Smart blanket: a real-time user posture sensing approach for ergonomic designs

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Abstract. We present a pervasive sensing system in the form of a wireless smart blanket that unobtrusively monitors people's posture on ergonomic design chairs by covering the back piece of the chair and measuring the pressure profile of the user's back. The sensor system has 1024 sensitive points, covering 48-by-48 cm^2 area. With simple and efficient classification algorithm, we reach around 80% among 10 postures, including lordotic and kyphotic lumber spine on different degrees, and lean to the sides on different degrees. The web browser based user interface offers timely and reprogrammable intervention from the user's posture history.

Keywords: User Activity Recognition · Ergonomic Design · Pressure Mapping · Smart Fabric · Sitting Posture

1 Introduction

In office, transportation, home, etc. ergonomic products that are designed to offer users better comfort, regulate their postures and help them relief stress for seating and relaxing are ubiquitous. However, the manufacturers and ergonomic designers have very little control or feedback on the proper usage of the post-sale ergonomic products; while the users on the other hand would mostly use the products in an intuitive way.

For example, many office chairs offer adjustable features to accommodate a wide range of sitting preferences. As studies have shown in [5], sometimes the users may use ergonomically designed chairs in a comfortable way which they were used to (before adopting the new chair), yet is not the way the designers and ergonomic engineers intended the products to be used, nor how physiotherapy studies have recommended. Moreover, as the user's attention may be occupied by their activities such as working, interacting with other people or objects, or relaxing, they could stay in certain postures for extended periods, which is also shown by physiotherapy studies to promote increased stress on the spinal region. [1] By making "bad postures" comfortable, this could have none or negative influence on the users' health and quality of life as we further explain in Section 2.

Paper Contribution and Structure

Therefore, in this paper we consider the applications of ergonomically designed chairs, and propose a pervasive sensing system in the form of a smart blanket, which monitors the users' usage of the ergonomic product by mapping the planar pressure distribution between their body and the chair surface.

In Section 2, we review clinical ergonomic and orthopedic studies about sitting postures and their health influences;

In Section 3, we describe the hardware of our system and the settings of the evaluation experiment;

In Section 4, the experiment data is first evaluated and discussed; then the software architecture of the runtime implementation that offers automatic timely intervention is introduced.

2 What Is a Good Posture?

In the modern society, people with sedentary occupations spend a major part of their time sitting on chairs. [6] [13] A wide range of clinical ergonomic and orthopedic studies have suggested that inappropriate postures can have negative effects on the cervical, thoracic, lumbar part of the spine region, shoulder and pelvis, including fatigue, stress or pain. [8]

Traditionally, children are taught to sit uptight for a better back; however, studies have shown different postures have different effects on the spine and muscles, without an agreement of which posture is the best for sitting. For example, in [2], two basic postures ('erected posture' and 'flexed posture') are studied, concluding that sitting with the flexed posture mechanically flattens the lumbar spine and is thus more beneficial when sitting and lifting heavy weights compared to an erected posture which imposes a lumbar lordosis. In [3], O'Sullivan, et al. investigated the trunk muscle activations in different postures similar in the last study; the findings suggest that in 'erected posture' the lumbar multifidus and internal oblique muscles are significantly more activated; while in the 'thoracic upright posture', the neck muscles are significantly activated, this posture thus causes more shoulder region stress as supported by the study in [10]; and in the 'flexed and slump posture', most of the trunk muscles investigated remain relaxed. Thus, it appears flexed and slump postures, or 'lumbar kyphosis postures' is more beneficial for the spine and disc structures and causes less muscle stress; however, it may cause greater stress to articular and ligamentous structures [7][11], as well as stress on the anterior annulus and an increase in the hydrostatic pressure in the nucleus pulposus at low load levels [12].

Based on various evidence, it appears that different postures have its own advantages and disadvantages. In [1], Vergara and Page suggest that low mobility are the principle causes of the increase in sitting discomfort. This study agrees with the muscle activation studies and consider that static muscular effort is a major contributor to short term lumbar and dorsal pain. It is supported in more recent studies such as [14], which shows less sitting fatigue in dynamic sitting compared to static sitting.

