toolbox™. The optimization of the Posture Classification is based on using the baseline pressure as an input to a Pre-Process Classification Algorithm that is going to classify the participants according to their anthropometric information.

2.3 Classification Algorithms

Here we use four supervised machine learning (ML) techniques: Artificial Neural Networks (ANNs), Support Vector Machines (SVM), Classification Trees (CT) and Naive Bayes (NB) to create a Pre-Process Classification Algorithm that splits the participants based on their anthropometric information. These techniques are widely used in biomedical applications (Kotsiantis, 2007; Singh et al., 2014), are the most reliable in supervised learning and can be easily implemented with specific libraries (Abeel, 2009) in simple computational architectures, such as a single-board computers (e.g. Raspberry Pi) or Mobile Devices (smartphones or tablets). To train and test each method we use the MATLAB® Neural Network Toolbox™ (MNNT) and the MATLAB® Statistics Toolbox™ (MST). To estimate the performance of each ML technique we used the 10-fold cross validation, using the '*cvpartition*' function. The results are obtained by calculating the Accuracy of the 2 class separation problem (below and above the specific anthropometric information), as the above the Median can be considered the True Positive and the Below the Median the True Negative of the test.

ANN-based algorithms have been shown to be useful in many engineering and biomedical applications (Paliwal and Kumar, 2009). We already use ANNs for the Posture Classification, as they showed the ability to handle very well that multiclass problem. They also have an advantage of being easily exported to mobile applications (using the weights and bias matrices).

The Classification and Regression Trees (CART) methods that are still being widely used in biomedical applications (Podgorelec et al., 2002), were first presented by Breiman and colleagues in 1984 (Breiman et al., 1984). In this work we use the *fitctree* from the MST.

SVM techniques were first presented to separate a binary class problem (Boser et al., 1992) and have been applied to Biomedical and Biotechnology applications, such as face recognition (Cyran et al., 2013) or using gene expression to classify different cancers (Noble, 2006) and classifying objects such mass spectra (Noble, 2003; Cyran et al., 2013), proteins (Noble, 2003), DNA sequences (Noble, 2003). Here we have also binary classification problem, so we used the *fitcsvm* function, present in the MST.

Naive Bayes is a simple and scalable technique that has been introduced in the 1950's and has also been used in biomedical applications (Singh et al., 2014). Here we use the '*fitcnb*' function, from MST and then changed the kernel distributions.

3 RESULTS AND DISCUSSION

3.1 Classification Optimization based on Anthropometric Information

3.1.1 Neural Network Optimization

To search for the optimized parameters of the Posture Classification based on Neural Networks, we tested various combinations of layers, neurons (as can be seen in Table 2), using the '*tansig*' transfer function and the '*scaled conjugate gradient backpropagation*' (SCG) training function (using the default parameters), which proved to be the most accurate parameters our previous work (Martins et al., 2014; Pereira et al., 2015). As can be seen in Table 2, the best overall result was with 15 Neurons and 1 Layer with an overall classification of 95.8% (overall separation of 95.6% for Height and 96.0% for Weight). Training with 3 Layers is not shown as the results were lower or around 90%. It is noted that the 1 layer-15 neurons also had the best results for the posture classification algorithm in the first prototype.

Table 2: Results from the Neural Network Optimization.

Number of Neurons	Class	Above the Median	Below the Median	Overall Class Separation
15	**Height**	**97.9**	**93.3**	**95.6**
	Weight	**97.6**	**94.4**	**96.0**
20	Height	93.1	91.7	92.4
	Weight	94.9	94.7	94.8
25	Height	93.9	96.7	95.3
	Weight	92.8	93.9	93.4
30	Height	96.8	94.7	95.7
	Weight	95.7	92.3	94.0
15/15	Height	94.4	92.2	93.3
	Weight	96.8	93.3	95.0
20/20	Height	93.7	93.0	93.4
	Weight	95.1	95.5	94.8
25/25	Height	97.0	92.4	94.7
	Weight	93.9	93.5	93.7
30/30	Height	96.1	94.0	95.0
	Weight	95.5	94.7	95.1

3.1.2 Classification Trees Optimization

Using the default values from the *fitctree* function, we changed the splitting criterion from the Gini's Diversity Index to the Twoing rule (Breiman et al.,

1984) and then to the calculation of the node deviance (Ritschard, 2006). The best score (97.8%) were obtained with the Gini Index with an overall separation of 97.8% for Height and 97.9% for Weight, as seen in Table 3.

