The Smart Chair: A UbiComp Solution to the Sedentary Workplace

Anirban Mookherjee, John Cavalieri, Nicholas Conlon

I Problem Statement

Consequences of poor posture include a myriad of health issues [5]. Decreased range of motion due to muscle contraction can lead to muscle strain which can lead to soreness and increased fatigue. Spinal curvature, one of the most serious posture related issues, is caused when increased pressure (from slouching in a chair for example) influences the spine in such a way that it loses the signature “s” shape. This change in curvature can diminish the spine's ability to absorb shock, leading to many other health issues. A common issue related to poor posture is nerve constriction, more commonly known as pinched nerves. Nerve constriction occurs when pressure, for example from poor posture, is put on the nerves surrounding the spine. Since the spine is the nerve center for the majority of the body, this may even cause pain in totally unrelated areas.

A recent article [6] points to a statistic that 80% of jobs in the US are sedentary or require only light activity. This majority of the working population faces a daily battle against the health problems outlined previously, and with the future prospects on technology related jobs, this statistic will only rise. The health effects of poor posture not only affect the individual, but they put an unneeded burden on an already full healthcare system, reduce employee productiveness, and cost companies. For example, in 2013 almost 31 million days of work were lost due to posture and ergonomic related problems in the UK [7], a cost which is estimated at 240 billion euros a year!

Ubiquitous computing personal health technology and smart devices have been heavily researched in recent years, including “smart-chair” technology. This technology, which uses some set of sensors, actuators, and processing power to gather data from a sitting user, could be used to sense, give feedback, and ultimately prevent the enormous loss of personal health, productivity at work, and overall cost to the economy. In section II we discuss the related work in the area of smart chairs, both on the market and in the literature. In section III we propose an innovative extension to existing technology. In section IV we discuss our evaluation methodologies, and in section V we summarise our research.

II Related Works

There are relatively few existing smart chair solutions to sedentary behavior available on the market. One company providing a solution however, which we will focus on here, is BMA Ergonomics [1]. BMA Ergonomics is a Scandinavian ergonomic technology company, and the maker of the Axia Smart Office Chair. The Axia Smart Office Chairs acts as a personal posture coach, teaching a user proper posture through a system of monitoring and feedback. Sensors in the seat and back cushion monitor a user's posture, and if necessary, cue a user to incorrect sitting behavior through gentle vibrations in the chair. The Axia Smart Office Chair can also be paired with a phone application, which displays metrics from the previous 35 days. In addition, Axia offers a cloud service which can store longer periods of user data and share said data with management or medical professionals, for example. Later in this paper, we will use the Axia Smart Office Chair as a baseline on which to evaluate our solution against.

Though this technology has the possibility of providing health benefits to the user, there are also drawbacks. The chairs themselves are quite expensive, reaching over $1,100, which limits the number of users who can afford it. The technology is also not portable. For example, if a user spends long periods of time in multiple locations, they would need to purchase multiple chairs, or bring the chair from location to location, which is also prohibitive. The smart chair technology proposed in the paper however, aims to build on this technology with a portable, less cost prohibitive design.

There are a number of solutions proposed in the literature. The SenseLounger, proposed by Hurst et. al [2], presents an inexpensive prototype home smart chair. The authors affix a series of force sensors the different parts of the chair (slip cover and legs) in an initial attempt to bring assistive technology into homes of the elderly. They propose a smart slip cover, which provides a portable solution, and use a low power processor to read and log sensor data, for which visualization software can then be run over. This approach is evaluated qualitatively through user studies, and points toward future work incorporating machine learning in the smart chair.

