Smart Arse: Posture Classification with Textile Sensors in Trousers

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ABSTRACT

Body posture is a good indicator of, amongst other things, people's state of arousal, focus of attention and level of interest in a conversation. Posture is conventionally measured by observation and hand coding of videos or, more recently, through automated computer vision and motion capture techniques. Here we introduce a novel alternative approach exploiting a new modality: posture classification using bespoke 'smart' trousers with integrated textile pressure sensors. Changes in posture translate to changes in pressure patterns across the surface of our clothing. We describe the construction of the textile pressure sensor that can detect these changes. Using simple machine learning techniques on data gathered from 6 participants we demonstrate its ability to discriminate between 19 different basic posture types with high accuracy. This technology has the potential to support anonymous, unintrusive sensing of interest, attention and engagement in a wide variety of settings.

CCS CONCEPTS

• **Human-centered computing** → *Ubiquitous and mobile computing design and evaluation methods*; • **Computer systems organization** → **Embedded systems**; • **Networks** → Network reliability;

KEYWORDS

E-Textiles; Posture Classification; Machine Learning; Social Interaction; Pressure Sensors; Embedded Systems; Smart Clothing; Ubiquitous Computing

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1 INTRODUCTION

Posture can reveal a lot about what is going on in an interaction. For example, bored members of an audience tend to sit back, prop their head on one hand and stretch their legs out in front of them whereas engaged audience members tend to sit upright, legs tucked under the chair and keep their hands down [4]. The richness of the cues available from posture and body orientation can be surprising. In conversation we can tell, just by looking, who is talking to whom, whether the interaction is, e.g. hostile or friendly and what the general level of interest and engagement is [20, 33].

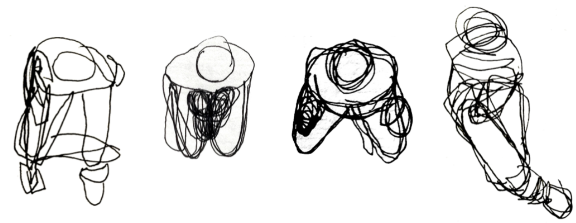

Figure 1: Sketches of different listener postures observed during seated conversations. From left to right: a) right over left leg, ankle touching knee, right hand on thigh; b) sitting straight, hands in crotch; c) legs spread, hands on thighs; d) right leg crossed over left, hands on right thigh

Many conversations happen when seated. Casual observation of these situations reveals an especially rich variety of different postures (see Figure 1) enabled, in part, by the relaxation of the need to use legs to support our body weight. People continually adjust their posture and re-arrange their hands and legs when seated. For example: hands resting on laps; elbows on thighs; a forward leaning posture; hands that are tucked between thighs; hands on knees and many other variations. Our basic question is, what can these different postural states tell us about conversational engagement and potentially even about more complex, affective states?

Although posture and body movements are typically analyzed using video or, more recently, computer vision and motion capture techniques (e.g. [15, 16]) there are some limitations to this approach. First, and most obviously, the presence of a camera is always to some degree intrusive. Consent to video may be difficult to obtain and even when it is obtained people's awareness of being videoed can affect the naturalness of their behavior. Optical motion capture markers in particular are cumbersome, visually intrusive, require special clothing different to the clothing materials we naturally engage with, and reinforce the potentially distorting effects of being in a laboratory.

Second, while camera based techniques can capture changes in overall body configuration they do not sense the shifting weights and forces that movements induce. These are potentially interesting cues in their own right. The extent to which they are perceived by human observers or are, in principle, capable of being captured by

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camera are also interesting questions. Even though depth-camera systems like Kinect can detect some shifts in pressure as well, they are limited in sensing postures that are easily occluded by the body and furniture.

Previous work has shown that the basic forces created by posture shifts can be detected by pressure sensors embedded in chair seat covers [25, 34]. For example, we established that pressure changes in the seat of the chair alone can provide enough information to distinguish between who is speaking and who is listening and also to detect moments of laughter [34]. Even though this work suggests that the changes of pressure on the surface of a seat are sufficient to identify different conversational states, the sensors were relatively coarse grained and intrinsically limited by the fact that seat chair covers are in contact with only a relatively small proportion of the body. Behaviors such as resting the hands in our laps or between the knees are difficult to detect in this way. Rather obviously, they also only work when someone is actually in contact with the chair.