Table 3: Classification Trees Optimization results.

Splitting Criterion	Class	Above the Median	Below the Median	Overall Class Separation
Gini	**Height**	**97.6**	**98.1**	**97.8**
	Weight	**98.9**	**96.8**	**97.9**
Twoing	Height	97.1	97.6	97.3
	Weight	98.4	97.9	98.1
Deviance	Height	97.3	98.9	98.1
	Weight	97.1	97.3	97.2

3.1.3 Support Vector Machine Optimization

We started the SVM optimization with the default parameters. In 'Change 1', we standardized the predictors (using the '*Standardize*' flag). In 'Change 2', we changed the '*KernelScale*' to automatic, which uses heuristic procedure to select the kernel scale value.

In 'Change 1+2' we combined both flags, which gave the best overall classification of 78.2% (overall separation of 73.1% for Height and 83.2% for Weight). In 'Change 3', we changed the 'Box Constraint' flag to 10 and 0.1 (default is 1), along with the flags from 'Change 1+2' (see Table 4 for all Classification Accuracies).

Table 4: Support Vector Machine Optimization results.

Parameter change	Class	Above the Median	Below the Median	Overall Class Separation
Default	Height	66.7	50.2	58.5
	Weight	60.5	69.1	64,8
Change 1	Height	76.8	65.9	71.3
	Weight	76.3	88.3	82.3
Change 2	Height	79.2	63.5	71.3
	Weight	80.3	85.6	80.3
Change 1+2	**Height**	**80.2**	**66.1**	**73.1**
	Weight	**83.1**	**88.3**	**83.2**
Change 3 (10)	Height	78.4	65.1	71.7
	Weight	75.7	88.5	82.1
Change 3 (0.1)	Height	80.0	61.9	70.9
	Weight	73.6	81.3	77.5

3.1.4 Naïve Bayes Optimization

Employing the the '*fitcnb*' function, we started with the default parameters, and adapted the data distribution from '*normal*' to '*kernel*' with 4 possible kernels: 'normal', 'box', 'epanechnikov' and 'triangle'.

The best results (see Table 5) was obtained with a '*normal*' kernel, with a global score of 79.8% (78.9% for Height and 80.7% for Weight).

Table 5: Naïve Bayes Optimization results.

Parameter change	Class	Above the Median	Below the Median	Overall Class Separation
Default	Height	52.3	71.7	62.0
	Weight	54.1	78.4	66.3
Kernel normal	**Height**	**72.5**	**85.3**	**78.9**
	Weight	**72.8**	**88.5**	**80.7**
Kernel box	Height	72.8	85.9	79.3
	Weight	67.2	86.9	77.1
Kernel epanech-nikov	Height	73.1	84.3	78.7
	Weight	66.7	86.4	76.5
Kernel triangle	Height	72.3	81.9	77.1
	Weight	65.6	84.3	74.9

3.2 Sitting Posture Classification based on Neural Networks

After doing the class separation (above and below the median height and weight), we now rely on using Neural Networks to classify the 12 standard Sitting Postures.

The chosen parameters were based on the best results obtained in the previous experiments (Pereira et al., 2015; Martins et al., 2014), so we also fixed the SCG algorithm training function and 'tansig' for the transfer functions and tested the Number of Neurons (15 and 30) and the amount of Layers (1, 2 or 3).

Table 6 shows the obtained results, the best result was with 15 Neurons and 1 Layer with an overall classification of 90.0% (overall separation of 90.2% for height and 89.8% for weight).

This simpler configuration is also advantageous to use, especially in real-time classification, to avoid the overfitting problem (Martins et al., 2014). Overtraining of the Algorithms was avoided by using the '*cvpartition'* (with 10-fold option), which then test's with 10% of the data and trains with 90%, and repeats this process 10 times and averages the results. Although there are a lot of parameters that could have been used for each of the previous machine learning algorithm, as we expressed in the previous sections, we wanted to use a simple approach to the classification process, because we want to export the Algorithms to a small single-board computer (e.g. Raspberry Pi) or to a mobile application.

Table 6: Results for Posture Classification based on Neural Networks.