In [8], the authors developed a chair cover consisting of an array of 240 textile pressure sensors. Textile pressure sensors are part of the textile and designed for simple integration into clothing and furniture. The textile sensor array is constructed with conductive textiles arranged on both sides of a compressible spacer; this configuration forms a variable capacitor that is capable of measuring the pressure exerted by the human body on the various regions of the chair cover. The sensor array has two main components--the textile sensors and measurement system. Data from the textile sensors is routed over conductive fabric to the measurement systems. The system in [8] was trained by recording sensor values for 16 sitting postures--each held for 30 seconds. Training conducted with 9 subjects over 3 rounds where each sitting posture is measured once within each round. The authors employed the Naive Bayes classifier with the following features: sensor values from each of 240 sensors, the center-of-force on the chair cover, and aggregate pressure applied to 4 and 16 equal areas of sensing mat; resulting in a total of 261 features. Using Sequential Forward Search algorithm, the K best features were identified according to leave-one-out cross validated classification accuracy. The SFS algorithm identified a subset of 12 of the 240 texture sensors, the X-coordinate of the center-of-force, and the pressure from just 1 of the 16 aggregate areas. The textile sensor array was evaluated by comparing LOO CV classification results to a commercially available pressure sensing mat and found a classification accuracy of 82 % for the 16 sitting postures.

Another approach for sitting posture classification is described in [9]. This system is more obtrusive than a sensing mat in that it requires the user to affix an accelerometer to the back of their neck. The system was trained on 6 subjects each holding one of five different sitting postures for 5 minutes. The accelerometer values from those 5 minutes formed a massive training set for each posture requiring a reduction in dimensionality. PCA was used to reduce the dimensionality of the dataset and construct feature vectors. The authors used two classification algorithms--SVM and K-Means. By using two different classification algorithms, the authors discovered that each algorithm had strengths and weaknesses for different sitting postures. Namely, SVM classification accuracy was higher for normal sitting posture, cross-leg posture, and leaning right whereas K-means was superior for classifying back-arch while sitting. Overall, the SVM achieved 95.33 % classification accuracy and K-means 89.35 %.

Yet another paper proposed a Capacitive Chair[4] - a regular office chair equipped with eight capacitive proximity sensors that is able to detect presence, posture, activity level and breathing rate of its occupants. The sensor system is invisibly integrated into the chair and uses variations of electric fields to determine the physiological data over a distance. It’s shown that a combination of different electrode materials and shapes, that are attached to a single evaluation board for capacitive proximity sensors, provide sufficient information about presence and proximity of occupants to gather physiological data. In user tests, the posture recognition achieved a very high overall classification rate of 98.6%.

A final literature worth mentioning proposed a posture sensing couch[3]. However, the posture information here is not used to correct posture but to enable implicit control of smart living room, such as turning on lights when the user sits down, turning on music when the user scoots back to get comfortable and checks phone and turning on the tv when the user leans back assuming a relaxed position. Regardless of the goal here, they were successful in determining user posture fairly accurately using a simple sensor setup. A total of six electrodes were attached to the couch. On both halves of the couch three electrodes are placed on the back rest, near the front edge, and towards the back. All electrodes are connected to an Arduino Uno in an RC network and each electrode's capacitance. They investigated six different seated postures and two lying down postures with various machine learning classifiers and finally obtained the best results with Naive Bayes with an accuracy of 92.9%.

The metrics to evaluate a given solution cover a wide variety of criteria, including cost, accuracy, durability, etc. Each metric is given a score of *HIGH*, *MEDIUM*, or *LOW* based on our research in the literature and on the market. We will use a similar set of metric to evaluate our proposed solution in section IV. Results of the competitive analysis can be seen in Table 1.

	Axia Chair	Capacitive Chair	Sense lounger	CapCouch
Cost	HIGH	MED	LOW	LOW
Accuracy	HIGH	MED	LOW	MED
Durability	HIGH	MED	HIGH	HIGH
Power	MED	MED	LOW	LOW
Portability	LOW	MED	HIGH	LOW
Size & Weight	HIGH	MED	LOW	LOW

Table 1: competative analysis table

III Proposed Solution

The proposed solution consists of three main components; (1) a smart office chair cover, (2) a phone application and (3) our software running on the user's desktop. First we will cover the chair cover, to include a parts list, and reasonings for each choice. After we will discuss the phone app and the benefits it provides.

