Sitting Posture Detection using Fuzzy Logic
Development of a Neuro-fuzzy Algorithm to Classify Postural Transitions in a Sitting Posture

Bruno Ribeiro[1], Leonardo Martins[1,2], Hugo Pereira[1], Rui Almeida[1], Cláudia Quaresma[1,3], Adelaide Ferreira[1] and Pedro Vieira[1,4]

[1]*Department of Physics, Faculty of Sciences and Technology of the New University of Lisbon, Quinta da Torre, 2829-516, Caparica, Portugal*

[2]*UNINOVA, Institute for the Development of New Technologies, Quinta da Torre, 2829-516, Caparica, Portugal*

[3]*CEFITEC, Faculty of Sciences and Technology of the New University of Lisbon, Quinta da Torre, 2829-516, Caparica, Portugal*

[4]*Centre of Atomic Physics, Faculty of Sciences and Technology of the New University of Lisbon, Quinta da Torre, 2829-516, Caparica, Portugal*

Keywords: Intelligent Chair, Pressure-distribution Sensors, Sitting Posture, Posture Classification, Fuzzy Logic, Neural Networks.

Abstract: In a previous work, a chair prototype was used to detect 11 standardized seating postures of users, using just 8 air bladders (4 in the chair's seat and 4 in the backrest) and one pressure sensor for each bladder. In this paper we describe a new classification algorithm, which was developed in order to classify the postures using as input the Centre of Pressure, the Posture Adoption Time and the Posture Output from the existing Neural Network Algorithm. This new Posture Classification Algorithm is based on Fuzzy Logic and is able to determine if the user is adopting a good or a bad posture for specific time periods. The newly developed Classification Algorithms will prompt the improvement of new Posture Correction Algorithms based on Fuzzy Actuators.

1 INTRODUCTION

Society sedentary behaviours are influenced by many factors and on various domains, including spending extended periods of time in a sitting position in a variety of settings, such as the occupational workspace, transports, leisure activities and household activities (Owen et al., 2011; Chau et al., 2010).

Low back pain has been identified as one of the leading causes of work-related disability and loss of productivity in industrialized countries (Ramdan et al., 2014; Punnett and Wegman, 2004), but systematic studies haven't been able to establish a causal and independent relationship between occupational sitting and low back pain (Hartvigsen et al., 2000; Roffey et al., 2010), although an increasing risk of this disorder has been associated with sitting during extended periods of time (Todd et al., 2007).

This situation happens because when a person has prolonged sitting behaviours, this will lead to a decrease of the lumbar lordosis (Van Dieën et al., 2001; Cagnie et al., 2007) which then increase the physical risk factors related to back, neck and shoulder pain (Ariëns et al., 2001; Juul-Kristensen et al., 2004). This pain is due to anatomical alterations and degeneration of the intervertebral disks and joints (Adams and Hutton, 1986; Kingma et al., 2000).

Recent studies have shown that still doesn't exist a consensus on what comprises a neutral spine posture in a sitting posture (O'Sullivan et al., 2012) due to the difficulty of doing quantitative clinical studies that target the identification of 'correct' and 'incorrect' postures. The main approaches of such studies is to use multiple camera sensors to build a 3D optical model of the body posture (Edmondston et al., 2007) or using sensors applied directly to the skin able to assess the spinal angles in different postures (Claus et al., 2009) or to calculate the relative distance between anatomical landmarks of

Ribeiro B., Martins L., Pereira H., Almeida R., Quaresma C., Ferreira A. and Vieira P..
Sitting Posture Detection using Fuzzy Logic - Development of a Neuro-fuzzy Algorithm to Classify Postural Transitions in a Sitting Posture.
DOI: 10.5220/0005287101910199
In *Proceedings of the International Conference on Health Informatics* (HEALTHINF-2015), pages 191-199
ISBN: 978-989-758-068-0

the spine (O'Sullivan et al., 2010).

In a normal sitting position, the ischial tuberosities, the thigh and gluteal muscles support most of the person's weight, while the remaining pressure load is transferred to the ground by the feet and to the backrest and armrests (Pynt et al., 2001). In most of the 'incorrect' postures the trunk is not totally supported in the backrest due to the lateral flexion of the upper part of the trunk, or due to forward or backward inclination of the trunk or due to leg crossing. In these positions, the weight is incorrectly transferred which can have an amplifying effect in back and neck associated disorders (Lis et al., 2007).

To promote a more dynamic sitting posture and increase physical activities, chair manufacturers have developed office chairs with structural elements such as, seat pan motors, seat pan suspension systems and moveable joints that can permit movement in the horizontal plane or even freely in all directions. Studies showed that different chairs didn't influenced a significant difference body dynamics (such as muscle activation), while each of the studied task strongly affected the body dynamics (Ellegast et al., 2012). This suggests the need to develop a intelligent chairs capable of identifying the user posture or the associated task, and alerting the users of prolonged sitting behaviours.