In this work, we look at such postures of the lower body and the positions of hands on upper legs from the perspective of legs themselves. The basic question of concern here is whether we can reliably detect different seated postures by detecting pressure changes on the surface of a pair of trousers. To do this we have developed an unobtrusive on-body textile motion capture system that uses a matrix of fabric pressure sensors around the thighs and buttocks. These trousers allow for a more fine grained tracking of pressure changes and, compared to chair covers, have the potential to capture hand and elbow contact as well as more distinct movement involving the thighs.

The postures we select for testing derive from detailed video-based observations of naturalistic seated multi-party interactions. Here, we collect a data set of posed postures collected in a controlled environment to benchmark the sensing capabilities using automatic classification techniques.

2 RELATED WORK

2.1 Textile Sensors

We have learned about the meaning of colour in textiles, have used various shapes, lengths, fits of clothes to encode and represent social, cultural and political statements through history. We can quite consciously depict our mood, profession, personal preferences with what we wear and how. We talk "through" our clothes, if we want or not. Recent developments in the textile industry and academic research have also shown that we are becoming able to talk "with" our clothes, for example turning them into interfaces for digital devices or use them as types of remote controls.

When deploying sensors on the body, there are restrictions as well as opportunities that come with it. More bendable, soft and in general more flexible materials comfort the sensing capacities for the body. Instead of using gadget like hard materials such as plastic that encapsulates electronic components in belts, wristbands or other accessories, fabrics have been explored as an appropriate sensing material for such purposes. This has been demonstrated in numerous works, whether this is on table cloths [12] or denim jackets [29]. But also other alternative sensing materials are being investigated to decrease intrusiveness. Everyday objects like doorknobs [32] or ceiling lights [22] can also serve as sensor networks to capture posture and gesture and help to create ubiquitous and ambient "smart" environments. In some cases, even the skin itself has been used as a sensing surface [40].

The idea to integrate electronics in fabrics, however, is not novel as such and has a decades long tradition. Especially through the body of work produced by Perner-Wilson, Satomi et al [27, 28], the field of smart electronic textiles, or e-textiles, has been fast growing.

Electronic textiles are conductive fabrics or yarns that, when connected to a micro controller, are turned into sensors and actuators. Such materials can be used as various sensor types (see e.g. [41]). The most common types that are used in the field of e-textiles are radio frequency identification (RFID), e.g. in [37], piezo-resistive (e.g. measuring stretch and pressure) and capacitive (e.g. measuring proximity) sensors. Most recently, a combination of the latter two has been introduced [35], which expands on the measurements that we can collect from e-textiles.

In our work, we focus on the use of piezo-resistive textile pressure sensors. Moreover, we are building on the work of Donneaud et al. [8, 9], who have designed a matrix of pressure sensors using conductive fabrics alone. A grid of multiple pressure points allows a more fine grained sensing compared to previously used larger sensing surfaces, that make it more difficult to determine the precise location of touch or pressure. The continuous tracking of the changes of pressure not only captures the intensity of touch, but also the movement across the surface of the matrix.

2.2 Sensing Trousers

With new technologies enabling to embed electronic components in textiles in less obtrusive ways, everyday pieces of clothing and accessories can be turned into smart and interactive products.

Exploring how soft circuits and electronics can be embedded in such products, most examples demonstrate designs and use cases for upper body garments. Only few have focused on the potential of trousers. This can be explained with the upper body being considered to contain more information about body movement and its social implications, e.g. through gestures that are captured with tilt sensors and accelerometers, or heart rate being measured with sensors around the chest. Tracking acceleration of hand movement or heart rate have become common measures for various on-body sensing applications in recent years.

There are, however, some works that have discovered trousers as an equally informative interface for sensors. For example, Dunne et al. [10] used motion capture markers on trousers to track leg movement, as well as conductive thread stitched on trouser fabric to detect joint movement and bending [13]. Shafti et al. measured muscle activity with ECG sensors in running trousers [30] with embroidered conductive threads. Also in other attempts, textile sensors have been deployed on trousers - for example patches on front thighs to recognize touch and envision new input formats for computer interaction [17]. What else trousers can be used for in the context of smart, interactive clothing is discussed by van Laerhoven et al [38], who ask what trousers should and could be taught by humans.

2.3 Non-Verbal Behaviors

Postural states and shifts are important cues for social behaviors in social encounters. It starts with the spatial formation of participants that can reveal the level of intimacy and relationship between them [20]. Especially when there are more than two participants, these so called F-formations can take complex arrangements, describing the space between members of the interaction, and also give implications as to who has what rights to speak and who can contribute in what way to the conversation. For example, the interpersonal distance reveals how intimate (or not) the relationship between individuals is [39]; and the orientation of the participants' bodies can give indications about who enters or leaves such a conversational formation [20].

