

eCushion: A Textile Pressure Sensor Array Design and Calibration for Sitting Posture Analysis

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Abstract—Sitting posture analysis is widely applied in many daily applications in biomedical, education, and health care domains. It is interesting to monitor sitting postures in an economic and comfortable manner. Accordingly, we present a textile-based sensing system, called Smart Cushion, which analyzes the sitting posture of human being accurately and non-invasively. First, we introduce the electrical textile sensor and its electrical characteristics, such as offset, scaling, crosstalk, and rotation. Second, we present the design and implementation of the Smart Cushion system. Several effective techniques have been proposed to improve the recognition rate of sitting postures, including sensor calibration, data representation, and dynamic time warping-based classification. Last, our experimental results show that the recognition rate of our Smart Cushion system is in excess of 85.9%.

Index Terms—Textile, pressure sensor, sitting posture, calibration, cushion, non-invasive.

I. INTRODUCTION

A. Background and Related Work

SITTING is one of the most common postures of human beings in life. It is reported that people sit for six hours each day. Sitting posture is related to many health issues, such as back pain [1], sciatica [2] and cervical spondylosis [3]; therefore, sitting posture analysis receives increasing attention in the medical community due to its extensive applications and significant impacts, such as chronic diseases [4], health education (correct sitting posture for back ache prevention [1]), and human computer interface for rehabilitation (real-time sitting posture analysis for gaming [5]).

A traditional method to analyze sitting posture is to let a patient sit on a hospital chair, and a therapist or a nurse observes the patient's sitting posture and ask questions about his feeling. In general, the normal diagnostic process will take half to one hour. However, it is still too short to obtain enough information for accurate diagnosis. Furthermore, the

diagnostic result has low reliability and can be biased by subjective factors from doctors to patients.

For the sake of reliable diagnosis, doctors are eager to obtain more comprehensive information from patients. Therefore, it is necessary to monitor patients 24/7 and offer the most comprehensive information for doctors. Camera is commonly used sensor for sitting posture analysis. Marschall et al. [6] deployed several cameras in an office setting to record sitting postures of subjects. However, this method always makes the subjects uncomfortable as cameras record other unnecessary information of the subjects, which will be related to personal privacy. Kazuhiro et al. [7] equipped chairs with four pressure sensors for sitting posture monitoring. Compared to cameras, pressure sensor has less privacy concerns and is dedicated to record the sitting pressure distribution only. However, a handful of pressure sensors are not enough to obtain the comprehensive sitting information, and on the other hand deploying more pressure sensors will increase the related cost. Currently, the community is still seeking a low-cost, high-accuracy, and reliable solution to analyze sitting postures.

B. Textile Sensor

Electrical textile, shorthand as *eTextile*, is a composite yarn made of fibers coated with conductive polymer. Its natural structure is loose and its inside fibers are air gapped. Considering its promising electrical characteristics, *eTextile* has become widely-used in fabricating sensors for diverse applications, such as pressure [8]–[10], stretch [11]–[13], strain [14], humanity sensors [15], and respiratory sensors [16]–[18]. Moreover, it can be used to measure human physiological signals for health care applications, such as EKG [19], blood pressure [20], and rehabilitation [21]. Different from silicon or piezoelectric based sensors [22], [23], *eTextile* offers much more comfortable touch feeling and economical price. Therefore, it can be unobtrusively integrated into apparels for daily use. For example, Mattmann et al. [24] presented a garment prototype using textile strain sensors to recognize upper body positions. Mitchell et al. [25] introduced an interactive system using a wearable textile sensor to monitor breathing patterns of human beings. Shu et al. [26] built textile pressure sensor arrays in a shoe for gait analysis.

However, the characteristics of a textile sensor are not well-described. Normally, a textile sensor suffers from several instable factors such as environmental noise, offset, scaling, and crosstalk. Especially, whenever it is integrated into clothes

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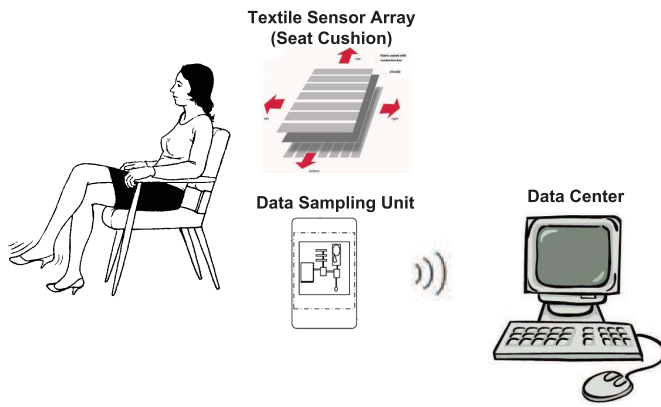