Such intelligent chairs have been developed in recent years by numerous research groups, by implementing sheets of surface-mounted pressure sensors placed in a 2D array or using pure mathematical and statistical approaches to find the best way to place singular force-sensitive resistors in the chair or even conductive textiles (Zhu et al., 2003; Forlizzi et al., 2005; Tan et al., 2001; Zheng and Morrell, 2010; Schrempf et al., 2011; Mutlu et al., 2007).

These intelligent chairs have been shown to be capable of detecting the presence of a person, detect the sitting posture of that person and alerting the person to improve their sitting posture or even as an input device in an office environment. They can be used as physiological monitor and create report tools of everyday activities which is already being implemented in real homes for year-long tests (Palumbo et al., 2014).

In a previous work, a chair prototype was used to classify 11 standardized seating postures of users, using 8 air bladders (4 in the chair's seat and 4 in the backrest) by using pressure sensor for each bladder to detect the bladder's interior pressure (Martins et al., 2014). The bladders from the previous prototype are shown in Figure 1-A. The classification algorithm was based on Neural Networks and Decision trees and was able to make a real-time overall classification 93% (for eight postures) and dropped to 70% (for the eleven standardized postures) (Martins et al., 2014).

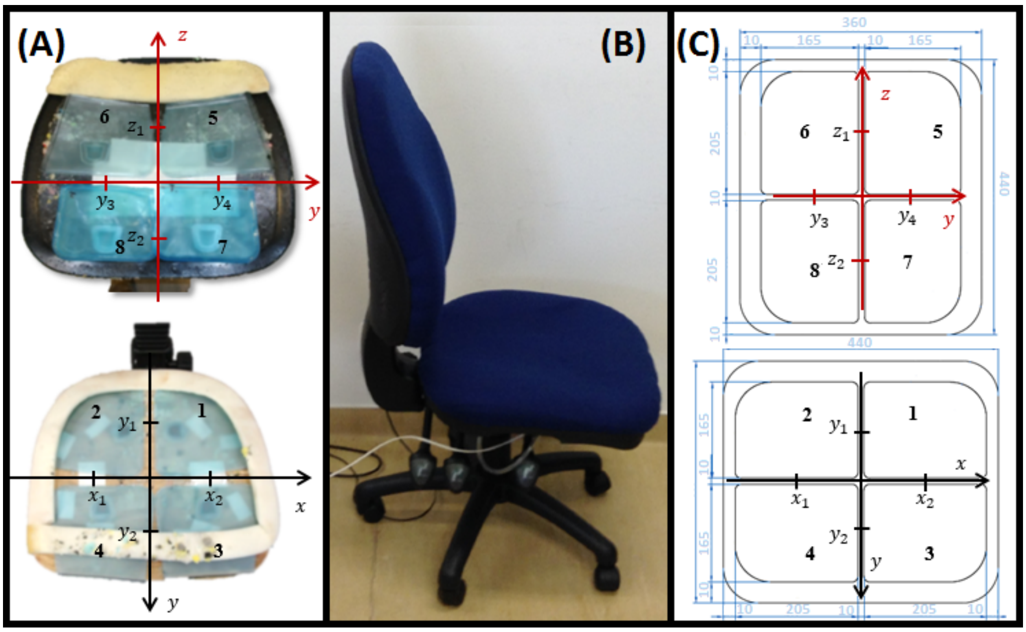

Figure 1: (A) Interior of the previous prototype and Centre of Pressure (COP) measurement (B) New Prototype (C) Schematic of the new air bladder system and COP measurement. Bladder 1 (Back Left – BL), Bladder 2 (Back Right – BR), Bladder 3 (Front Left - FL), Bladder 4 (Front Right - FR), Bladder 5 (Up Left – UL), Bladder 6 (Up Right – UR), Bladder 7 (Down Left – DL) and Bladder 8 (Down Right – DR).

In this work we integrate Fuzzy Logic to the existing Neural Network-based Algorithm to classify the transition between postures and intermediate postures that cannot be accurately classified using the previously developed algorithms.

2 EXPERIMENTAL SECTION

2.1 Equipment

In a previous work, a chair prototype was built with a 2-by-2 matrix of air bladders (see Figure 1-A). Each individual air bladder was made with thermoplastic polyurethane, were manually sealed and had 20x19cm of dimensions and were placed in the seat pan and the backrest (as can be seen in figure 1). This arrangement cover the most important and distinguishable areas of the seated posture (Pynt et al., 2001), such as the ischial tuberosities, the posterior thigh region, the lumbar region of the spine and the scapula (Martins et al., 2014).