When looking at bodily constructs of individual participants, similar cues can be retrieved from gaze, gestures, body torques or fidgeting [5, 15, 33, 42]. For example, nodding can signal who is being addressed, and the direction of the torso can embody to which degree someone participates in a conversation or is involved in side activities [33].

Again, most observations are directed towards activities on the upper body, focusing on gestures and facial expressions, through which, for example, knowledgeability can be predicted automatically [2]. Nevertheless, some behavioral cues have been retrieved from leg movement as well. When speakers draw legs back and lean forward, they indicate interest and attention, while stretched out legs are observed more in boredom [4]. Mehrabian and Knapp also point out the "honest" information signals postures comprise because of their unconscious nature [21, 23]. This, so it is argued, occurs more in leg movement than in the torso [21]. But also very conscious social cues happen through legs, such as revealing a thigh, or sitting with open closed legs to indicate "openness" for interaction [23].

Also in screen based interactions, the lower body reveals a great deal about engagement and affect. It has been found, for example, that fidgeting and thigh movement [5, 42] play a significant role in detecting attention levels, and also that tracking feet movement alone has proven to be a good indicator for detecting overt postures as well as movements referring to gestures and nodding [6]. It goes that far as to identify people through tracking their movement on a seat [31].

Many of these behaviors can and have been measured with pressure sensors. D'Mello et al., for example, found that frequent changes in pressure refer to boredom and restlessness of learners [7]. Together with pressure, other modalities have been explored and combined with information of postural shifts, such as facial cues [11].

2.4 Classifying Cues

Many of these measurements are taken from Human-Computer-Interaction (HCI) scenarios, such as investigating user behavior for screen based tasks. Also when measuring affect, it is often done in single user interactions with a device. The advantage of measuring behaviors of a human working with a computer is of course the variety of sensing methods. A computer can monitor eye movement, track actions like mouse clicks, or record audio and video data. These more or less conventional sensing technologies are still amongst the most common. When evaluating interaction between humans, more recently, other multimodal systems have been introduced to develop classification models based on non verbal cues (and their co-occurrence), e.g. in [26]. Such a network of sensors relies on both visual and physiological measures and features both, off- and on-body sensing. It is often stated that this combination of different sensors is required to achieve a high accuracy for classification models. There are works, however, that suggest that even one simple sensor type has the capacity of picking up rich cues of conversational behavior.

Especially when focusing on capturing sitting postures in that regard, it has been shown that pressure sensors on chairs have the potential of replacing more complex data collection, like from accelerometers, IMU sensors (Intertial Measurement Units) or motion capture markers (see for example [1, 6, 25, 34, 36]). For example, Tan et al. achieved a 96% accuracy with 20 participants when testing pressure maps created from 64 pressure sensors [36], similar results with only 5% error were modeled by Meyer et al. [24]. Also Cheng et al. reported about an accuracy of 0.88 with sample data with 4 subjects [6]. Less accurate classification is reported in [31], although in this work, the highest resolution of pressure sensors was used. This again implies that not the amount of sensors used is key for better posture detection, but other measures come into play just as much.

It is also worth noticing that, when using more simple methods like pressure measurements, the sensors are almost always deployed on the chair, and are never integrated in clothing. Moreover, these sensors are not made of fabrics or other ubiquitous materials that we would find on a chair, but often out of plastic and hard components.

We are introducing an unobtrusive on-body sensing system, having designed costumized trousers that capture postural movement around the thigh and the buttocks using fully embedded fabric pressure sensors.

3 TROUSER DESIGN

Conductive textile materials like yarns can be turned into smooth textile surfaces and sensors which can be embedded in everyday objects and surfaces we come in touch with. This has been shown in projects turning chair covers [36], table cloths [12] or floor carpets [6] into smart objects.

Deploying fabric sensors in garments has the benefit of having an unobtrusive, non-distracting and therefore less distorting sensing interface that is also comfortable to wear and doesn't modify our common surroundings. These properties have led us to focus on textile sensors in clothing, and the choice of materials as well as the pattern cutting design was guided by this approach on ubiquitous technology.

3.1 Materials

Our trousers consist of three different types of material: non conductive base fabric that would be the material in direct contact with the wearers' skin; conductive fabrics that are concealed on the inside of the trousers and are turned into sensors; and the electronic components that collect the data. All conductive material was integrated into the trousers so that it wouldn't come in direct contact with the skin when being worn.

Figure 2: Left: pattern of one trouser leg, the back (buttocks) on the left with the more defined curve, and the front (crotch) with the steeper curve on the right. The sensor matrix ends around the knee (light blue fabric). Right: finished trousers turned inside out, before wires are inserted in tube panel on inside legs.