Fig. 1. The Smart Cushion architecture.

or facilities, other uncertainties from the environment will make the signal too fuzzy to be understood. For instance, in sitting monitoring application, pressure distribution is not only related to the subject's sitting posture, but also depends on other factors such as body size, weight, and sitting orientation. Therefore, signal processing and analysis on textile sensors is a challenging research topic.

C. Contribution

In this paper, we introduce a smart wearable system, called Smart Cushion, to analyze the sitting posture of users in daily life. Different from the traditional medical devices, Smart Cushion is based on textile material and is capable of recording patients information non-invasively. We model the textile sensor array and propose an effective framework to tackle the challenges in sitting posture analysis. The contributions of this paper are three-folds. First, we develop a textile sensor based cushion system to sense human sitting postures. The system consists of textile sensor array, data aggregator, and data analysis module. Secondly, we propose a new model to characterize and calibrate the textile sensor array. This model addresses the major issues of textile sensors, such as background noise, offset, scaling, and cross talking. Second, we present an efficient algorithm for sitting posture recognition. The algorithm reduces the dimensionality of sensor data and analyzes sitting postures based on dynamic time warping. We evaluate the performance of Smart Cushion system with 14 subjects. The experimental results show that the recognition rate can reach up to 85.9%.

The remainder of this paper is organized as follows. Section II presents the overall structure and the key components of Smart Cushion system. Section III elaborates on the design of the textile sensor array. Also, we introduce the significant uncertain factors in sensor signal processing. Section IV describes the new proposed sensor calibration method. This method is general for textile sensor calibration and not restricted to any specific application. Section V discusses the algorithm of sitting posture analysis. Experimental results are shown in Section VI, and the paper is concluded in Section VII.

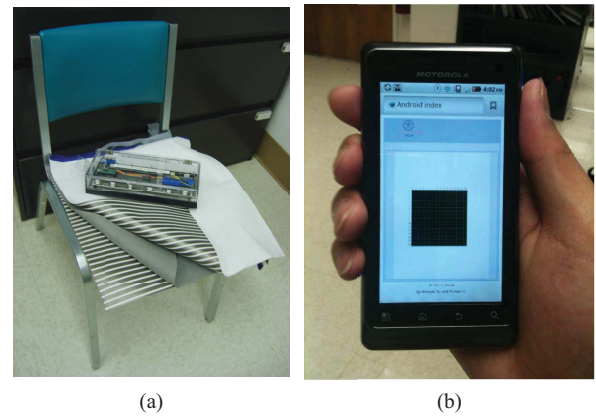


Fig. 2. The prototype of Smart Cushion. (a) Textile sensor array. (b) Smart phone.

II. SYSTEM DESCRIPTION

Smart Cushion is developed to be used in hospital settings and daily use, such as at home or in the office. Therefore, the essential problem is how to make the system convenient to access, straightforward to deploy, and unobtrusive to use. In addition, the system is low-cost and compatible with existing computer systems found in hospitals or homes. Fig. 1 shows the architecture of the Smart Cushion system. Basically the system is composed of three components: textile sensor array, data sampling unit and a data center. Textile sensor array captures sitting pressure distribution of the user when he sits on Smart Cushion, data sampling unit acquires the sensor values and it wirelessly transmits the data to a data center. The data center stores and analyzes the sensed data for health status monitoring.

Fig. 2(a) shows the implementation of the textile sensor array in Smart Cushion. The total sensor surface area is 10 by 10 inch, where the area of each square sensor is $5/8$ by $5/8$ inch as each row and column bus is $5/8$ inch wide, and the space between sensors is $1/8$ inch. The design structure of the sensor array will be introduced in detail in Section III. The data sampling unit is designed based on Arduino Dev. board. A bluetooth module is built on the board to enable wireless data transmissions. A driver circuit is around the Arduino microcontroller for sensor array scanning. The sampling frequency is adjustable. Given that the frequency of sitting posture changes is lower than other body movements, the default data rate in Smart Cushion is set to 10 Hz. Data storage and analysis are performed in the data center, including sitting posture analysis, human movement indexing, and statistics of motion. Considering the accessibility for mobile users, as shown in Fig. 2(b) a user-friendly application is also developed for smart phones, which conveniently displays real-time feedback of the sitting pressure distribution and facilitates continuous visualization of sitting postures.