For this project we started by projecting a new set of air bladders that were industrially made (this makes a big difference as it is guaranteed that the volume inside each bladder is the same when they are fully inflated) and integrated in a different office chair (seen in Figure 1-B). The new bladder system and its measurements can be seen in figure 1-C. The bladder placement had the same strategy of the previous work. The original padding foam was also used, and placed above the pressure bladders, in order to keep the original anatomical cut of the seat pad and backrest. As it is guaranteed that each bladder has exactly the same geometry, in this case we also used the same pressure sensors for the backrest and seatpad (in the previous work, the sensors were different), which were the Honeywell 24PC Series piezoelectric gauge pressure sensor, with a max rate of 15 psi, with a sensitivity of 15mV/psi. The values of x_1, x_2, z_1, z_2 correspond to around 10.5 cm and y_1, y_2, y_3, y_4 to around 8.5 cm. This values is calculated by halving the bladders sizes (20.5 and 16.5), adding half of the 10 mm spacing between each bladder, and make rounding adjustments due to the curvature of the bladders.

Bluetooth communication was also added to this prototype, as in the previous prototype, making it capable of transferring the daily postural information to computers and smartphones, allowing a statistical analysis of the postures taken during the day (Martins et al., 2014).

2.2 Experimental Procedure and Participants

Two experiments were done for this work. The first one (A) followed a similar protocol then in the previous work (Martins et al., 2014) and served for data acquisition in order to create the Seated Posture Classification Algorithms, based on Neural Networks. The second experiment (B) was used to study how the Neural Network behaves during standard posture changes (in intermediate postures).

From the previous experiments (Martins et al., 2014) we increased the number of subjects from 30 to 50, and also tried to have more indicative sample of office workers (increasing the Age of the participants from around 21 to 26). The dataset for both experiments is presented in Table 1. Based on the knowledge from previous experiments (Martins et al., 2014) and since now the bladders have exactly the same volume, we inflated all the bladders for 5 seconds (instead of having different inflation times for each bladder) so we could take precise reading of the bladder interior pressure, but not enough to originate discomfort to the users. Before the experiment, the participants were asked to empty their pockets and to adjust the stool height to the popliteal height.

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]*
Experiment A			
50 (25/25)	26,4±9,9	66,8±12,1	170,9±10,0
Experiment B			
12 (6/6)	25,8±6,6	72,8±12,1	173,1±10,7

For the first experiment, we used a similar protocol then the previous work (Martins et al., 2014), and showed a presentation of postures P1 to P6 (as can be seen in figure 2), each for a duration of 20 seconds. First we asked the participants to mimic the postures without leaving the chair. Then we asked them to repeat the same postures two more times, but after every postural change we asked the participant to walk out of the chair and move to a certain point in the room and sit back again. The chosen postures were the same as the previous work (Martins et al., 2014), which were based on the most familiar postures observed in office environments (Zhu et al., 2003; Forlizzi et al., 2005; Tan et al., 2001; Zheng and Morrell, 2010; Mutlu et al., 2007; Vergara and Page, 2000)

Figure 2: Seated postures used in the experiments and respective class label: (P1) seated upright, (P2) leaning forward, (P3) leaning back, (P4) leaning back with no lumbar support, (P5) leaning right, (P6) leaning left.

As in previous work, on experiment A we also didn't use the entire 20 seconds of acquired data, because when a user changes its posture, the sensed pressure values oscillate (Transition zone) and then stabilize (Stable zone) as shown in figure 3. The chosen data to be used as input was extracted only from the Stable zone.

Here, using a sampling rate of 8 Hz (which is enough to classify sitting posture behaviour), we took 100 time-points (which correspond to 12.5 seconds out of 20 for each posture), and divided them in groups of 20 pressure acquisition. Each group was averaged, forming 5 pressure maps that serve as input to the Neural Networks, contributing to a total of 4500 pressure maps (50 participants * 6 postures * 5 averages * 3 repetitions).

For experiment B, we wanted to see how the Neural Network algorithm worked during the Transition zone (see figure 4) between Posture P1 and other Postures (which for this first experiment is only done to P5 and P6). For this, we asked the participants to move from P1 to P5, back to P1, then move to P6 and back to P1 (and repeat this 5 times). We observed that during a postural transition, the classification was intermittent (this corresponds to the Transition Zone identified in Figure 4). So for this experiment we took a picture when the ANN algorithm first changed its value (entering the Transition Zone), and a second picture when the algorithm kept giving the right answer (entering the Stable Zone) The observed results from the influence of the lateral angle in the Neural Network, prompted the integration of Fuzzy Logic to cope with the instability of the Neural Network.

2.3 Classification Methods

Artificial neural network-based classification algorithms have been shown to be useful in many engineering and biomedical applications (Paliwal and Kumar, 2009). In the previous work we have used them and since they show the ability to handle very well our multiclass problem, we took the decision to continue using them. They also have the advantage of being easily implemented in other systems (by importing the weights and bias matrices).

For the parameterization of the ANN, we tested again the same parameters as in the previous work, by making combinations of layers, neurons, training and transfer functions (Martins et al., 2014).