3.1.1 Conductive fabrics. As described in numerous other textile sensor works, piezo-resistive pressure sensors usually consist of 3 layers: 2 conductive layers, and a resistive layer in between, preventing the two layers to touch directly and short the circuit. This resistive layer is also conductive, but with a much lower conductance than the other layers. For this resistive layer, we used EeonTex stretch jersey from Eeonyx[1], which has a resistance of 10-20 kilo ohm per square. The more conductive layers are a single jersey 'zebra' fabric, purchased from Hitek[2], made of conductive nylon yarn and textured polyester (for the non conductive parts). All fabrics used to make this sensor matrix can be commercially purchased per meter.

3.1.2 Non-conductive fabrics. The outer layer of the trousers consists of viscose-cotton single jersey knit in a fine gauge (see black fabric in Figure 2), and the pattern parts on the inside of the trousers, like lining fabric, covering the thighs and buttocks up from the knees, are made of a cotton elastane mix single jersey knit (light blue fabric in Figure 2) that conceals all conductive layers.

This layering of non conductive and conductive fabrics make the trousers thicker on some parts: around the thighs and buttocks. However, since all fabrics are light weight and single jersey knits, participants and prior fitting models reported the trousers to be comfortable and only a bit 'warmer' around the upper legs.

3.1.3 Electronic components. All materials that are not fabric are placed on a solid circuit board that houses a micro controller, a Teensy 3.2, a battery and a datalogger with a micro SD card on which the data was stored. The individual rows and columns of the matrix were linked to the input pins of the micro controller through thin and flexible insulated wires, embroidered to the fabric and soldered to the circuit board.

[1] https://eeonyx.com
[2] https://www.hitek-ltd.co.uk

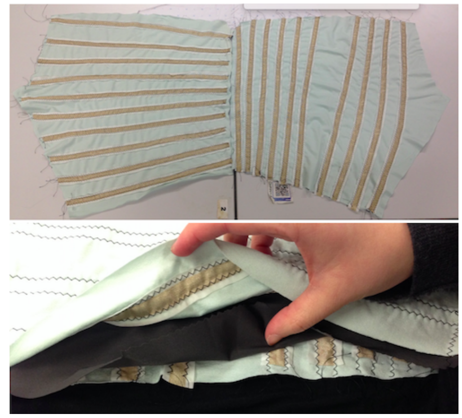

Figure 3: Top: arrangement of rows and columns of the sensor matrix. Bottom: layers of the matrix: conductive nylon stripes as rows and columns on outer layers, stitched onto non conductive jersey (light blue), resistive EeonTex stretch jersey (gray) in between

3.2 Sensor Design

The sensing area around the thighs and buttocks of the trousers consists of a 10x10 grid, which is made of cut up stripes of the zebra fabric described above and is designed in the shape of trouser patterns. The width of the conductive stripes is 1cm, so that all 100 pressure points are the same size of 1x1cm. The arrangement of the grid is not symmetric or distributed equally, but designed to be more dense (or fine grained) on the areas where hand touch occurred as more likely, and less dense, for example, along the side of the thigh and the buttocks, which is displayed in Figure 3.

While the schematic of the sensor matrix as well as of the circuit board (PCB) follows the work of Donneaud et al. [3], the size, PCB design and data processing was altered and modified to our use case.

Each leg has its own sensor matrix, micro controller and circuit board, so each leg collects data independently from the other. This has practical reasons, such as the limited number of input possibilities on the micro controller or the design of the cabling integration not interfering with wearability comfort, but also reduces the risk of error, when one leg fails to collect data, the other one still functions without interruption. A drawback of this, however, is certainly the increased cost with two micro controllers per pair of trousers.

3.3 Pattern Construction

Trying to accommodate different clothing sizes and body shapes, three different trouser patterns were developed, having constructed a grading system that draws from sample data of 11 different subjects (7 male and 4 female). Using an elastic fabric is the easiest way to make a garment fit multiple sizes, as well as making the garment loose. In our case, the aim was to have a pair of trousers that sits close to the body, enabling more precise data collection and posture tracking. We decided to make leggings because they are both, elastic and tight, and are a piece of clothing that most

