Economical dynamic surface sensing: recognition of affective touch and toucher

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ABSTRACT

Social touch is an essential non-verbal communication channel, whose interactive possibilities can be unlocked by the ability to recognize gestures directed at the kinds of surfaces likely to invite them. To assess impact of sensor noise due to motion, substrate and coverings, we collected gesture data from a low-cost custom multi-touch fabric location/pressure sensor and compared data features and recognition performance. For seven gestures identified as most relevant in a haptic social robot context, we carried out two studies: (1) sensor stationary, varying *substrate*, and *fur covers* (n=10); (2) sensor attached to a robot under a fur covering, flexing or stationary (n=16).

For a stationary sensor (study 1), a random forest model achieved 90.0% recognition accuracy (chance 14.2%) when trained on the full dataset, but as high as 94.6% (mean 89.1%) when trained and tested on the same individual. . For (2), a curved, flexing surface achieved 79.4% overall but averaged 85.7% when trained and tested on the same individual. These results suggest that under realistic conditions, recognition with this type of flexible sensor is sufficient for many applications of interactive social touch. We further found evidence that users exhibit an idiosyncratic 'touch signature', with potential to identify the toucher. Both findings enable varied contexts of affective or functional touch communication, from physically interactive robots to arbitrary sensed objects.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous; D.2.8 [**Software Engineering**]: Metrics—*complexity measures, performance measures*

General Terms

Measurement

Keywords

Haptics, Tangible interaction, Social touch, Affective touch, Piezoresistive pressure sensing, Gesture recognition

1. INTRODUCTION

Flexible wearable touch sensors have become affordable and very accessible. Due to inexpensive electronics and Do-It-Yourself (DIY) guides [7], anyone with a healthy interest in constructing their own touch sensor, can do so. While this low barrier to entry has provided a variety of low-cost pressure sensors, there remains a need for sensors that recognize not just pressure or location, but both. Balancing multidimensional fidelity with cost is an important step towards making effective wearables, but part of that balance comes through developing good sensing techniques as well as technologies. We are interested in leveraging this multidimensional touch data to be able to perform gesture recognition with a 2 cm^2 per pixel grid. This kind of sensor could allow for a variety of touch interfaces that may afford a range of interesting interactions while keeping materials and construction costs low.

1.1 Motivation and Requirements

This project began as an attempt to approximate the sensory capabilities of animal skin, however, the sensor we developed should work in a wider paradigm of touch devices, especially those that incorporate fabric into their design. Since any object made with fabric is typically neither static nor uniform, our sensor needed to withstand the noise generated by a dynamic environment.

Previous work related to gesture recognition on low cost sensors has employed the interplay between "below surface" pressure sensors and "above surface" touch activation [2], somewhat analogous to human skin with pressure sensors below the surface of the skin and hairs above it. For example, Flagg and MacLean built a furry zoomorphic creature [2] that had a pressure sensor installed below a conductive fur surface. With it, the creature could sense the high pressure forces of the touch using the "below surface" sensing capabilities as well as determine location based on conductivity activation of the "above surface" conductive fur. However, the conductive fur did not contribute as greatly to the gesture recognition capabilities as did the pressure and location data [2]. We attempted to build a sensor that could capture these two dimensions with just a "below surface" construction.

Since our sensor was required to perform well while mounted on non-rigid and/or actuated surfaces, it was a priority that it be highly flexible and somewhat elastic. We chose to construct it from a conductive flexible fabric, and explore its capabilities for gesture recognition under duress.

We also needed to accurately interpret a wide range of pressures to allow for full expressiveness. Based on a preliminary survey of touch pressures, we determined that our sensor needed to register touches between 0.005 and 1 kg.

1.2 Research Questions and Approach

We explored how accurate our flexible fabric sensor could be in predicting gesture and differentiating between users. Further, we wanted to determine how the sensor would perform under deformation due to curvature and motion, specifically on a zoomorphic social robot. Last, we hoped to determine the viability of running our simple machine learning algorithms to do real-time gesture recognition.