Fuzzy logic and specially Neuro-fuzzy

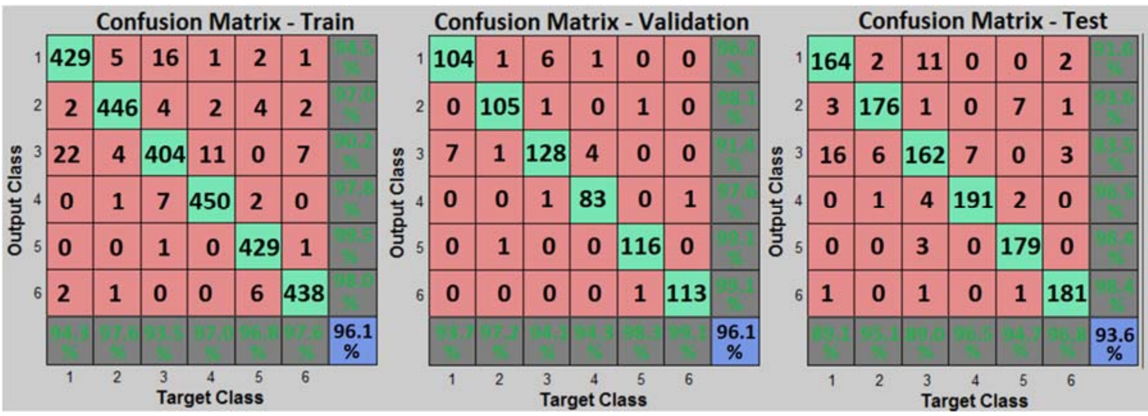

Figure 3: Confusion matrices for the training data (left matrix - corresponding to 60% of the total data), validation data (centre matrix – 15 % of data), and testing data (left matrix – 25% of data).

integrations have also been used in many engineering and biomedical applications (Kar et al., 2014). Here we use as input variables for the Neuro-fuzzy algorithm, the Centre of Pressure (COP) of the seat pad and backrest (which are calculated based on equations 1-4 and figure 1), the posture output from the Neural Network and the time spent in that output posture. This algorithm evaluates the posture each 15 minutes.

$$x_{seat} = \frac{(P_2 + P_4) \times x_1 + (P_1 + P_3) \times x_2}{\sum_{i=1}^{4} P_i} \quad (1)$$

$$y_{seat} = \frac{(P_1 + P_2) \times y_1 + (P_3 + P_4) \times y_2}{\sum_{i=1}^{4} P_i} \quad (2)$$

$$y_{back} = \frac{(P_6 + P_8) \times y_3 + (P_5 + P_7) \times y_4}{\sum_{i=5}^{8} P_i} \quad (3)$$

$$z_{back} = \frac{(P_5 + P_6) \times z_1 + (P_7 + P_8) \times z_2}{\sum_{i=5}^{8} P_i} \quad (4)$$

3 RESULTS AND DISCUSSION

3.1 Results from Experiment A

As in the previous study, the best result was again using the Resilient-back Propagation algorithm, with the tansig function, but now with 1 layers of 40 neurons (comparing with the 1 layer of 15 neurons from the previous work). This result shows that our new bladder system changed slightly the pressure maps, which influenced how the classification algorithms adapted. The confusion matrix for the training, validation and testing data, using the best parameters is shown in figure 3.

3.2 Results from Experiment B

For experiment B, first we studied how the lateral angle influenced the classification algorithm. Figure 4 shows one cycle of this experiment, where it shows the Transition Zones between postures. To calculate the angle where these transitions occur, we took a picture of the participants every time they entered into a new Zone, and then measured the trunk inclination in Position P1 (for reference) and the trunk inclination in the other positions. In order to include the variability among raters this measurements were done by 3 different experts, so we also calculated the degree of reliability among raters by using two way Intra Class Correlation (ICC) for each Angle measurement (Fleiss., 1986a).

The average, standard deviation values of each Transition Angle and the ICC score are presented in Table 2. For the first Transition, we identified an average angle of 11.0º (for P5) and 13.5º (for P6), and for the second Transition we identified an angle of 17.6º and 20.0º, respectively for P5 and P6. This