Extending on previous work, the smart chair cover was designed with affordability and portability in mind. The cover itself is a piece of fabric, similar to a slipcover and can be seen in Figure 1. Velcro straps affix the cover to a chair. The cover has two columns of three pressure sensor, which when in use, will run along either side of a user's spine. The seat is also covered with a series of pressure sensors.The sensors along the spine will detect differences in pressure between columns (in the case of a user leaning), and differences between rows (in the case of a slouch), while the sensors along the seat will detect difference which could indicate poor leg position.

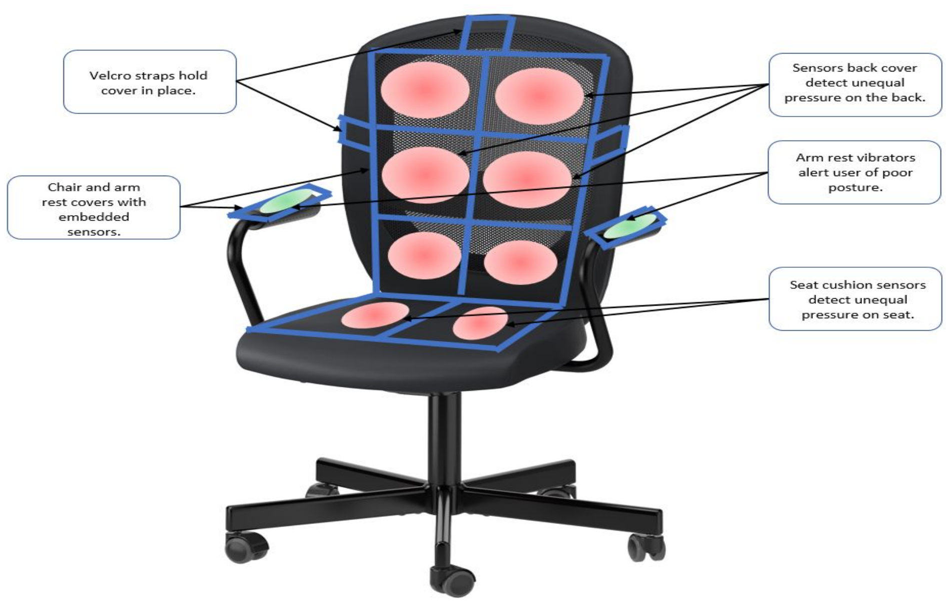


Figure 1: smart chair mockup

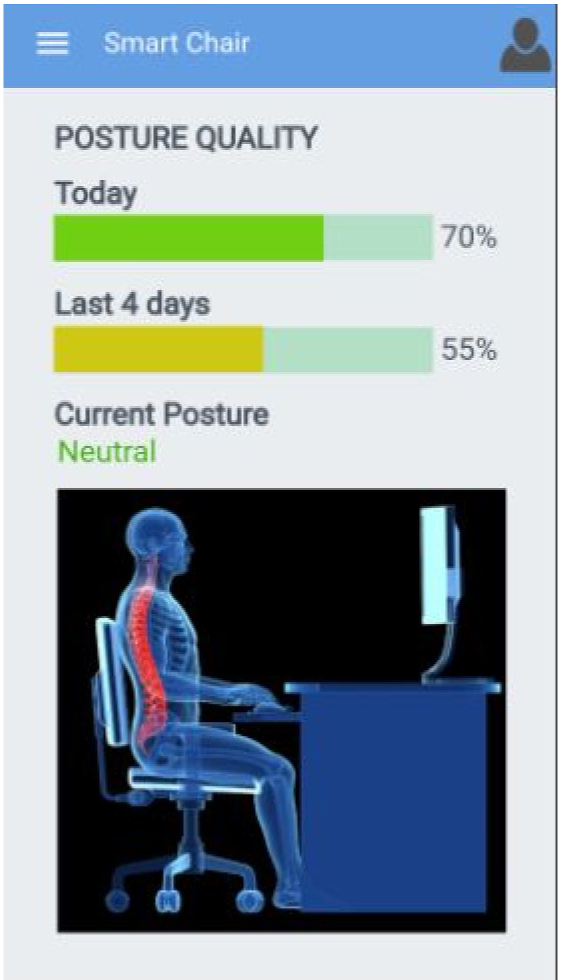
Hardware choices were made with SWaP (Size Weight and Power) considerations in mind, and a cost roll up can be seen in Table 2. Adafruit FSR pressure sensors were chosen due to their cost and affordability. The Arduino 101 a lightweight, low power development board with bluetooth connectivity was chosen for computation. It will be affixed behind the chair, out of the way of the user, and connect to the sensors via in-fabric wiring.