This calls for a method that automatically detects the user's real-time posture, compare to the recommendations from clinical ergonomic expert knowledge and distinct chair manufactures, and offer timely feedback. Studies have shown that pressure sensors placed between the user and the chair can be a useful source of information. For example, in [15], four pressure sensors are placed at the back of the chair, and in [16], an 8-by-8 pressure sensor matrix is placed on the seating surface. However, most of the systems used in such studies are not suitable for public consumers in their everyday life.

3 Hardware and Experiment setup

In this paper, we use our fabric based pressure mapping sensing technology to unobtrusively measure the user's posture. The sensor system is used for exercise recognition on a sport mat in our previous work in [17].

3.1 Sensor hardware system

The sensing fabric is a three-layer fabric structure:

- the top and bottom layers are 'universal fabrics', conductive metallic strands woven into a non-conductive fabric sheet, forming conductive stripes that can be used as line electrodes. The electrode stripes are distanced;
- the middle layer is 'CarboTex', pressure sensitive fabric sheet made of carbon polymer material.

The middle layer has measurable electronic resistance. Its resistance changes with the surface planar pressure. The top and bottom layers have parallel electrode stripes, forming a mesh from the top view. The matrix then measures the resistance distribution, which can be interpreted as the surface planar pressure mapping. The distance between each point is 1.5 cm and the matrix has 32 lines on every orientation.

Fig. 1 The smart fabric and electronic module of the sensing blanket.

A custom electronic printed circuit board (PCB) is connected to each line electrode to scan and measure the volume resistance at every cross point of the sensor matrix, and stream the sensor data wirelessly to receiver devices such as a computer or smartphones with Bluetooth connection. The specifications of the electronic module are listed in Table 1. The sensor electronics consumes 100mA current during normal operation, therefore with a 1300mAh battery, it can operate for 13 hours, which is sufficient for an 8-hr workday scenario. In our prototype, the device is charged with a USB cable. In the future, wireless charging is also possible, such as in [18], a research prototype wirelessly charges electronics through coils coupling installed on the floor and chair legs.

Table 1. Electronic module specification

Sensing points	1024 (32-by-32 matrix)
Analog resolution	12-bit
Bluetooth bandwidth	>32KB/s
Refresh rate	20 frames per second
Battery life	13 hours (with 1300mAh)
Housing dimension in mm	22 (H) × 62 (W) × 76(L)

The electronic PCB, connectors and battery are enclosed in a 3D-printed box. The fabric sensor is covered in a large microfiber sheet, which is sewn as a square blanket. From the fabric sensor to the PCB there are 64 connections, we use flat ribbon cables and double row headers with plastic housing as the connection. The ribbon cables and the PCB housing are also embedded into the square blanket. As shown in Fig. 1, the result is a thin and soft fabric piece and fully wirelessly connected.

3.2 Posture monitoring scenario setup

We use an office chair, the 'Please' model from Steelcase [9], which is ergonomically designed to offer many adjustment options, including: height and horizontal retraction of the seating piece for different leg lengths; back piece height and maximum tilt; the back piece is also separated into two parts, with spring support so the curvature can fit the user's back. We put the smart blanket hanging on the back piece to measure the seater's back pressure profile. It is also possible to place the sensor at the seating piece; however, we opted for the back piece because (1) the pressure under the user's body is much greater than behind the back, which may cause deep wrinkles to the fabric and (2) from the user experience point of view, people are generally more comfortable being monitored at the back than under the buttocks.

3.3 Controlled experiment

First to validate the methodology and to establish a training dataset, we set up a controlled experiment, where participants are asked to sit at the chair with defined postures listed in Table 2, with visual demonstrations in Fig. 2 and Fig. 3. The postures are decided based on observations of daily office activities, the descriptions in Table 2 instructs how the postures are performed, and the definitions emphasizes variations of the spine movement.

Overall 16 people (5 females and 11 males) participated in our experiment. Their age ranges are 23-30 (males) and 22-27 (females), and their height ranges are 170-193cm (males) and 144-171cm (females). Every participant is asked to progress through the postures for two iterations. In every iteration, each posture is performed for three instances, every instance lasts for at least thirty seconds. Between every instance, regardless of the posture class, the participants are asked to step away from the chair and sit down again, so that they do not stay at the same spot every instance.