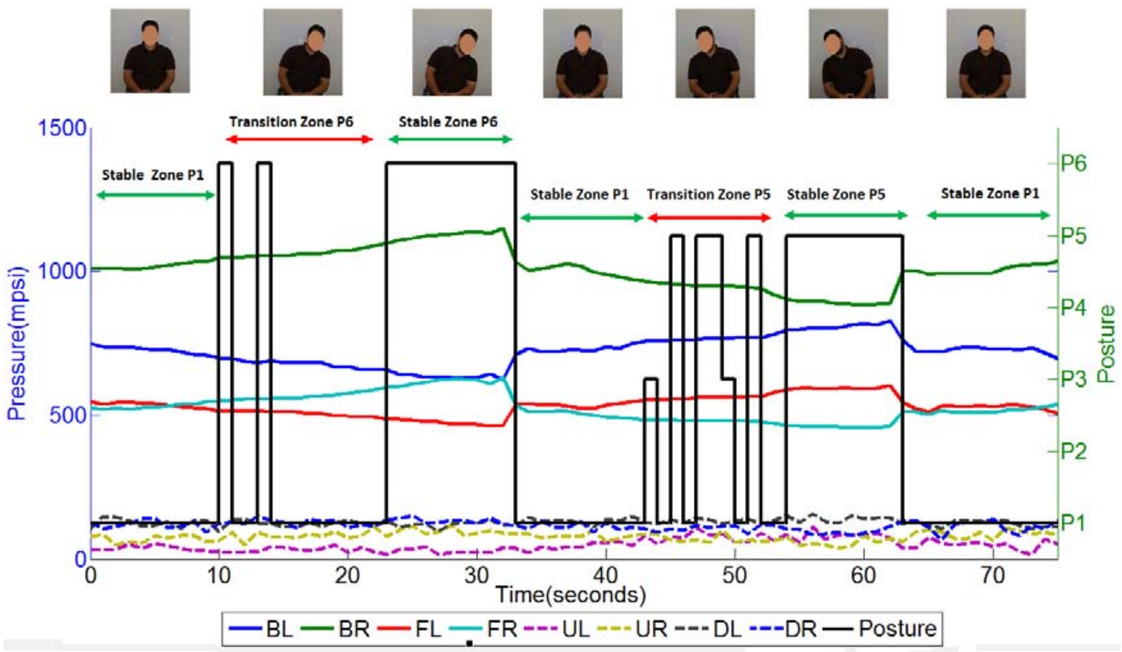

Figure 4: Example the pressure map for one cycle of Experiment B. The transition from a Stable Zone in P1 to a Stable Zone in P6 (in green arrows) and then P1 to P5 goes through a Transition Zone (in red arrow), where the classification is intermittent. Legend of each bladder is according to figure 1.

values are in good agreement with the identification of a lateral trunk bending angle, which has normally been defined at 15º (Hobson, 1992). This angle is in our Transition Zone, where we are able to classify as a lateral bending posture (P5 or P6), but there are also mistakes with other postures, due to shear movement (P3 and P1). The ICC values show that the angles measured by each expert rater have good reliability (values between 0.5 and 0.75 have a good reliability, and higher than 0.75 have an excellent reliability), validating our measurements (Fleiss., 1986b).

We use a two-sample Kolmogorov-Smirnov (KS) test, to check if the P5 and P6 angles have of each subject have the same distribution. Table 2 shows the results of the KS tests for each Transition and for each subject at a 1% significance level.

Table 2: Measurement of the lateral angle when the Transition Zone if identified from P1 to the respective Posture, and when the angle when the Stable Zone is identified of the respective Posture.

Subject	1st – P5 (/º)	2nd – P5 (/º)	1st – P6 (/º)	2nd – P6 (/º)
1	10.7±2.2	17.5±2.6	12.9±3.4	20.6±2.4
2	6.5±0.7	11.8±1.1	6.7±1.2	11.4±1.0
3	13.5±2.4	19.6±2.7	16.7±3.6	23.9±2.2
4	8.4±1.4	15.1±1.9	9.2±1.1	14.0±1.6
5	11.6±3.4	22.2±2.9	13.9±3.0	25.7±6.0
6	12.9±2.2	21.4±2.5	17.3±3.5	22.9±5.0
7	16.2±3.6	23.2±2.5	26.7±4.3	35.5±3.3
8	11.3±1.4	17.2±1.6	10.4±1.5	16.8±2.4
9	7.4±1.7	12.9±2.7	10.4±1.6	15.2±1.8
10	11.5±1.4	17.3±2.3	11.5±1.4	17.2±2.1
11	12.0±2.0	16.8±2.4	12.8±1.8	18.1±2.7
12	10.5±2.6	16.6±1.7	13.7±2.3	18.7±2.9
Average	11.0±3.4	17.6±4.0	13.5±5.5	20.0±6.9
ICC	0.53	0.74	0.77	0.70

From these results we can see that participant 7 had both of their angle measurements rejected (and we can easily see that the right and left angles are quite different (16.2 compared to 26.7 and 23.2 compared to 35.5). This can happen because participant 7 was the person with the lowest height and weight (1.58 m and 48 kg respectively), and the classification algorithm can have problems with persons with anthropometric data far from the average population. This can also happen when the participant doesn't seat symmetrically compared to the air bladders in posture P1 or they move their pelvis during posture transitions. There were 2 other measurements that were rejected (participant 6 – test 1 and participant 3 - test 2), which means that the classification system can have a small bias to one of the lateral sides. In the Stable Zone during posture P5/P6, the ANN classification algorithm does not differentiate between smaller lateral flexion and larger flexion (e.g. 20º compared to 35º), as the output of the ANN is the same for these postures. We implement Fuzzy Logic to differentiate between these types of postures and also integrate the adopted time in each sitting posture.