III. TEXTILE SENSOR ARRAY DESIGN

eTextile is a fiber-based yarn which is coated with piezoelectric polymer [27]. The initial resistance between the top-bottom surfaces is high. When extra force is applied on the surface of the *eTextile*, the intra fibers will be squeezed

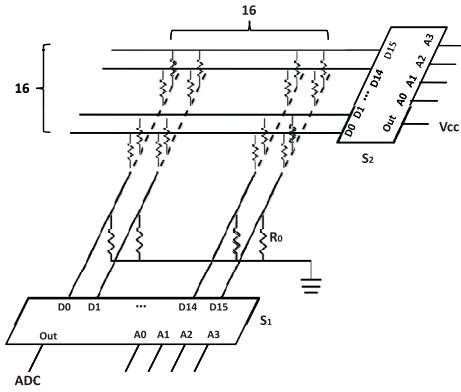


Fig. 3. The peripheral circuit for pressure distribution scanning.

together and the throughout resistance become decrease. Therefore, we can take advantage of this electrical characteristics and design a high-density and low-cost pressure sensor array.

A. Sensor Array Architecture

One type of the textile sensor sheet has been implemented in [27]. In that structure, each sensor needs an independent analog to digital channel (ADC) to sample the pressure. For example, to build an N by N sensor array, $N \times N$ I/O pins are required. This is prohibitive for large-scale sensing applications. In Smart Cushion, we use a three-stacked-layer structure to build the sensors, where the middle layer is *eTextile*. The advantage of this structure is that the top layer and the bottom layer are normal fabric uniformly coated with parallel conductive buses. As shown in Fig. 3, the conductive buses on the top layer are orthogonal to those on the bottom. The intersection area in between of the orthogonal buses is the sensing unit. Fig. 4(a) shows the sensor implementation. The top layer and bottom layer are both coated with 16 buses. Therefore, the number of sensors located on this sheet is 256. Moreover, with regards to Fig. 4(b) the total thickness is 1.5 mm only, which makes Smart Cushion flexible and thin enough for noninvasive use. This $N \times N$ sensor structure only requires $2N$ I/O pins. The functionality of this circuit will be discussed in the following subsection.

B. Scanning Method

The peripheral circuit shown in Fig. 3 is used to scan the zebra pattern sensor array. Each conductive bus on the bottom is connected to an ADC from analog switch module S_1 to ground via an offset resistor R_0 . Each conductive bus on the top is connected to a voltage supply via analog switch model S_2 . Both S_1 and S_2 are used together in to determine which sensor is selected, and the scanning sequence is synchronized by a microcontroller. For example, when S_2 connects bus i on the top layer to a voltage supply and S_1 connects bus j to ADC, Smart Cushion will read the sensor located in row i , column j , which is denoted as V_{ij} . Therefore, this peripheral circuit has random accessibility for an arbitrary sensor in the system.



Fig. 4. The structure of textile sensor and sensor array design. (a) Sensor implementation. (b) Sensor thickness.

C. Uncertainties in Textile Sensor Data

When a user sits and applies forces on the sensor sheet, the *eTextile* output will not just depend on the sitting posture. In fact, the sensor value can be interfered by other uncertain factors, which make the textile sensor data difficult to be analyzed. Here, we list the dominant factors of signal distortion in *eTextile*. Basically, there are four different kinds of uncertain issues. Offset and scaling are caused by sheet-to-sheet variation, and crosstalk and rotation are due to within-sheet variation.

1) Offset

In the ideal case, the initial pressure on each sensor should be zero. However, due to the sandwiched structure, initial offset pressure is unavoidable, and its value highly depends on the assembling method of the sensor. If the three layers are laminated tightly, the offset value will become high and vice versa. Obviously, different sheets should contain different assembling status, and this assembling variation implies different offset pressure values from sheet to sheet.

2) Scaling

The characteristics of *eTextile* have a large resistivity variation. Even if the same forces are applied to two similar *eTextile* sensors, their outputs are not necessarily the same. It is impossible to build up a general look-up table which describes the relationship between applied forces and sensor outputs in all cases. However, *eTextile* sensor is still promising for applications because the sensing repeatability and relativity are stable. It is possible to use a scientific method to predict the scaling variation.