[3] https://matrix.etextile.org

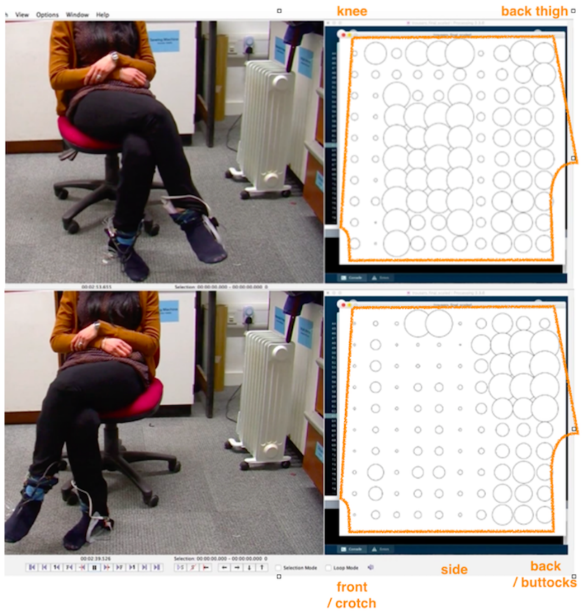

Figure 4: sensor visualization of the participant's left leg for two different leg crossing postures. top: right leg over left, bottom: left leg over right. Aligned with annotation software Elan [3]

people are familiar with and use. Differences in body shape also entail that the sensor points of the matrix are not always in the very same position, regardless the range of sizes. With the choice of material and pattern, however, we minimize this variation.

Informed by our observations of lower body movement, we defined the sensing areas around thighs, knees and buttocks and have developed a design for the sensor matrix that covers most of the front, side and back leg. Accounting for this, side seams were eliminated in pattern cutting, and instead, a tube fabric panel was inserted on the inner leg. This panel was double layered to serve as a tube like seam[4] to encapsulate thin wires that were embroidered onto the fabric rows and columns of the sensor matrix and were stitched down along the inner leg to the bottom hem, where each wire would be connected to the micro controller (see gray wires on the left in Figure 2). The circuit board was cut as small as possible to be stitched onto the hem of the trousers. A battery could be tucked into the hem, too.

4 STUDY DESIGN

To assess the reliability and overall performance of our sensing trousers, a user study was conducted[5]. We tested 19 different postures that were identified through ethnographic observations, drawing from a video corpus of 12 seated three-way conversations (36 different subjects).

The design for this experiment follows settings of similar user studies, in particular orientating towards the work of Meyer et al. [24], who identified 16 similar postures and tested these with 9 subjects in three rounds for classification purposes. Other works evaluated gesture classification with even fewer subjects (e.g. [6, 19]), or tracked leg movement with one tailor mannequin [10]. Examples like this show that even with collecting posture data of only one person [36], but having multiple recordings per posture, results are accurate enough for classification models.

4.1 Participants

The data was collected from initially 10 participants, aged between 19 (2) and 42 (1) (the rest between 26 and 36years). 5 female and 5 male subjects were recruited, and different clothes sizes were taken into account to test all 3 sizes of trousers that were manufactured, but also to compare the data sets of postures across different body sizes and shapes. Later we had to discard the data of 4 participants due to an error with sensors and the data files.

4.2 Procedure

The study consisted of single user actions. Participants were asked to perform sitting postures and gestures, following verbal instructions. The 19 posture types are:

(1) standing up (hands to the side, natural standing position)
(2) sitting down, up straight = "home position" (first "natural" position taken when sitting down, without hands, knees or lower feet touching)
(3) sitting straight with knees touching
(4) leaning back
(5) leaning forward (without hands touching thighs or knees)
(6) slouching
(7) leg crossing: left on right leg (e.g. Figure 4 bottom)
(8) right on left leg (Figure 4 top)
(9) leg crossing: left on right leg with ankle touching knee
(10) right on left leg with ankle touching knee
(11) sitting up straight, hands touching knees
(12) leaning forward with hands on knees
(13) hands in crotch, see e.g. Figure 5
(14) hands between thighs, knees touching (thighs pressing on hands, hands touching each other)
(15) hands on mid thighs
(16) elbow on thighs, leaning forward
(17) lower feet postures: both lower feet stretched out
(18) lower feet bent in
(19) lower feet crossed.

While the different order of crossing legs was accounted for in separate postures for the thighs, the last posture, crossing lower legs, was not separated into two instructions and we didn't distinguish as to which lower leg crossed which (since there were not sensors covering the lower legs and we overall focus on upper leg movement).

Each posture was held for 5 seconds and returning to the "home position" for 2-3seconds in between. The instantaneous pressure readings from the 200 sensor points for the duration of one posture are defined as an instance (this accounts for 4 instances per second). Each participant repeated this sequence of instances three times (approximately 60 instances per participant per posture).

