Flexible Force Sensors Embedded in Office Chair for Monitoring of Sitting Postures

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I. Summary And Motivation

Six flexible force sensors, two on the backrest and four on the seat, were embedded in the upholstery of an off-the-shelf office chair to enable non-intrusive monitoring of sitting postures. Besides the sensors, the monitoring platform comprises an Arduino Nano microcontroller with Wi-Fi transmitter, embedded on the chair, a Wi-Fi receiver communicating with a remote server and a Graphical User Interface (GUI) showing real-time readings. Approximately 26,000 observations corresponding to 9 different postures were collected, labelled and classified using supervised machine learning. The results show that only a subset of the 6 sensors is needed for predicting these 9 sitting postures with high accuracy. This opens up the possibility for intelligent, real-time monitoring systems that can improve safety and wellbeing of today's office workers.

II. Advances over Previous Works

Posture detection using sensors can become an effective tool in preventing musculoskeletal disorders [1] and improving the safety, wellbeing and comfort of modern-day office workers. To date the detection of sitting postures has primarily pursued two approaches: (a) the sensors were embedded in a cushion placed on a seat of the chair [2,3] and (b) the sensors were attached to a chair or a user [4,5,6]. The embedded approaches tend to use a large number of flexible sensors (8x8 in [2] and 42x48 in [3]), while the attachment of discrete sensors to the user or the outside of the chair permitted wider spectrum of sensors, e.g. accelerometers [4-6]. Textile-based capacitive pressure sensors fabricated using conducting threads have also been reported (16x16 sensors in [7] and 240 sensors in [8]).

Machine learning has been used in [2,3,6-8] for posture classification. In [2], Support Vector Machine (SVM) is used to classify 9 postures, yielding 93-99% accuracy. Principal Component Analysis is used in [3] to classify 14 postures and yielding 79-96% accuracy. [6] used Random Forest algorithm (RF) to classify 18 postures, yielding 80% accuracy. In [7], a Dynamic Time Warping based approach is used to classify 7 postures, yielding accuracy of 79-92%. In [8], Naïve Bayes is used to classify 16 postures with up to 84% accuracy. However, all above mentioned approaches reported a small set of experiments.

This paper focuses on a development of the smart chair by adding 'intelligence' to an off-the-shelf office chair. The chair

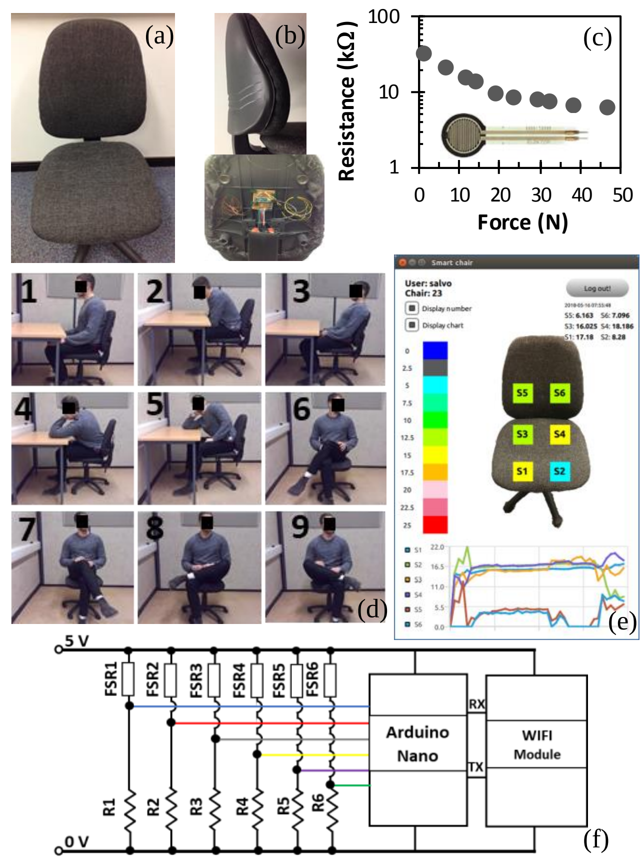

Fig. 1: The front (a) and back, closed and open, (b) of the smart chair; response of the flexible force sensor (c); tested sitting postures (d); part of the graphical user interface (e); and system diagram (f).

has 6 flexible force sensors embedded in its upholstery and can sense the presence of a sitting person and provide real-time sensor readings and a heat map of the force distribution to its user. Our proposed design benefits from simplicity and necessity for only a subset of these 6 sensors, enabled by robust machine learning classification and rigorous testing on ~26,000 observations. We assessed the effectiveness of the Naïve Bayes, SVM and RF algorithms.