3) Crosstalk

The crosstalk effect is one of the most challenging issues to deal with in textile sensors. Due to the limited space between sensors, all adjacent sensors are mechanically coupled together. As shown in Fig. 5, the initial sensor sheet is uniform, and the thickness value of each sensor is H_1 . Once some force is applied on Sensor S_3 , its thickness will be reduced to H_2 . In the meanwhile, the adjacent sensors also become squeezed more or less: the sensor values of S_2 and S_4 change because S_3 is pressed. The thickness of S_2 and S_4 changes to H_3 , though there is no direct force applied on them. This phenomenon implies that the sensor readings are not only linked with the applied force but are also related to its neighboring sensors' conditions.

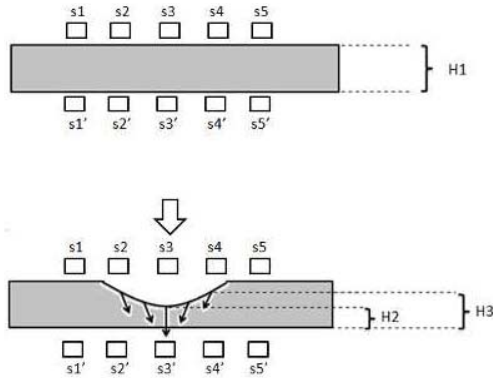
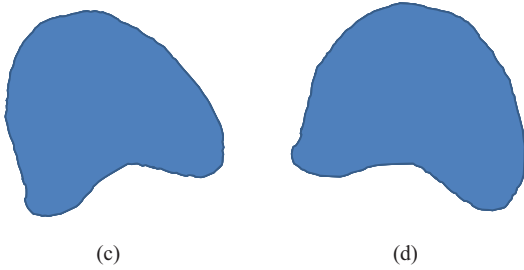


Fig. 5. An demostration of the crosstalk effect in the textile sensor array.



(a)

(b)



(c)

(d)

Fig. 6. The effect of the pressure map rotation. (a) Sitting A. (b) Sitting B. (c) Pressure map A. (d) Pressure map B.

4) Rotation

Even if the same user sits on Smart Cushion with the same gesture, the collected pressure map may not be the same due to the different sitting orientations. Fig. 6 shows two pressure distributions with the same gesture but different orientations. The pressure map in Fig. 6(c) is fairly similar to the one in Fig. 6(d). However, it is considerably difficult to match them with each other using pattern recognition techniques, since “rotation is always something hard to handle compared to translation and scaling” [28].

In this section, we presented the sensor design and imperfection of the textile sensor array. To achieve good performance in applications, all issues described above should be effectively handled. In the next section, we will introduce our proposed model to improve the quality of textile sensor data.

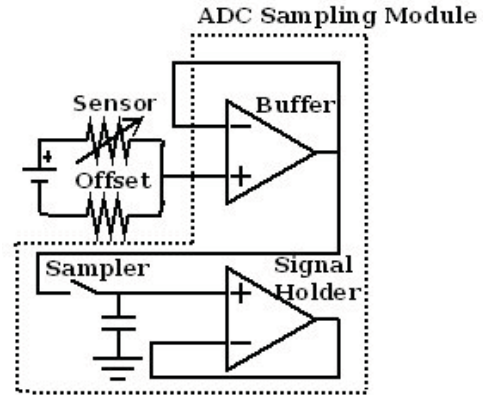


Fig. 7. Parametric modeling of a single textile sensor.

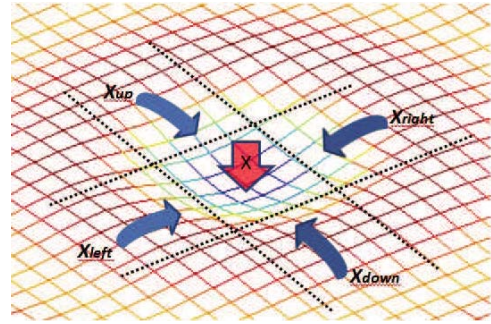


Fig. 8. The illustration of sensor x and its neighbors.

IV. SENSOR CALIBRATION

A. Preliminary

To make reasonable inferences for applications, such as sitting position analysis, it is necessary to have accurate measurements from textile sensor. To address the uncertain issues we discussed from Section III-C, we analyzed the sensor signal model to learn the intrinsic relation between an applied force F_a and a sensor reading V_o .