Table 3: Two-sample KS test at a 1% significance level. Test 1 checks the null hypothesis that the data from the 1st angles of P5 and P6 are from the same distribution. Test 2 checks the null hypothesis for the 2nd angles.

Subject	Test 1	p-value	Test 2	p-value
1	0	1.6786e-02	0	1.6786e-02
2	0	3.0794e-01	0	8.8990e-01
3	0	5.1467e-02	1	2.3766e-04
4	0	5.8861e-02	0	1.3586e-01
5	0	1.6786e-02	0	5.1467e-02
6	1	4.7152e-03	0	3.0794e-01
7	1	8.7713e-07	1	1.0054e-07
8	0	1.3586e-01	0	5.8861e-01
9	0	5.1467e-02	0	5.1467e-02
10	0	9.9832e-01	0	9.9832e-01
11	0	8.8990e-01	0	3.0794e-01
12	0	5.1467e-02	0	1.6786e-02

4 CLASSIFICATION BY FUZZY LOGIC

To develop the fuzzy logic algorithm, we created membership functions (shown in figure 5) dependent on the COP of the backrest and seatpad and the time spent in each posture. The set of rules are presented in Table 4. The max time for the time function is 900 seconds (15 minutes), as we will evaluate the sitting posture every 15 minutes. The interval for each time membership function is based on ISO standards for trunk inclination (Standardization, 2000), although those values are for standing postures instead of sitting postures, so they were increased accordingly. The maximum values for the Centre of Pressure were previously mentioned and are shown in figure 1-C. As an example, if in 15 minutes, the user was found to have been in two postures P3 and P6 (respectively for 360 and 540 seconds), with an average value for the COPx_seat, COPy_seat, COPy_back, COPz_back respectively of [2.38; -1.76; 1.22; -2.17] cm for P3 and [-5.61; -1.68; -2.97; -4.48] cm for P6. Using the MATLAB© Fuzzy Logic Toolbox and the Mamdani Centre of Gravity Defuzzification algorithm (Mamdani E. H., 1974), we can reach a value of 0.354 and 0.443 (for

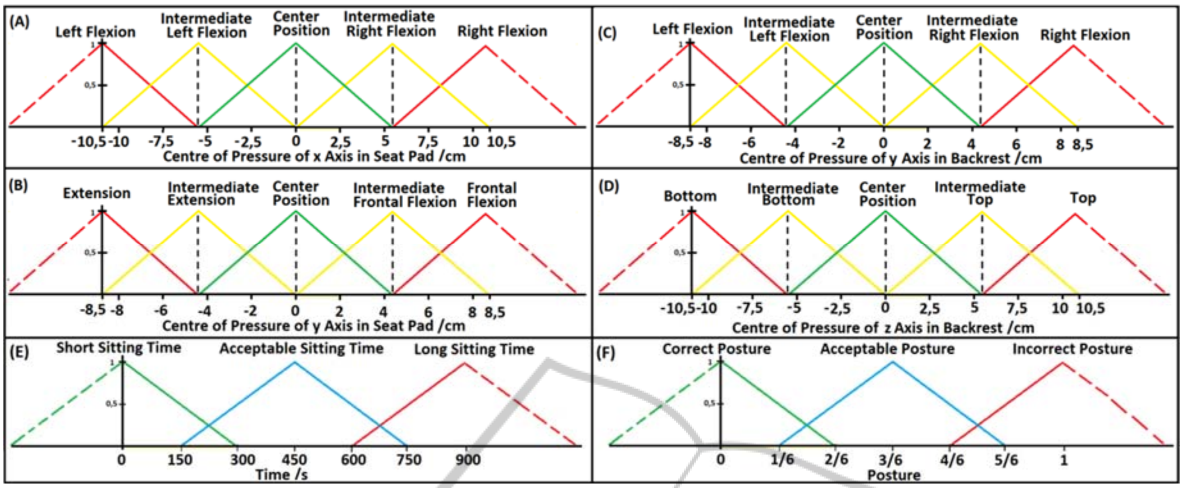

Figure 5: Membership functions of the fuzzy logic algorithm. Dashed lines represent values that are not possible to attain, but we use a full triangle function to avoid asymmetric distributions. (A), (B), (C), (D) and (E) represent the antecedent membership functions and (F) represents the consequent membership functions.

Table 4: Set of rules for the Fuzzy Logic Algorithm.