[4]similar to what is called "french seam" in tailoring vocabulary
[5]Ethics Approval Reference: QMREC2133a

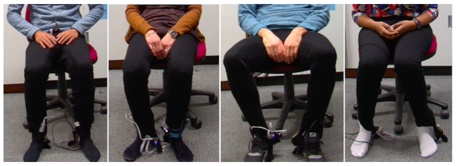

Figure 5: the same posture "hands in crotch" executed by four different participants

4.3 Data Collection and Pre-Processing

The raw sensor data was collected following the principle of Donneaud et al. [8, 9], the rows forming the digital inputs and the columns the analog inputs on the corresponding microcontroller, a Teensy 3.2. Pulling the digital pins high and reading analog input values from the column creates a sensor reading for all data points across the matrix - each sensor being stored in a separate column, and each row accounting for the readings over time. A time stamp was included for later synchronization between the legs as well as with the video recording. A detailed documentation of this method can be found in [8, 9].

Alongside the sensor data, a video recording documents the session capturing the verbal instructions and posture of the participant. Unlike in [8, 9], we do not process and visualize the data immediately in real-time, but store it on a micro SD card for off-line analysis. After the completion of the postures by each participant, the data is normalized so that the maximum sensor value is 1.0. The data can then be visualized and mapped to the corresponding location on the sensor grid using the open source software platform Processing[6].

The mapping of the data visualization and sensor numeration is arranged as shown in Figure 6, where the first sensor sits on the front inside leg and the last sensor on the top of the back pattern. A screenshot of the animation can be found in Figure 4, showing each data point as a circle increasing in size when the pressure on the sensor increases (e.g. bigger circles on the top end mean more pressure on the buttocks, which would indicate a sitting position). Note that one grid depicts the data of one leg only, so it is not representative for the whole pair of trousers.

4.3.1 *Data Annotation.*

To generate a ground-truth data set of the 19 different postures, annotations for each of postures were added to the video recordings using the software package Elan [3]. All postures were hand coded as static positions, discarding any transition periods between them. For example, the movement between crossing a leg and returning to the home position was not included in the posture, but treated as noise and removed.

The sensor data was then time-aligned with the video annotations and exported into ARFF format. While we collected the raw sensor data in the study, the normalized pressure readings used as the input for our training model.

5 RESULTS

The aim for the trouser sensing system is for it to automatically recognize the posture of the wearer. The first steps towards achieving this is to generate ground-truth data to train a machine learning model performing a classification task in order to provide a baseline indication of the system's performance.

[6]https://processing.org

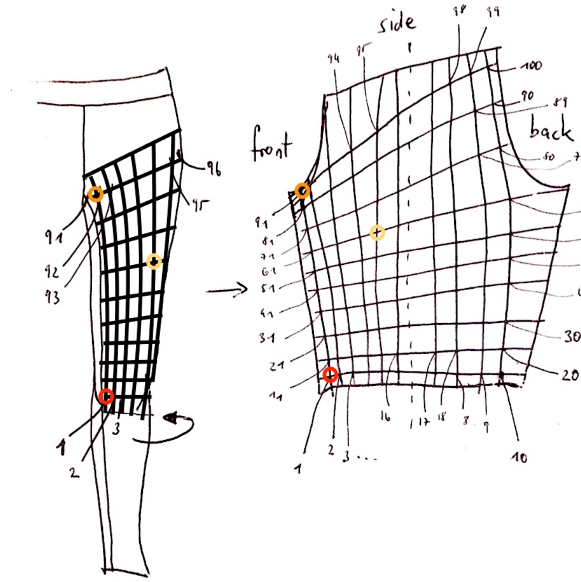

Figure 6: Mapping of the sensor numeration across the matrix on the leg: sensor 1 on front inner leg on knee, sensor 100 on back inner leg on buttocks, 10 sensors per rows.

The 200 sensor data points were captured at 4 Hz resulting in over 9000 total postural instances across six participants. Of these 1327 were instances of the standing posture with 325 to 626 instances of each of the remaining seated postures. The higher number of standing postures is due to longer standing periods in between the cycles of posturing, which were also taken into account for analysis. Instances where the participant was not clearly displaying one of the postures were discarded from the data set.

5.1 Posture Classification

Weka [14, 18] was used to train and evaluate a Random Forest model with bagging with 100 iterations. It was first evaluated with individual participants, then as a population-level model with all participants, and finally with individual participants withheld from training.