Fig. 7 models intrinsic parameters in a single textile sensor. The textile resistor, R_t , and the offset resistor, R_o are connected in serial. One end is connected to a voltage supply, V_s , and the other is connected to the ground, GND . The middle joint point is connected to an ADC to obtain a sensor reading V_o . According to the mechanics of the *eTextile* [27], the extra applied force, F_a , is approximated to be inversely proportional to the sensor resistor R_t :

$$R_t = \frac{C}{F_a}, \quad (1)$$

where C is a constant. Based on the parametric model in Fig. 7, we can derive a relational expression between sensor reading S_o and applied force, F_a :

$$F_a = \frac{C \times V_o}{R_t \times (V_s - V_o)}. \quad (2)$$

From Eq.2, we can see that the applied force is not linearly proportional to the ADC reading. This non-linearity makes the uncertain factors more difficult to deal with.

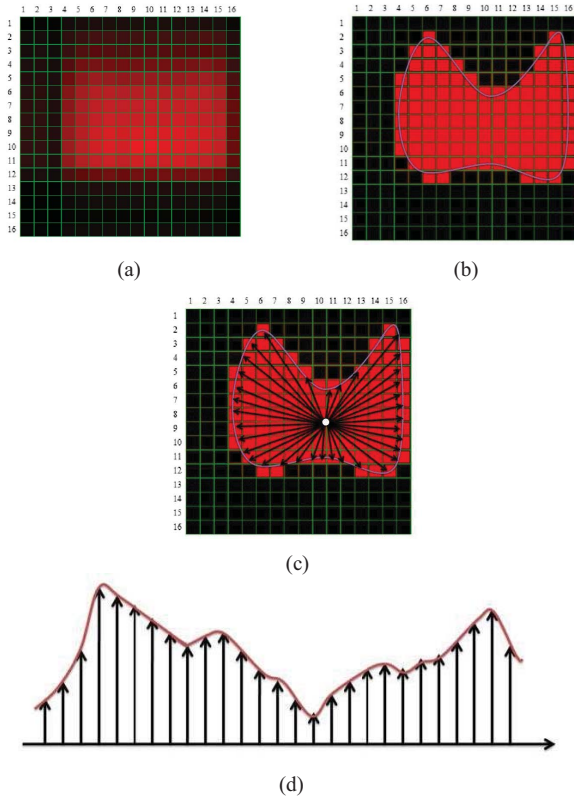


Fig. 9. Data representation procedure. (a) Map. (b) Boundary. (c) Distance. (d) Pressure profile sequence.

B. MRF/Gibbs-Based Re-Sampling Method

Our previous method to calibrate the sensors is to establish a pressure-resistance look-up table to exhaustively model the *eTextile* formulation via repeating voltage measurements under a number of imposed pressure values [29]. However, there are several difficulties involved. For example, even though we can measure the voltage of the voltage divider circuits one by one for each pressure sensor, we still cannot predict its output voltage if a number of its neighbor sensors are pressed at the same time because of the coupling effect mentioned in Section III-C. Furthermore, pressure-resistance relationship changes from one *eTextile* to another. Therefore, measuring each pressure-resistance relationship for each *eTextile*-based pressure sensor might result in an inefficient model.

In this paper, we proposed a new re-sampling based statistics technique under MRF/Gibbs distribution [30] to calibrate the uncertainties in eCushion, instead of directly building an ad-hoc modeling for each *eTextile* sensor. The basic idea is to find an up-threshold, Th_{up} , a down-threshold, Th_{dn} , and the sensors that need to be calibrated. Firstly, we should decide which sensor needs to be re-sampled based on the following algorithm:

Here, we assume that the noise in Smart Cushion without any subject follows a Gaussian distribution. Once we have the re-sampling table $Mask$, we filter out the pressure values within the threshold range by randomly initializing the values. Then we start re-sampling under MRF/Gibbs probability