IF (Time = Long) THEN (Posture = Incorrect)
IF (Time = Short) OR (Cxh OR Cxv OR Czv OR Cyh = Center THEN (Posture = Correct)
IF (Cxh = Right flexion) OR (Cyh = Frontal Flexion) THEN (Posture = Incorrect)
IF (Cxv = Right flexion) OR (Czv = Top) THEN (Posture = Incorrect)
IF (Cxh = Left flexion) OR (Cyh = Extension) THEN (Posture = Incorrect)
IF (Cxv = Left flexion) OR (Czv =Bottom) THEN (Posture = Incorrect)
IF (Cxh = Int. Right Flexion) OR (Cyh = Int. Frontal Flexion)) AND (Time = Long) THEN (Posture = Incorrect)
IF ((Cxv = Int. Right Flexion) OR (Czv = Int. Top)) AND (Time = Long) THEN (Posture = Incorrect)
IF ((Cxh = Int. Left Flexion) OR (Cyh = Int. Extension)) AND (Time = Long) THEN (Posture = Incorrect)
IF ((Cxv = Int. Left Flexion) OR (Czv = Int. Bottom)) AND (Time = Long) THEN (Posture = Incorrect)
IF (Cxh = Int. Right Flexion) OR (Cyh = Int. Frontal Flexion)) AND (Time = Accept.) THEN (Posture = Incorrect)
IF ((Cxv = Int. Right Flexion) OR (Czv = Int. Top)) AND (Time = Accept.) THEN (Posture = Accept.)
IF ((Cxh = Int. Left Flexion) OR (Cyh = Int. Extension)) AND (Time = Accept.) THEN (Posture = Accept.)
IF ((Cxv = Int. Left Flexion) OR (Czv = Int. Bottom)) AND (Time = Accept.) THEN (Posture = Accept.)

P3 and P6 respectively). Using these values, we can now try to implement a fuzzy logic actuator system to inflate and deflate specific air bladders depending on the detected postures.

5 CONCLUSIONS AND FUTURE WORK

In a previous work, a chair prototype was used to classify 11 standardized seating postures of users, using 8 air bladders (4 in the chair's seat and 4 in the backrest). Here we showed that using industrialized air bladders, improved the stability of the previously developed Posture Classification Algorithm, which was based on Neural Networks integrated with Decision Trees. One of the identified gaps in that system was the classification behaviour in intermediate postures or during posture changing, as the previous classification was only made in a so called "stable zone".

In this paper we studied how the classification algorithm handled lateral postural changes, and identified a stability and instability zones. During lateral flexion, the stability zone was found to be around an interval of 9º, between 11º and 20º. After 20º, the ANN algorithm is stable in classifying the lateral flexion postures. To differentiate between intermediate trunk flexion and extension we devise an approach based on integrating Fuzzy logic into the existing Neural Network-based Classification Algorithm that was capable of classifying 6 standard sitting positions

For future work we will need to check the influence of the angle in frontal flexion and during trunk extension, and lateral flexion during leg crossing positions. Based on the output of the

Neuro-fuzzy classification algorithm we will devise a Fuzzy actuation system to create a new Posture Correction algorithm, since the previous algorithm is based on simple Boolean logic (Martins et al., 2014).

ACKNOWLEDGEMENTS

This project (QREN 13330 – SYPEC) is supported by FEDER, QREN – Quadro de Referência Estratégico Nacional, Portugal 07/13 and PORLisboa – Programa Operacional Regional de Lisboa. The authors wish to thank Eng. Pedro Duque, Eng. Rui Lucena, Eng. João Belo and Eng. Marcelo Santos for the help provided in the construction of the first prototype.

REFERENCES

Adams, M. & Hutton, W., 1986. The effect of posture on diffusion into lumbar intervertebral discs. *Journal of anatomy*, 147, pp.121–34.

Ariëns, G.A. et al., 2001. Are neck flexion, neck rotation, and sitting at work risk factors for neck pain? Results of a prospective cohort study. *Occupational and environmental medicine*, 58(3), pp.200–7.

Cagnie, B. et al., 2007. Individual and work related risk factors for neck pain among office workers : a cross sectional study. *European Spine Journal*, 16(5), pp.679–686.

Chau, J.Y. et al., 2010. Are workplace interventions to reduce sitting effective ? A systematic review. *Preventive Medicine*, 51(5), pp.352–356.

Claus, A.P. et al., 2009. Is " ideal " sitting posture real ?: Measurement of spinal curves in four sitting postures. *Manual Therapy*, 14(4), pp.404–408.

Van Dieën, J.H., De Looze, M.P. & Hermans, V., 2001. Effects of dynamic office chairs on trunk kinematics, trunk extensor EMG and spinal shrinkage. *Ergonomics*, 44(7), pp.739–750.

Edmondston, S.J. et al., 2007. Postural neck pain : An investigation of habitual sitting posture , perception of " good " posture and cervicothoracic kinaesthesia. *Manual Therapy*, 12(4), pp.363–371.

Ellegast, R.P. et al., 2012. Comparison of four specific dynamic office chairs with a conventional office chair: impact upon muscle activation, physical activity and posture. *Applied ergonomics*, 43(2), pp.296–307.

Fleiss., J.L., 1986a. Reliability of Measurement. In *The design and analysis of clinical experiments*. pp. 1–32.

Fleiss., J.L., 1986b. Reliability of Measurement. In *The design and analysis of clinical experiments*. pp. 1–32.