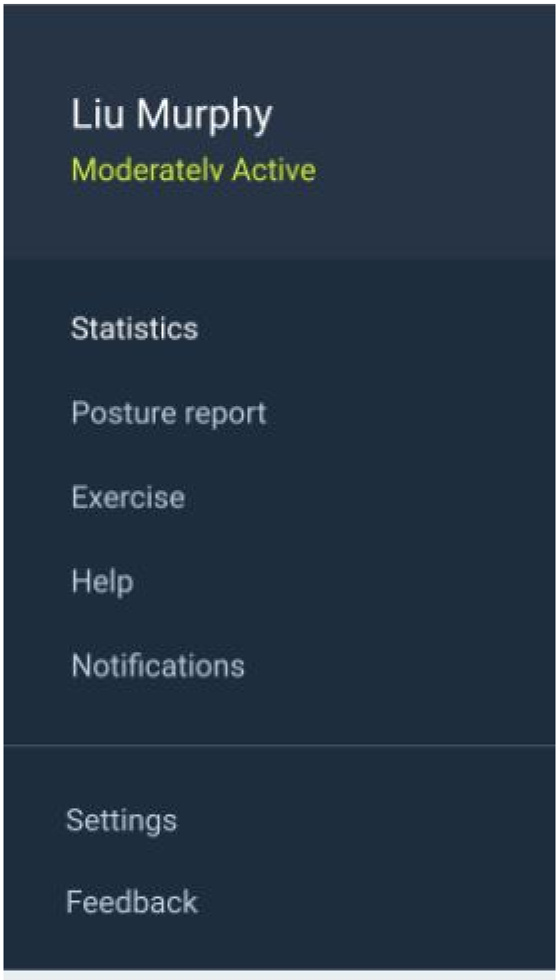
The Arduino will continuously collect raw sensor data and average these values over 30 second period--this is different from [9] where the entire time-series of sensor values is maintained and PCA is used to reduce dimensionality of final feature vector. A vector consisting of these average sensor values will be handed off to the user's desktop running our software for posture classification. Our software will consist of a pre-trained convolutional neural network (CNN) that will classify 2xK feature vectors representing the average sensor values for the K sensors on the 2 surfaces: bottom and back. Every 30 seconds a new posture classification is completed to determine if (1) user is sitting with poor posture and (2) user has been sitting for too long. When either event happens, the Arduino does two things: (1) sends a vibration signal to the user via a series of vibration motors embedded in the armrest portion of the smart cover, providing a gentle reminder that the posture is poor, or (2) sends a cue to the users phone over bluetooth, indicating posture is poor and showing a human avatar indicating how the spine is negatively affected by current posture.