Table 2. Posture class definition

Posture Class Index	Posture description
C1	**Sit straight up**, with the spine up tight (the back piece is locked straight, all the others the chair is unlocked)
C2	**Sit with flexed spine**, look forward (as if looking at a computer screen)
C3	**Sit with flexed spine**, look deep downwards (as if writing on the desk, or looking at a smartphone on the legs)
C4	**Lean back**, the back fully in contact with the chair
C5	**Lie on chair**, slide down from the lean back posture, with the lower back suspended from the chair
C6	**Reach to left**, with body facing the side (as if talking to people, or operating the telephone, etc. on the side)
C7	**Lean left**, with the upper body's weight focused on the armrest, face front (as if looking at a computer screen)
C8	**Slight lean left**, the difference from C7 is that the person's weight is still on the back piece, without elbow support, but the spine is slightly bent to the side
C9	**Reach to right**, with body facing the side (as if talking to people, or operating the telephone, etc. on the side)
C10	**Lean right**, with the upper body's weight focused on the armrest, face front (as if looking at a computer screen)
C11	**Slight lean right**, the difference from C10 is that the person's weight is still on the back piece, without elbow support, but the spine is slightly bent to the side
C12	**Not a posture**, no user is seated on the chair, instead, some bags may be put on the chair or jackets hang on the back piece.

4 Algorithm and software design

4.1 Posture detection algorithm

Various data mining and machine learning strategies have been used for activity recognitions with such pressure mapping fabrics. For example, in [17] image descriptors and linear discriminant analysis were used for detecting different exercises on a sport-mat; wavelet analysis was used for fast actions and support vector machine was used for classification on a smart soccer shoe in [19]; and convolutional neural networks were used for identifying people from footprints in [20]. The above-mentioned methods offer superior, even super-human classification accuracies, yet at a cost of great computational effort. In this study, we adopt a more simple and computational-efficient approach.

In Fig. 2 and Fig. 3, example pressure mapping data are shown side by side with the corresponding postures. The posture detection algorithm aims at distinguishing the differences of them. For every instance of the participant's sitting, in the time domain we evenly select 10 frame samples, and manually annotated the data according to Table 2, giving each pressure mapping profile a ground truth.

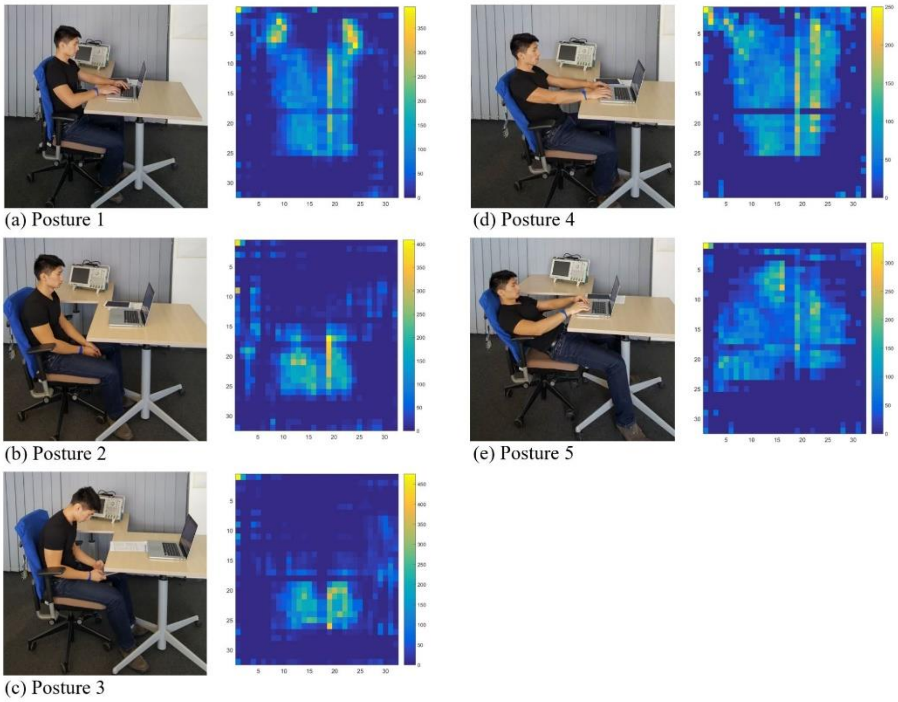

Fig. 2 The examples of Postures 1 to 5 and the corresponding pressure mapping data examples