Algorithm 1 Re-sampling Strategy

```

1: /* Step 1: Data Annotation and Setup */
2: Initial arrayed sensor reading:  $ArrayValue(i, j)$  denotes
   the sensor value located at  $(i, j)$ 
3: Calculate the up-threshold value  $Th_{up}$  and the down-
   threshold value  $Th_{dn}$ 
4: Decide the re-sampling table  $Mask$ , where  $Mask(i, j) =$ 
   1 means that the pressure sensor needs to be re-sampled,
    $Mask(i, j) = 0$  means that the pressure value does NOT
   need to be re-sampled
5:
6: /* Step 2:  $Th_{up}$  and  $Th_{dn}$  setup */
7:  $Th_{up} = \text{mean}(ArrayValue) + \text{std}(ArrayValue)$ ;
8:  $Th_{dn} = \text{mean}(ArrayValue) - \text{std}(ArrayValue)$ ;
9:
10: /* Step 3: Re-sampling Table Calculation */
11: for  $i = 1$  to  $n$  do
12:   for  $j = 1$  to  $n$  do
13:     if  $ArrayValue(i, j) < Th_{up}$  and
        $ArrayValue(i, j) > Th_{dn}$  then
14:        $Mask(i, j) = 1$ ;
15:     else
16:        $Mask(i, j) = 0$ ;
17:     end if
18:   end for
19: end for
20:

```

distribution as follows:

$$P(X = x) = \frac{1}{Z(\beta)} e^{-\beta E(x)}. \quad (3)$$

In Eq. 3, Z is used for normalizing the probability distribution. E is the energy function derived from the neighboring pressure values around x . β is a free variable for a finer tuning, such as using simulated annealing method. In our case we just decrease the β value monotonously by a constant factor. Norm-2 energy function is the summation of the squared differences between x and its neighbors. The neighborhood definition is shown in Fig. 8. The energy function is denoted in Eq. 4 to calculate the probability density function of x :

$$pdf(x) = e^{-\beta((x_{up}-x)^2 + (x_{dn}-x)^2 + (x_{left}-x)^2 + (x_{right}-x)^2)}. \quad (4)$$

In our algorithm, whenever a corrupted pressure value detected out of Th_{dn} and Th_{up} , the probability distribution of the corrupted pressure value will be re-computed and the new value will be generated by the re-sampling formulation Eq. 3. Traveling all corrupted pressure values once is called 1-sweep. After a few sweeps, the corrupted pressure value will be closer to its neighboring pressure value, since the probability distribution will become narrower when the energy decreases. In other words, the newer sampling values drawn from the new probability distributions will be similar to their neighborhood pressure values.

Based on the above analysis, a heavier pressure point on the Smart Cushion system will have more impact on its

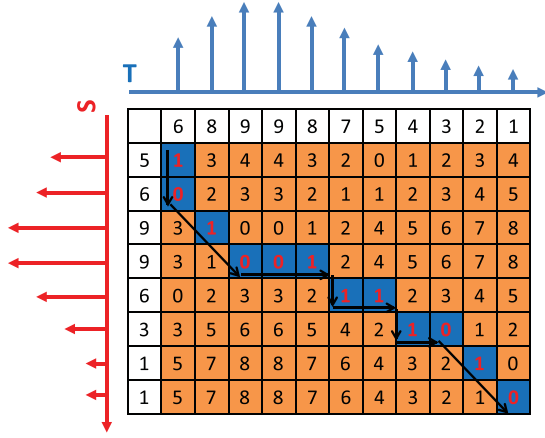


Fig. 10. A DTW example of two pressure profile sequences.

surrounding neighbors. It means that the pressure values inside the subject area will be boosted to a higher value close to the average pressure value of the heavy object imposed. This conclusion can be derived by the following proof:

Given that the boundary pressure value will be determined by the equation:

$$pdf(x) = e^{-\sum_i (x_{neighbor_i} - x)^2}. \quad (5)$$

The maximum likelihood can be obtained by its differentiation equation:

$$\frac{\partial pdf}{\partial x} = 0, \quad (6)$$

$$\sum (x_{neighbor_i} - x)^2 = 0. \quad (7)$$

Eq. 7 indicates that x is more likely to be a value around the average of its neighbors. After applying the proposed algorithm, the *holes* inside the uniform weighted subject are filled. Less noisy pressure values will affect the summation result. Hence, the pressure estimation is approximately linear along with the weight of the subject on Smart Cushion. Since the threshold range is adaptive and only those pressure values in the suspicious zone will be modified, the proposed algorithm will not over-smooth the pressure readings.

In this section, we describe a re-sampling mechanism to iteratively adjust up and bottom threshold range based on a re-constructing probability distribution. After calibration, these sensors have higher precision, and the shape of the subject is also preserved. It is worth noticing that our method can be adapted in a variety of *eTextile* based sensors without manually tuning.