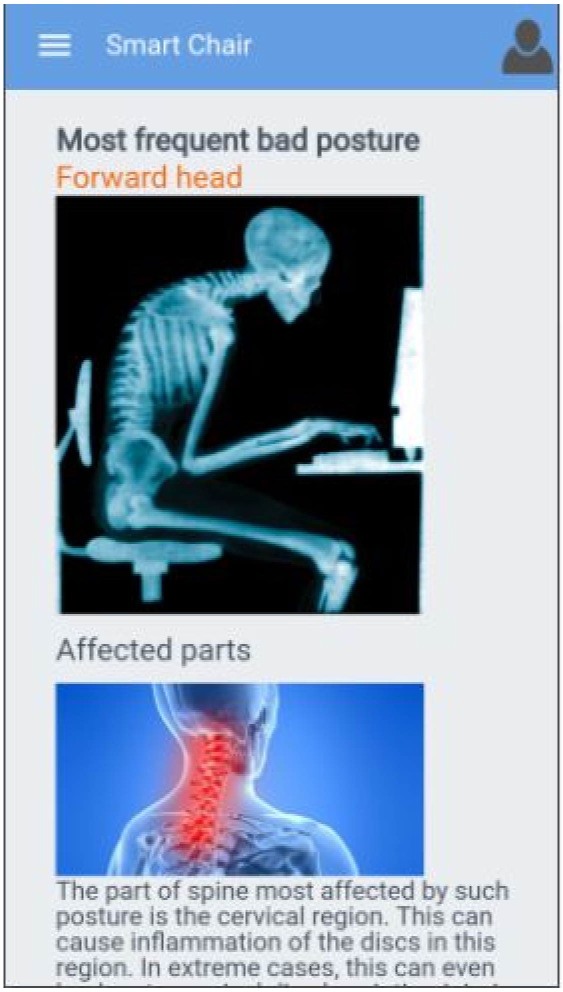
Item	Description	Quantity	Unit Cost ($)	Reasoning
Arduino 101	Development board	1	30.00	Inexpensive, lightweight, low power, and built in bluetooth. https://store.arduino.cc/usa/arduino-101
Adafruit FSR	Pressure sensor	8	7.95	Inexpensive, lightweight, and low power. https://www.adafruit.com/product/1075
Vibration motor	Vibration motor	6	4.95	Small, lightweight, low power, and inexpensive. https://www.sparkfun.com/products/8449
Arduino WiFi Adapter	Wireless connection to desktop	1	16.95	Offload feature vectors to user's desktop for posture classification using CNN. https://www.adafruit.com/product/2821

Table 2: smart chair parts list

Following are the screen mockups for the smartphone application


Smart Chair
POSTURE QUALITY
Today
70%
Last 4 days
55%
Current Posture
Neutral


Liu Murphy
Moderately Active
Statistics
Posture report
Exercise
Help
Notifications
Settings
Feedback


Smart Chair
Most frequent bad posture
Forward head
Affected parts
The part of spine most affected by such posture is the cervical region. This can cause inflammation of the discs in this region. In extreme cases, this can even

Link to prototype: https://marvelapp.com/44hf9j1

IV Evaluation Methodologies

In evaluating our solution, there are two important research questions we would like to answer. First, can we decrease in size, cost, and power, while keeping a comparable level of accuracy to a baseline chair? Second, can we use machine learning techniques to recognize poor posture, and determine the proper corrective action? From initial observations, we suspect our solution will be an effective one, and we will be able to answer the two stated questions. We will use the Axia Smart Office Chair, presented in section II, as a baseline.

To perform a quantitative evaluation, we first need to develop a series of metrics on which to measure. We chose 5 metrics. (1) *Speed* at determining poor posture. How long does one need to be in a position considered poor before detected and notified by the device.? How does it compare to baseline? (2) *Accuracy* in detecting poor posture. How far from what is considered good posture must a user slip in order to be detected? Are there false positives/negatives, and what are their rates? How does it compare to baseline? (3) *Power* consumptions. Being a ubiquitous computing device, what are the power requirements? How does this compare to the baseline? (4) *Size* and *Weight*. Does the device fit the "typical" footprint of an office chair? What is the size and weight difference compared to the baseline? (5) *Mobility*. How portable is the device compared to baseline?