Forlizzi, J. et al., 2005. The SenseChair : The lounge chair as an intelligent assistive device for elders. In *DUX '05 Proceedings of the 2005 conference on Designing for User eXperience*. p. Article No. 31.

Hartvigsen, J. et al., 2000. Is sitting-while-at-work associated with low back pain? A systematic , critical literature review. *Scand J Public Health*, 28(3), pp.230–239.

Hobson, D.A., 1992. Comparative effects of posture on pressure and shear at the body-seat interface. *The Journal of Rehabilitation Research and Development*, 29(4), p.21.

Juul-Kristensen, B. et al., 2004. Computer users' risk factors for developing shoulder, elbow and back symptoms. *Scandinavian Journal of Work, Environment & Health*, 30(5), pp.390–398.

Kar, S., Das, S. & Ghosh, P.K., 2014. Applications of neuro fuzzy systems: A brief review and future outline. *Applied Soft Computing*, 15, pp.243–259.

Kingma, I. et al., 2000. Monitoring water content in deforming intervertebral disc tissue by finite element analysis of MRI data. *Magnetic Resonance in Medicine*, 44(4), pp.650–4.

Lis, A.M. et al., 2007. Association between sitting and occupational LBP. *European Spine Journal*, 16(2), pp.283–298.

Mamdani E. H., 1974. Control & Science Application of fuzzy algorithms for control of simple dynamic plant. *Electrical Engineers, Proceedings of the Institution of*, 121(12), pp.1585–1588.

Martins, L. et al., 2014. Intelligent Chair Sensor: Classification and Correction of Sitting Posture. *International Journal of System Dynamics Applications*, 3(2), pp.65–80.

Mutlu, B. et al., 2007. Robust , Low-cost , Non-intrusive Sensing and Recognition of Seated Postures. In *UIST '07 Proceedings of the 20th annual ACM symposium on User interface software and technology*. pp. 149–158.

O'Sullivan, K. et al., 2010. Neutral lumbar spine sitting posture in pain-free subjects. *Manual Therapy*, 15(6), pp.557–561.

O'Sullivan, K. et al., 2012. What do physiotherapists consider to be the best sitting spinal posture? *Manual therapy*, 17(5), pp.432–7.

Owen, N. et al., 2011. Adults' sedentary behavior determinants and interventions. *American journal of preventive medicine*, 41(2), pp.189–96.

Paliwal, M. & Kumar, U. a., 2009. Neural networks and statistical techniques: A review of applications. *Expert Systems with Applications*, 36(1), pp.2–17.

Palumbo, F. et al., 2014. Sensor network infrastructure for a home care monitoring system. *Sensors (Basel, Switzerland)*, 14(3), pp.3833–60.

Punnett, L. & Wegman, D.H., 2004. Work-related musculoskeletal disorders: the epidemiologic evidence and the debate. *Journal of Electromyography and Kinesiology*, 14(1), pp.13–23.

Pynt, J., Higgs, J. & Mackey, M., 2001. Seeking the optimal posture of the seated lumbar spine. *Physiotherapy Theory and Practice*, 17(1), pp.5–21.

Ramdan, N.S.A. et al., 2014. On Lower-back Pain and Its Consequence to Productivity. *Journal of Industrial and Intelligent Information*, 2(2), pp.83–87.

Roffey, D.M. et al., 2010. Causal assessment of occupational sitting and low back pain: results of a systematic review. *The spine journal : official journal of the North American Spine Society*, 10(3), pp.252–61.

Schrempf, A. et al., 2011. PostureCare - Towards a novel system for posture monitoring and guidance. In *18th World Congress of the International Federation of Automatic Control (IFAC)*. pp. 593–598.

Standardization, I.O. for, 2000. Ergonomics—Evaluation of static working postures. , 2000, pp.1–26.

Tan, H.Z. et al., 2001. A Sensing Chair Using Pressure Distribution Sensors. *IEEE/ASME TRANSACTIONS ON MECHATRONICS*, 6(3), pp.261–268.

Todd, A.I., Bennett, A.I. & Christie., C.J., 2007. Physical implications of prolonged sitting in a confined posture-A literature review. *Ergonomics SA: Journal of the Ergonomics Society of South Africa: Special Edition*, 19(2), pp.7–21.

Vergara, M. & Page, A., 2000. System to measure the use of the backrest in sitting-posture office tasks. *Applied Ergonomics*, 31(3), pp.247–254.

Zheng, Y. & Morrell, J., 2010. A Vibrotactile Feedback Approach to Posture Guidance. In *IEEE Haptics Symposium*. pp. 351–358.

Zhu, M., Mart, A.M. & Tan, H.Z., 2003. Template-based Recognition of Static Sitting Postures. In *Proceedings of The Workshop on Computer Vision and Pattern Recognition for Human Computer Interaction, held at the IEEE Conference on Computer Vision and Pattern Recognition (CVPR03), IEEE Computer Society, Madison, Wisconsin*. pp. 1–6.