5.1.1 *Individual models.*

When training a Random Forest model and evaluating using 10 fold cross validation with stratified data on a single participant, it showed excellent results in classifying postures with an average of 99.31% of postures classified correctly. The percentage correct classifications for each participant can be seen in Table 1. The models showed particularly good performance when classifying between standing and seated postures, with only misclassifying one posture for two participants as seated with knees touching or the home position instead of standing (participants C and D). The success in the classification between seated and standing is likely because of the significant difference in sensor values on the underside of the trousers, however the data captured

Participant	Individual	Withheld
A	99.75%	64.26%
B	99.58%	42.71%
C	**99.68%**	**27.93%**
D	**99.21%**	**10.97%**
E	98.80%	32.20%
F	98.84%	50.10%

Table 1: Percentage of correct classifications for each participant when trained on a single participants and evaluated using cross-validation, and when that participant was withheld from the training set then used as the test set. Participants C and D in bold are the two participants who misclassified standing postures.

may also play a role. For each participant there was up to four times as many instances of standing than any other posture in the data set due to the sequence of positions recorded.

When examining the F-measures, four of the six participants had the best classification performance with standing and worst with the feet crossing and hand-dependent postures such as the ones shown in Figure 5. For the two participants with misclassified standing postures, their leg crossing postures performed better than other postures.

5.1.2 Population models. The next step was the examine the potential of building a generic, population-level model. We started by training a Random Forest model on the aggregate collection of postures from all six participants and then evaluating it using 10 fold cross validation with stratified data. This had excellent results with 99.18% of postures classified correctly.

Similar patterns occurred as when building individual models for each participant. Again, standing performed well when compared to non-standing positions, though it still has up to 4 times as many posture instances than other postures. It had one more misclassification when compared to the individual models – along with being confused by knees touching and the home position, it misclassified a slouching posture.

The ideal trouser sensing system would be able to train from data sets of lab-based postures, and then correctly classify the postures of a new wearer who had not previously gone through an individual training phase. To evaluate the feasibility of this application, we generated six Random Forest models withholding a single participant from the set, and then tested that model with the withheld participant data. As was expected, all participants performed much worse than when their data was included in the training set, but all performed better than random chance.

The two participants that performed the worst were the same that performed the worst at classifying between standing and seated postures. Those whose individual models could better distinguish between standing and non-standing also performed better when their data was not included in the training data with the best performance being 64.26% from participant A. The classifications from the model built without participant A can be seen in the confusion matrix in Figure 7. The matrix also compares which postures were confused with which other postures. For example, "hands between

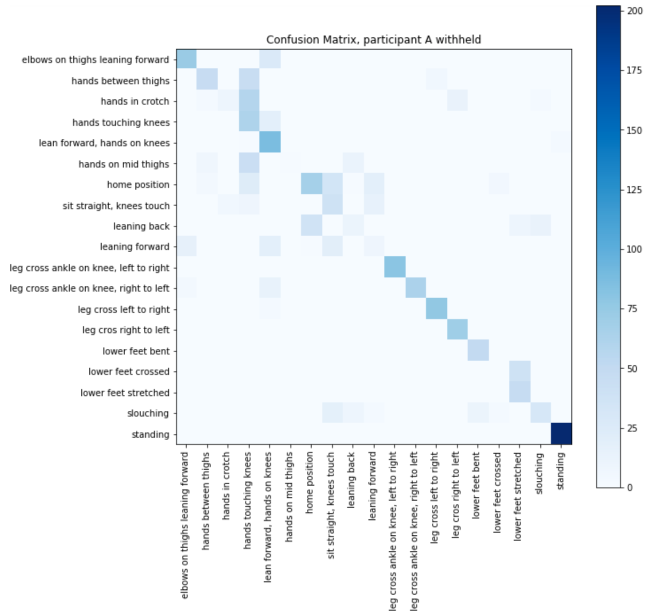

Figure 7: Confusion Matrix, participant A withheld. Number of instances are colour coded as shown on side bar (0-202 instances, white to dark blue).

thighs", "hands in crotch" and "hands on thighs" were often misclassified as "hands on knees". This can be explained with the similarity of the postures as well as the variations of hand positioning per participant and posture repetition. Other postures that were confused with each other are "leaning back" and "home position", both only performing movement of the upper body. More, less common misclassifications can be deducted from Figure 7.

These four participant tests were able to recognize standing better than any other posture. This indicates that may be a potential application in recognizing the postures of a wearer who has not gone through a training phase, but much more data needs to be collected to better inform the machine learning model.

6 DISCUSSION

Given the small number of sample data, there is much room for improvement for this classification model. And yet, the implications for use cases that emerge from the results of these sensing trousers are promising.