To quantitatively measure speed and accuracy of posture classification, we choose to follow the experimental design of [8], [9]. We will devise an experiment where N subjects will be asked to sit on an office chair overlaid with our sensing cover. Subjects will hold each of the 16 different sitting postures (figure 2) for a period of 30 seconds

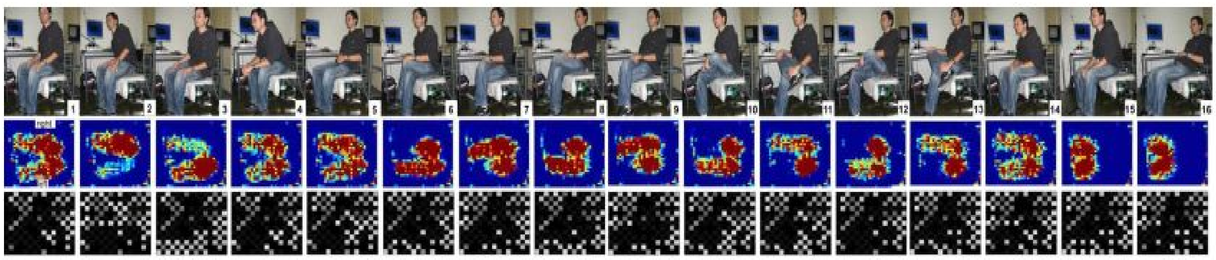


Figure 2: 16 sitting postures, heatmap generated from sensors

and repeated over 3 rounds of training. By averaging the raw sensor values over the 30 second period, we obtain a heatmap showing sensor values to visualise each posture in sensor-space in addition to a 2xK feature vector where K is the number of sensors on the 2 surfaces: bottom and back. Structuring the feature vector this way will allow the convolutional neural network to determine whether back or bottom sensor values are more discriminative in classifying sitting posture. We will employ a final softmax layer to achieve multi-class classification for each of the 16 sitting postures. For each posture, we will have 3*N training feature vectors and these will be used to train the weights of our C-NN via RMSprop optimization algorithm. Following the procedures laid out in [8],[9] we will use leave-one-out cross validation to simultaneously determine optimal parameters for maximizing classification accuracy and speed of classification.

VI References

1. "Axia Smart Chair – your personal posture coach", *BMA Ergonomics*. https://www.bma-ergonomics.com/en/axia-products/axia-smart-technology/
2. A. Hurst, J. Zimmerman, J. Forlizi, C. Atkeson, F. Gemperle, C. DiSalvo, M. Peeters, N. Jafarin, R. Kemnitzer, "The Sense Lounger: Establishing an Ubicomp Beachhead in Elders' Homes", in *CHI EA '05 Extended Abstracts on Human Factors in Computing Systems*, Portland OR, 2005, pp. 1467-1470. http://www.cs.cmu.edu/~./akhurst/chair_pix/9-13-04-final-color-names.pdf
3. H. Polh, M. Hettig, O Karras, H. Otzturk, M. Rohs, "CapCouch: Home Control With a Posture-Sensing Couch", in *Ubicomp/ISWC '15*, Sept. 2015. http://hci.uni-hannover.de/papers/Pohl2015UbiCompPoster.pdf
4. A. Braun, S. Frank, R. Wichert, "The Capacitive Chair", in *3rd International Conference on Distributed, Ambient and Pervasive Interactions*, Los Angeles, 2015. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.714.2380&rep=rep1&type=pdf

5. C. Sherwood, “Negative Effects of Poor Posture”, *Livestrong*, Nov. 2009. http://www.livestrong.com/article/31223-negative-effects-poor-posture/
6. T. Parker-Pope, “Less Active at Work, American Have Packed on pounds”, *Well*, New York Times, May 2011. https://well.blogs.nytimes.com/2011/05/25/less-active-at-work-americans-have-packed-on-pounds/?_r=0
7. J. Miller, “Is back, neck and muscle pain hurting the UK economy?”, *BBC Business*, Feb. 2014. http://www.bbc.com/news/business-26338889
8. J. Meyer, B. Arnrich, J. Schumm and G. Troster, "Design and Modeling of a Textile Pressure Sensor for Sitting Posture Classification," in *IEEE Sensors Journal*, vol. 10, no. 8, pp. 1391-1398, Aug. 2010.
9. S. Ma, W. H. Cho, C. H. Quan and S. Lee, "A sitting posture recognition system based on 3 axis accelerometer," *2016 IEEE Conference on Computational Intelligence in Bioinformatics and Computational Biology (CIBCB)*, Chiang Mai, 2016, pp. 1-3.