Number of Neurons	Class	Above the Median	Below the Median	Overall Separation
15	**Height**	**90.5%**	**89.9%**	**90.2%**
	Weight	**89.8%**	**89.7%**	**89.8%**
30	Height	87.9%	88.3%	88.1%
	Weight	86.9%	87.3%	87.1%
15/15	Height	89.5%	87.2%	88.4%
	Weight	87.9%	90.0%	89.0%
30/30	Height	89.8%	86.4%	88.1%
	Weight	87.7%	90.6%	89.2%
15/15/15	Height	89.0%	90.4%	89.7%
	Weight	88.2%	89.2%	88.7%
30/30/30	Height	89.2%	88.6%	88.9%
	Weight	87.8%	89.3%	88.5%

4 CONCLUSIONS AND FUTURE WORK

In prior works, we developed two intelligent sensing chair prototypes. The first one was developed to classify 11 standardized sitting postures using 8 pneumatic bladders connected to pressure sensors (Martins et al., 2014). The second solved the identified limitations of the first one (using a vacuum pump to control the deflation of the bladders, the design of industrially built bladders and the use of simple computational architectures) and had a classification score of 80.9% of 12 standard sitting postures . This work aimed to demonstrate how we could optimize this classification based on the identification of the user, and split them by their anthropometric information (above or below the median height and weight), with each class having their specific ANN for Posture classification.

The workflow of the classification optimization process is shown in Figure 4. This process starts with the user sitting on the chair prototype and the pressure sensor acquisition. If the user is identified in the computer interface, we just directly select the specific Neural Network for Posture Classification, based on the anthropometric features. If the user is not identified, we need to detect which Neural Network should be used, by using the best Pre-Process Algorithm. The workflow then continues with the Calibration and Data processing, finalizing with the Posture Classification Process based on the specific ANN.

The Best Pre-Process Algorithm (Classification Trees with the Gini Index) for our specific problem, gave an automatic separation score (97.8%), with an overall separation of 97.8% for Height and 97.9% for Weight.

Results showed that the best result for the Posture Classification (using the ANN) was obtained with Layer of 15 Neurons with an overall classification of 90.2% for height and 89.8% for weight, which translates into an overall optimization of 9.3% (with the height) from the previously reported result of 80.9% score for 12 standard sitting postures (Pereira et al., 2015) and a 1.2% increase over the previous optimization (using the sex of the user) (Ribeiro et al., 2015) when the user is identified with their anthropometric information.

Combining the automatic separation (when the user is not identified), we use a pre-process classification (based on Decision Trees) to determine the specific Anthropometric Neural Network, so by multiplying each specific result we get an overall classification optimization of 88.3% for the Height and 87.8% for the Weight, resulting in an overall optimization of 7.4% over the normal Posture Classification Algorithm and an increase of 1.2% over the previous optimization process.

Although using the Height optimization gave the best results, we believe that combining all three factors (Height, Weight and Sex) into a very personalized Classification Algorithm will be our best option to get scores higher than 90% and optimize the sitting posture process, which will only be achieved by increasing the participant's database.

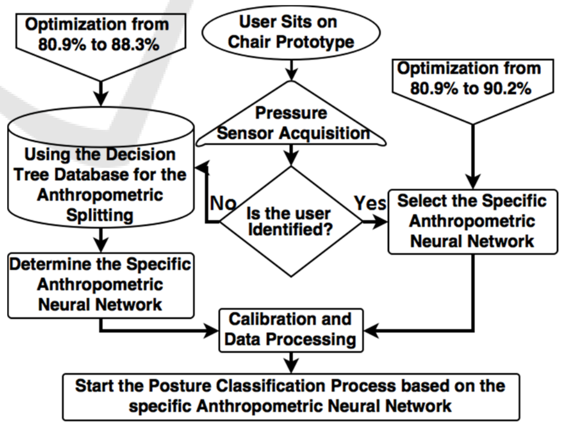

Figure 4: Workflow of the Posture Classification Optimization Process.

The prototype is still undergoing a series of operational trials in an office environment to evaluate the classification algorithms to get realistic statistical data from of daily postural habits. The correct classification of different sitting postures is necessary for the implementation of the posture correction algorithms that hopefully will have a societal impact of reducing the common back and neck disorders.

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