First, for a single participant we randomly separate the data (evenly each posture) into training groups and testing groups, the algorithm is given the ground truth of the training data and will predict the class of the testing data. For every testing frame, we calculate the normalized cross-correlation between this frame and every training data frame (templates) one by one. Every normalized cross-correlation returns a value between -1.0 and 1.0, corresponding to the correlation coefficient between the testing frame and the template. For N templates, every testing frame will have an array of N correlation values corresponding to every template, which we name as the correlation score vector. We find the K (in this case, K=20) largest values form the score vector, and the majority of their corresponding templates' ground truth is taken as the prediction class. If an alias occurs (two different classes occupy the same number in the K largest values), for each class in the K largest values, the sum of the values is calculated, and the prediction is determined by the bigger sum. The process from taking a new testing frame to conclude the final posture class takes 0.4-0.5 second in our test with a Dell XPS 9550 (i7 CPU) machine.

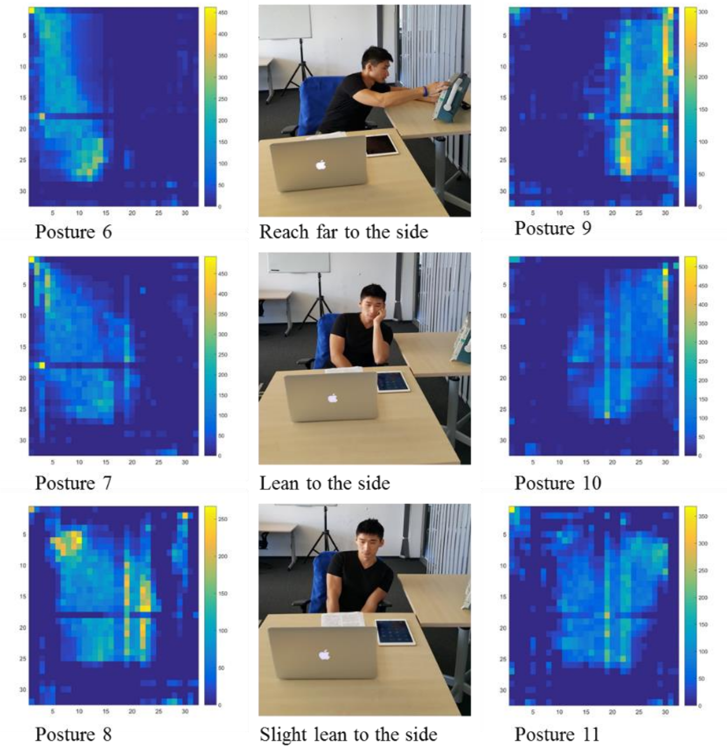

Fig. 3 The examples of Postures 6 to 11 and the corresponding pressure mapping data examples

4.2 Cross-validation

Cross-validation method is used to evaluate the posture classification algorithm described above with the experiment data. For every participant, we use one iteration of the postures as training and another iteration as the testing data, and reverse the training and testing for another validation. The predicted results are compared with the ground truth of the testing data, and visualized in Fig. 4 as a confusion matrix. In the confusion matrix, each cell stands for how many data samples are of the corresponding ground truth of the column, and is classified as the prediction class of the row; therefore, the diagonal cells are correctly classified samples (true positives). The values in every cell is the proportion of the number of samples belong to the cell to the total amount of the samples of the same ground truth. For example, the value 0.17 in ground truth – prediction coordinate C1-C4 means 17% of the original C1 are classified as C4, and the 0.22 at C4-C1 means 22% of the original C4 are classified as C1. The F1 and ACC are measures that indicates the accuracy. F1 is calculated as the harmonic mean of the average precision and recall of every class, and the ACC is the average of true positive rates.

From the confusion matrix, it can be seen that a great majority of the data samples are correctly classified. For 12 classes, the random chance level is 8.3%, therefore an average accuracy of 72.1% can be considered high.