III. Results and Methodology

A. *Smart chair system for office environment*

The creation of the smart chair (Figs. 1(a) and 1(b)) was divided into three parts, i.e. sensor placement (Fig. 1(e)) and data logging electronics (Figs. 1(b) and 1(f)), graphical user interface (GUI) (Fig. 1(e)) and communication with the server, and data collection and posture (Fig. 1(d)) classification. The chair design uses 6 resistive sensors (FSR402, Interlink Electronics), that exhibit a decrease in resistance with increasing applied force (Fig. 1(c)). The sensor placement was determined using anthropometric sitting measurements and thus 4 sensors were embedded in the seat (S1-S4) and 2 in the backrest (S5-S6). An Arduino Nano with ATMEGA 328p microcontroller was used for signal conditioning, ESP8266 Wi-Fi module for transmitting the data between micro-controller and server, and a 5 V rechargeable battery for powering the chair electronics, all enclosed within the back cover of the chair. The data from the smart chair is managed using one Linux server with MYSQL, php and Apache databases. The server connects users with optional number of smart chairs using wireless pairing through the custom-designed GUI. The GUI provides the users with full access to their real-time and previously stored data using login credentials and chair identification number. Three forms of real-time data representation can be accessed by the user, i.e. numerical and graphical sensor values and a heat map of the force distribution, i.e. deviation from the ideal sitting posture.

B. Posture data collection and classification

Predefined sitting postures were identified as shown in Fig. 1(d). The selected postures are – the recommended upright posture (1), leaning forward (2), slouching back (3), leaning left with left elbow on desk (4), leaning right with right elbow on desk (5), female-style sitting with left (6) or right (7) leg crossed, and male-style sitting with left (8) or right (9) leg crossed. This is in line with similar studies [2,7,8].

In the first set of experiments (data set of 64×9×40) each of the 9 postures was measured for 1 minute and produced 40 measured values. This set of experiments was very rigorous to avoid any noise in the data. In the second set of experiments (data set of 10×9×30) more movement was allowed during and in-between postures to capture more realistic conditions. Each posture was held for 2 minutes, producing 30 measurements. Finally, the large number of observations/ measurements collected in varied conditions assured that any time drift or hysteresis in the sensor response was captured.

Three classification algorithms including Naïve Bayes, SVM and Random Forest were used to determine the most suitable method for the sitting posture detection using the designed smart chair. Table 1 shows a comparison of the accuracy and fitting time of the three techniques employed when all ~26,000 observations were used. The accuracy is reported using the cross-validation measure. The results are shown for generalized learning, when training and testing are performed on the entire dataset. 75% of data was used for training and the rest for testing. The results identified Random Forest as the most suitable technique with 97% accuracy and fitting time of 0.35 s, followed by SVM with 77% and 0.37 s respectively. Finally, while Naïve Bayes displayed the fastest fitting time, the accuracy was the lowest with only 51%.

The next experiment was carried out using only the second dataset and RF algorithm. The training/testing was 70/30 and accuracy of 94% was achieved. The slight decrease in accuracy is a result of the intentionally induced noise in the dataset by relaxing the test conditions.

TABLE I. ACCURACY AND FITTING TIME COMPARISON OF THREE CLASSFIERS

Classifiers	**Accuracy (%)**	**Fitting time (s)**
Naïve Bayes	51	0.0036
SVM	77	0.37
Random forest (RF)	97	0.35

The optimal performance of the RF classifier was achieved by tuning its parameters. They include the number of estimators (trees), maximum depth, and a number of features. The performance of the algorithm was the most significantly affected by the number of trees that was subsequently used to calculate the accuracy and fitting time. The optimal number of trees results in the best possible accuracy without severely increasing the fitting time. Figure 2 shows the saturation behavior of the accuracy (Fig. 2(a)) and the linear dependence of the fitting time (Fig. 2(b)) on the number of trees. From the plots the optimal number of trees was determined to be 20.