V. SITTING POSITION RECOGNITION

A template-based algorithm [31] is proposed to distinguish sitting postures; however, it cannot handle the scenario where the sensing data is imperfect. In addition, Naive Bayes Network [32] method [15] is used to train the data and selected significantly featured sensors for classification. This method highly depends on the training data and cannot deal with the uncertain factors such as different weights, sizes and sitting

orientations. In this section, we introduce our algorithm to efficiently address sitting posture analysis.

A. Data Representation

To facilitate the effort of pattern recognition, it is important to choose an appropriate way of data representation. Instead of dealing with pressure map (2D image) directly, we convert it into a pressure profile sequence (1D time series). In general, there are multiple advantages to work with 1D sequential data. First, the dimension of is data reduced; therefore, the algorithm complexity decreases dramatically (compared to 2D pressure image). Second, there are a number of existing algorithms to process 1D data sequences. Thirdly, it is much easier to tackle the rotation issue.

Our proposed procedures for data representation contain the following steps:

- 1) Step 1: Get the calibrated data as 2D image shown in Fig.9(a).
- 2) Step 2: The Canny edge detector is applied to the data to obtain a binary image as shown in Fig. 9(b).
- 3) Step 3: Extracting the outline curve of the binary image. Note that it is always a closed curve due to the shape of human body.
- 4) Step 4: Measure the distance between every point and an image center (Fig. 9(c)).
- 5) Step 5: Signals can be treated as the Y-axis of a sequentially expanded signal waveform (Fig. 9(c)).

Fig. 9(a) shows the different steps of this method. After the last step, the pressure distribution information has been transformed to a 1D sequential data. In the next subsection, we will introduce a sitting posture recognition algorithm for this new data representation.

B. Signal Matching Using Dynamic Time Warping

We use dynamic time warping to classify different sitting postures. The targeted sequential signals are extracted from the corresponding pressure map while a user sits on Smart Cushion. Dynamic time warping (DTW) is a similarity evaluation method of two time series signals. Compared to Euclidean distance, DTW is more robust, allowing similar shapes to be matched even if they are out of phase [33].

Assuming there are two pressure sequences denoted as:

$$S = [s_1, s_2, s_3, \dots, s_i, \dots, s_n], \quad (8)$$

$$T = [t_1, t_2, t_3, \dots, t_j, \dots, t_m]. \quad (9)$$

To evaluate the similarity of these two sequences, DTW constructs a n by m matrix D , where $d_{ij} = (s_i - t_j)^2$. Each element d_{ij} denotes the similarity between s_i and t_j . The main idea of DTW is to find a continuous and monotonic path W from d_{11} to d_{mn} with minimal cost. The time and space complexity of $DTW(S, T)$ is $O(mn)$. Using *LB_Keogh* bounding can effectively make DTW run in $O(n)$ [34], [35]. Fig. 10 shows an example of DTW-based similarity evaluation between two pressure profile sequences.

In order to speed up the algorithm, we set two bounds to reduce DTW searching space. In this application, our

TABLE I
THE EXPERIMENTAL RESULTS: PRECISION V.S. RECALL

| | Situp | Forward | Backward | LL | RL | LFOR | RFOL | Total | Recall |
|-----------|-------|---------|----------|-----|-----|------|------|-------|--------|
| Situp | 85 | 7 | 8 | 0 | 0 | 0 | 0 | 100 | 85% |
| Forward | 3 | 92 | 5 | 0 | 0 | 0 | 0 | 100 | 92% |
| Backward | 9 | 4 | 87 | 0 | 0 | 0 | 0 | 100 | 87% |
| LL | 1 | 2 | 0 | 74 | 0 | 15 | 8 | 100 | 74% |
| RL | 1 | 1 | 4 | 0 | 82 | 1 | 11 | 100 | 82% |
| LFOR | 0 | 0 | 0 | 5 | 1 | 90 | 4 | 100 | 90% |
| RFOL | 1 | 1 | 1 | 2 | 3 | 2 | 91 | 100 | 91% |
| Total | 100 | 107 | 105 | 81 | 86 | 108 | 114 | | |
| Precision | 85% | 86% | 83% | 91% | 95% | 83% | 80% | | |