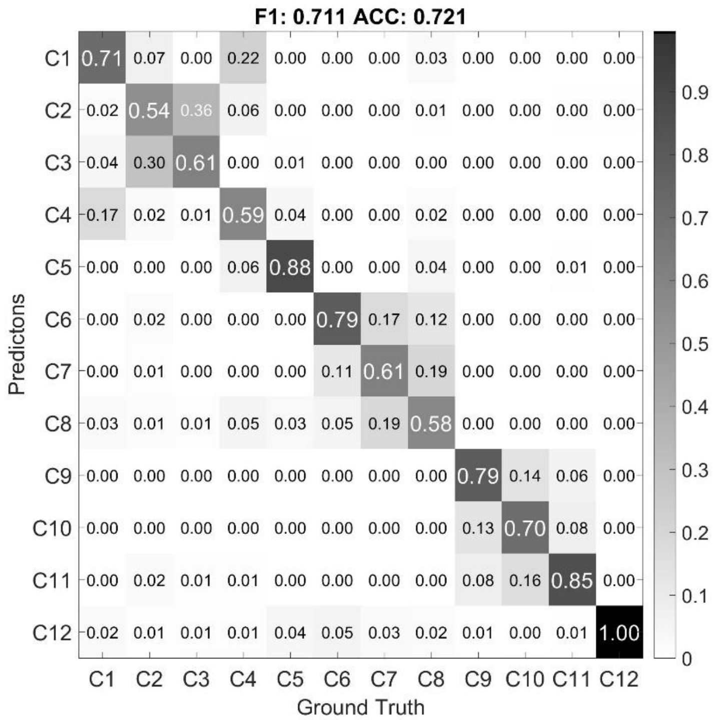

Fig. 4 Confusion matrix of the classification result for 12 classes.

C1 and C4 are confused by an average of 20%, from Table 2 and Fig. 2, these two classes are very similar to each other. In the actual experiment, the participants do not subjectively distinguish these two postures in general, except for that the chair back is locked at the vertical position in C1 and unlocked in C4. More miss-classifications happen between C2 and C3. These two postures share the feature of a kyphotic curvature of the spine. It is worth mentioning that C8 and C11, slightly lean to the side, are very well separated from the frontal neutral postures (C1 to C5). Moreover, all the side postures are very well separated from each side, most miss-classifications only happen within the same side (C6 to C8 and C9 to C11). Therefore, it makes sense to group C1 and C4, C2 and C3 and redraw the confusion matrix as in Fig. 5. From it, a much clearer separation between different classes is presented, and the accuracy progresses to near 80%.

The algorithm in Section 4.1 is then taken as the classification engine, and all the data used in the cross-validation is taken as the training database. The cross-validation result measures how trustworthy the classification engine with the database is in the unsupervised scenario in the following sections.

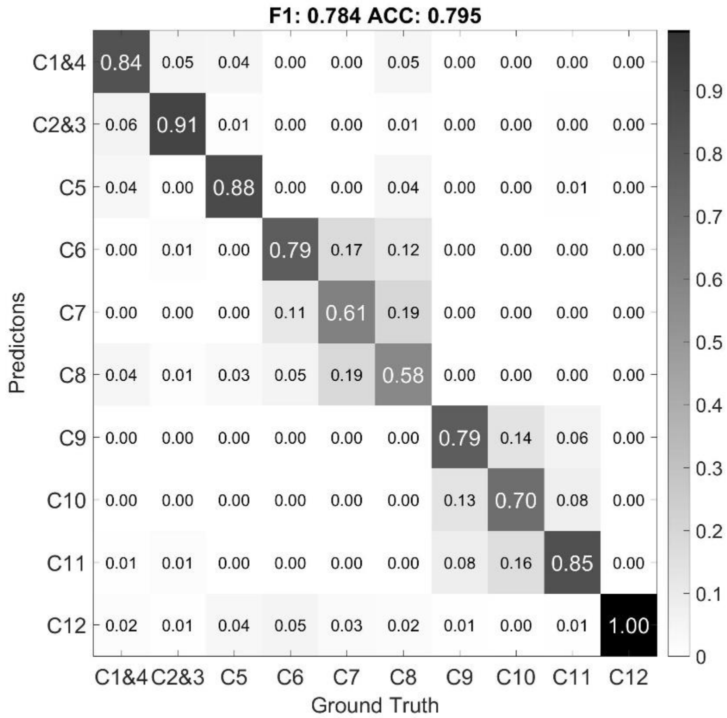

Fig. 5 Confusion matrix of the classification results for 10 classes after combining 1&4, 2&3.