The machine learning model shows good performance when building a general population-level model, as long as the participant being tested is represented in the training of that model. It has significantly worse performance when testing a model with a participant who is not represented within the training set. This indicates that the sensors could be effectively used to automatically identify postures as well as individuals, if that participant goes through a data collection phase. Without more data and model refinement, this is not yet ready for generic use where an unknown participant could have their postures detected without training. Another aspect of our study set up that may affect the results is the controlled data collection with static postures in a repeating order. The trousers were worn once by each participant and have not been tested with variations in order and duration of postures, or for consistency in multiple wearing sessions, which could lead to minimal changes in sensor positions. In social interaction, dynamic postures are more common, and occur in different order and with different transitional movements. We have accounted for the potential noise in the data regarding repetition and order effects, and we plan to dedicate future work to investigate these points further by testing our trouser design in conversational scenarios.

Our evaluation has shown that there may be a much richer collection of postural cues yet to explore that has so far been invisible to more conventional sensing technologies. If thighs and buttocks can provide such details about behavioral cues with their shifts in movement and touch interactions, there are potentially additional and complimentary cues to be collected from lower legs, feet movement or other areas of the lower body that haven't been explored in detail and that go beyond gesturing and apparent twists in posture.

Translating the classified postural movements to affective states and a measure for conversational engagement, trousers have the potential of identifying a "smart arse", or could detect if someone is listening, interested, bored or restless. For example, future work is directed towards specific questions as to whether leg crossing correlates with gaze and determining addressees; whether the position of hands on legs bears information about levels of arousal and valence to detect stress, comfort, anxiety, etc.; or elaborate further on findings of existing work [42] that suggest that thigh movement implies user attention level. This also leads to questions that expand on the sensing capacities of this sensor design. Having trousers that can not only capture leg movement, but that also pick up touch of the hands, it is intriguing to explore how well, or if at all, trousers can also pick up upper body movement, like nodding, head turns or conversational states like speaking and listening; and, if not, how an equivalent design would look like for garments for the upper body. The contribution this body of work can make towards affect detection and understanding different modalities of human communication could benefit applications in the medical sector for the design of therapies, like physiological rehabilitation, as well as cognitive therapies. Furthermore, such trousers could be designed to feed back this information to participators of social encounters and thereby help to improve human interaction scenarios. Such "socially aware trousers" are not only potentially enriching for interaction between humans, but also for applications in Human-Computer-Interaction - even if that is only by replacing rigid interfaces with soft, flexible textile sensing surfaces that can be worn unobtrusively on the body.

Our sensing trousers explore the possibilities of textile pressure sensing to detect touch and postural states. Using the same materials and data processing techniques, however, other sensing modalities like stretch can be captured, too (for measuring the bending of a limb, for example). But even beyond piezo-resistive sensing, reaching towards hybrid sensing methods like Strohmeier et al. have introduced [35], different types of touch can be identified with "smart" fabrics that feel like everyday clothing items. Textiles, electronically enhanced or not, are a material we already engage with traditionally, and clothes are something omnipresent. This is their foremost advantage compared to other modalities with similar sensing capacities, for example Kinect v2, which may be able to sense muscular force, but is vision dependent and requires special spatial settings to take bodily measures.

The ability to monitor postural shifts and pressure applications has also the potential to inform garment construction and pattern cutting in direct dependency with the intended use case. This could range from applications for fashion retail, e.g. clothes that take size measurements[7], to the simple objective to develop more comfortable trousers for professions that require a lot of sitting (e.g. in offices). Other smart clothes can be made to identify their wearer with application scenarios in health and safety, and could also be a gateway for an even less intrusive, embedded contactless payment option. Such implications to the design of trousers would give the saying "you are what you wear" yet another notion and would make our clothing not only subject of personal expression, but also of identification and a more active part of our everyday actions. In the future, clothes may not only be objects that project communication, but potentially be aware of how we communicate with others.

7 CONCLUSION

In this paper, we have presented a new unobtrusive method of capturing different sitting postures that is integrated in stretch trousers. Using a textile pressure matrix around the thighs and buttocks, it is possible to detect different leg movements as well as gestures on the lower body. We demonstrate that shifts in pressure on the upper leg are enough to train machine learning models to identify leg crossing, positions of hands on thighs and knees, lower leg postures, as well as more subtle weight shifts with high accuracy, that are usually difficult to be picked up by other motion capture systems relying on visible cues. Automatic classification models were tested to distinguish between 19 posture types, and have shown promising results towards an objective to make garments "socially aware".

Our work introduces textile sensing as a new ubiquitous method to detect social behavior and analyze conversation. By exploring fabrics as an interface so close to our body, we anticipate that we will be able to identify additional postures as important cues in social interaction.

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