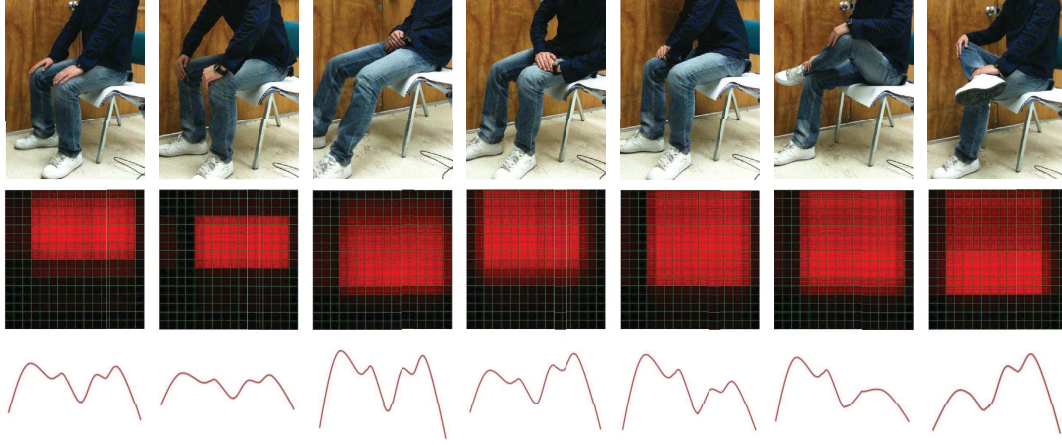


Fig. 11. Sitting posture analysis: seven sitting postures (top) are evaluated and each eTextile pressure map (middle) is transformed to a corresponding pressure profile sequence (bottom).

algorithm has adaptive bounding values according to the signal. Given any $2r$ length subsequence $S' = [s_{i-r} : s_{i+r}]$ in S , we can find that the upper bound of S' is U_i , and the lower bound of S' is L_i . The values of U_i and L_i are calculated as follows:

$$U_i = 1.5 \times \max(s_{i-r} : s_{i+r}), \quad (10)$$

$$L_i = 0.75 \times \min(s_{i-r} : s_{i+r}). \quad (11)$$

With these bound settings, $LB_Keogh(S, T)$ becomes:

$$LB_Keogh(S, T) = \sum \begin{cases} (t_i - U_i)^2 & \text{if } t_i > U_i \\ (t_i - L_i)^2 & \text{if } t_i < L_i \\ 0 & \text{otherwise} \end{cases} \quad (12)$$

Notice that, similar to [34], DTW similarity measurement will converge to the Euclidean distance when r is 1.

VI. EXPERIMENTS

A. Experimental Setup

To evaluate the effectiveness of our Smart Cushion system, we performed a pilot study on-campus. There are 25 subjects participated in the experiments, including 15 males and 10 females. Each participant sits on Smart Cushion with seven most common sitting postures. These data are used as training data. The seven postures, considered for classification, include 1) situp, 2) forward, 3) backward, 4) left lean (LL), 5) right lean (RL), 6) right foot over left (RFOL) and 7) left foot over right (LFOR).

Fig. 11 shows an example indicating the procedure of data acquisition and preprocessing. The figures on the top row illustrate seven sitting postures. The middle row pictures show the corresponding pressure map of each posture. Each pressure map has 256 pixels in total. The bottom row pictures are the corresponding sequential representation using pressure maps. Each sequence is evaluated and classified using our proposed algorithm.

B. Recognition Results

The experimental results are shown in Table I. We list the recognition results of all sitting postures with the precision and recall calculation. The overall accuracy of our proposed algorithm over all sitting postures is 85.9%, which outperforms the previous method (79% in [29]). This is because the re-sampling based calibration method deals with the uncertainties in eTextile sensor data in a more accurate way. Furthermore, we notice that “situp”, “forward” and “backward” postures are similar in the sense that their samples are never misclassified into other postures; however, they are confused with each other to a great extent. This observation indicates that these three sitting postures share many common features. This experience is helpful for us to further improve the algorithm performance while considering these sitting postures in particular.

VII. CONCLUSION

In this paper, we design and implement the Smart Cushion system for sitting posture monitoring. In order to overcome

several uncertain factors in *eTextile* sensors, including offset, scaling, crosstalk, and rotation effects, we propose a re-sampling based method to calibrate the sensor values. We also develop a dynamic time warping based algorithm to recognize different sitting postures. The experimental results show that the overall accuracy of Smart Cushion over all sitting positions is 85.9%, which outperforms the previous method (79% in [29]). We also learn that a number of sitting postures are similar to each other and harder to be differentiated from each other. In the future, we will attempt to improve the recognition rate with the experience we learned. Meanwhile, we consider to further scale up our system for other applications such as a bedsheet for sleeping monitoring and a carpet for gait analysis.

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