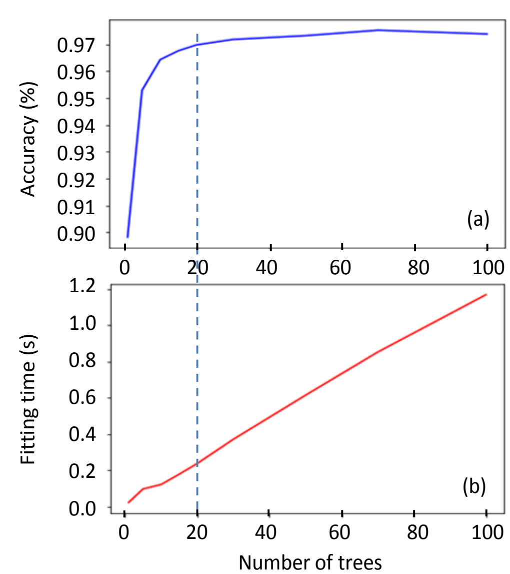

Fig. 2: Accuracy (a) and fitting time (b) for random forest algorithm.

Finally, an investigation was carried out on the significance of individual sensors in the RF decision making and the resulting accuracy. The results showed that sensor S2 (see Fig. 1(e)) had the greatest significance, closely followed by S1, then S3, S4, S5, and S6. Three combinations of sensors were used to measure the effect of the decreasing number of sensors on the accuracy. The results showed an accuracy of 94.5% when only the seat sensors (S1-S4) were used, 89% when S1, S2 and S3 were used, and 65% when only S1 and S2 were used.

ACKNOWLEDGMENT

This project has received funding from the European Union’s Horizon 2020 research and innovation program under the Marie Skłodowska-Curie grant agreement No 734331.

REFERENCES

[1] Haynes, S., & Williams, K. (2008). Impact of seating posture on user comfort and typing performance for people with chronic low back pain. *International Journal of Industrial Ergonomics*, *38*(1), 35-46.

[2] Kamiya, K., Kudo, M., Nonaka, H., & Toyama, J. (2008, December). Sitting posture analysis by pressure sensors. In *2008 19th International Conference on Pattern Recognition*(pp. 1-4). IEEE.

[3] Tan, H. Z., Slivovsky, L. A., & Pentland, A. (2001). A sensing chair using pressure distribution sensors. *IEEE/ASME Transactions On Mechatronics*, *6*(3), 261-268.

[4] Nevins, R. J., Durdle, N. G., & Raso, V. J. (2002). A posture monitoring system using accelerometers. In *IEEE CCECE2002. Canadian Conference on Electrical and Computer Engineering. Conference Proceedings (Cat. No. 02CH37373)* (Vol. 2, pp. 1087-1092). IEEE.

[5] Wong, W. Y., & Wong, M. S. (2008). Detecting spinal posture change in sitting positions with tri-axial accelerometers. *Gait & Posture*, *27*(1), 168-171.

[6] Otoda, Y., Mizumoto, T., Arakawa, Y., Nakajima, C., Kohana, M., Uenishi, M., & Yasumoto, K. (2018, January). Census: Continuous posture sensing chair for office workers. In *2018 IEEE International Conference on Consumer Electronics (ICCE)* (pp. 1-2). IEEE.

[7] Xu, W., Li, Z., Huang, M. C., Amini, N., & Sarrafzadeh, M. (2011, May). eCushion: An eTextile device for sitting posture monitoring. In *2011 International Conference on Body Sensor Networks* (pp. 194-199). IEEE.

[8] Meyer, J., Arnrich, B., Schumm, J., & Troster, G. (2010). Design and modeling of a textile pressure sensor for sitting posture classification. *IEEE Sensors Journal*, *10*(8), 1391-1398.