4.3 Real-time intervention system

The classification engine is implemented in Python, since it is a widely welcomed open source platform. To have a more flexible and fluent user interface implementation, we utilize the recent progress in web development. The software structure is illustrated in Fig. 6. The central part of the software system is implemented in html and JavaScript that runs in a browser.

The basic structure includes critical data links across different language platforms for bi-directional real-time data transmission (webchannel between Qt and JavaScript, Flask Socket-IO between python and JavaScript). First, the raw sensor pressure mapping data from the smart blanket is received by the Bluetooth receiver executable program, and forwarded to the JavaScript program. The JavaScript program can visualize the pressure mapping data, but more importantly, it relays the data to the Python classification engine. If the system is shared by different users, the user can also select his or her ID from the Web browser, and the ID is also sent to the Python engine. The classification program then predicts the current posture based on the algorithm described in Section 4.1, and sends the prediction result back to the JavaScript program. This process can operate on a 1-second cycle, giving a fine time grain posture information.

The JavaScript program then keeps the history of the user's posture of the day, and offers timely interventions via means of sound and desktop notifications. For the scope of this work, the intervention is decided on two criteria: (1) if the user has been in a bad posture (out of C5, C6, C7, C10 and C11) for more than 1 minute: (2) if the user has been in the same posture for the majority (over 80%) of the past 10 min.

This decentralized design makes it easier for future modifications. The classification engine can be changed into other methods that is implemented in Python without modifying the other components of the software; the intervention decision can be easily modified within the JavaScript program for other orthopedic or clinical ergonomic opinions.

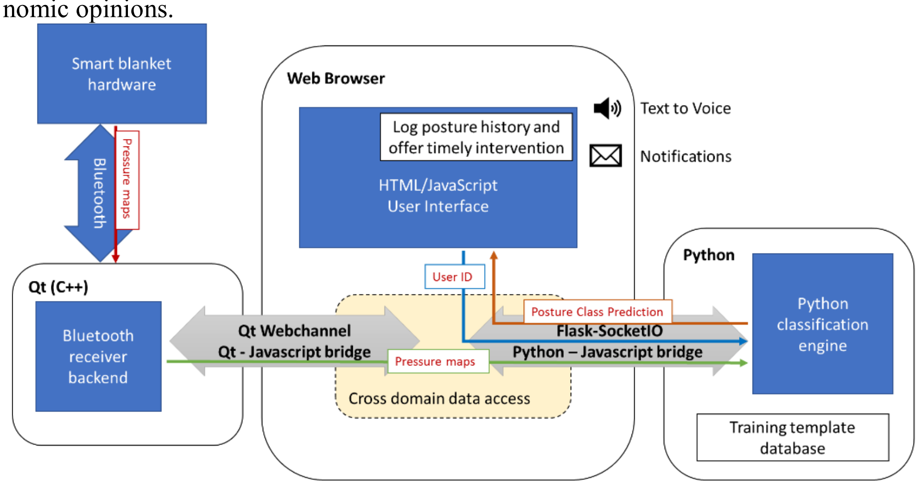

Fig. 6 The structure of the software for real-time feedback and notification.

5 Conclusion and Outlook

In this work, we developed a smart blanket sensor system that can be used to gather user seating posture data. It is unobtrusive since the users do not need to carry any gadget and the chair in use is not tethered to cables. The wireless and fabric sensing hardware has the flexibility that it is independent of the ergonomic design of the chair and the user environment. Based on our evaluation, the simple classification algorithm has near 80% accuracy distinguishing 10 different postures. The software system can monitor the real-time pressure mapping at 20 Hz, and automatically classify the posture every second.

For the users, the data can be used to help correct and maintain their daily seating behaviors per orthopedic suggestions. The data (including both the raw pressure mapping data and predicted posture data) itself is also helpful for gathering reliable databases for orthopedic studies and ergonomic manufacturers.

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