To explore these questions, we collected touch data on a stationary sensor to serve as a baseline for accuracy. As a follow-up study, we mounted the same sensor on an actuated robot skeleton and collected data to measure gesture recognition when varying cover (fur or not) and motion (stationary or moving).

We hypothesized that there would be high variability (or lower recognition rate) when adding noise. We hoped for low variability (or higher recognition rate) when testing and training data came from the same participant, even under very noisy conditions [2]. Due to promising results from initial testing, we also hypothesized that we could differentiate participants by the way they interacted with the sensor, or 'touch signature'.

1.3 Contributions and their implications

We used a pliable sensor made with an elastic conductive fabric, able to localize pressure data at 1cm spatial resolution. For fabrication costs potentially practical for consumer applications, performance is relatively low compared to other touch sensors; but herein, we demonstrate it is nonetheless adequate for credible social touch recognition. Specifically, using 20-fold cross validation on random forest models, we contribute:

- a demonstration of deployable accuracy in gesture recognition (7 key gestures): 86.6% on a firm and flat surface, 86.6% on a foam and curved surface, and 85.4% on a curved moving surface

- a demonstration of differentiating toucher (using all 26 participants touch data) with 91.1% accuracy.

- finer-grained investigations into factors underlying the recognition performance we found.

- a discussion of the feasibility of embedded real-time gesture recognition.

Our study compares gesture recognition performance across variety of conditions which approach real-time dynamic gesture recognition on a curved, moving surface. Furthermore, we have demonstrated gesture prediction accuracy at a rate of XX. This may be sufficient for a touch-based fabric interface as explored below, and shows promise for systems that incorporate personalized responses to an individual touch signature.

In context of social robots, a flexible sensor that can enables a robot to recognize and respond to gestural social touch could present a way for robots and humans use touch as a method of communication. This could have applications particularly in robots designed for healthcare since close proximity and direct contact is a requirement for many healthcare-related tasks.

However, we foresee applications that go beyond touch-sensitive skin for robots. Accurate gesture recognition on fabric touch sensors opens up gesture-based controls on any electronic device that could incorporate a flexible, low-cost sensor. For example, patients with limited speech capacity could use a smart blanket's gesture recognition capabilities to perform a gesture that could be mapped to a set of requests for comfort or health-reporting purposes.

There are also applications outside of explicit gesture recognition. Inpatients who have been rendered effectively immobile often require nursing staff to regularly shift and rotate their body so as to prevent bed sores. Sheets fitted with pressure and location sensors could help to alert hospital staff to areas that are at high risk of bedsores and require pressure relief.

2. RELATED WORK

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2.1 Sensing and Recognizing Social Touch

In order to achieve a touch sensor that would be able to represent pressure and location despite deformations including stretching, curving, masking etc, we were restricted to materials that had characteristics that afforded these conditions. Luckily, there have been a lot of advancements related to fabric touch sensors and there were a variety of them that are now commercially available. Stretch sensors have been designed for medical purposes by Vista Medical which we used as inspiration for much of our implementation. These stretch sensors, however, recognized just the pressure readings.

A significant basis for our design is based off of the sensing capabilities described by Flagg [2] informed many of our requirements but we also sought to improve the "below surface" sensor in order to remove any dependence on the fur cover.

We have used an Arduino microprocessor for our touch sensor, in part because it is affordable, but also because the Arduino Playground supports a variety of touch sensing approaches. A quick perusal of the website highlights examples of pressure sensing projects as well as a library specifically designed for capacitive sensing.

Still more comprehensive is the collection of touch sensor projects developed by Perner-Wilson [7]. The demonstrations depicted on the Plusea site boast a range of textile based sensors with a myriad of purposes including a stroke sensor featuring conductive threads and a flexible neoprene sensor that could recognize when the surface was being bent.

While many of these designs addressed recognizing touch contact and/or position, we wanted to evaluate the quality of the touch recognition on a sensor employing both position and pressure by testing how well the data held up to gesture classification.

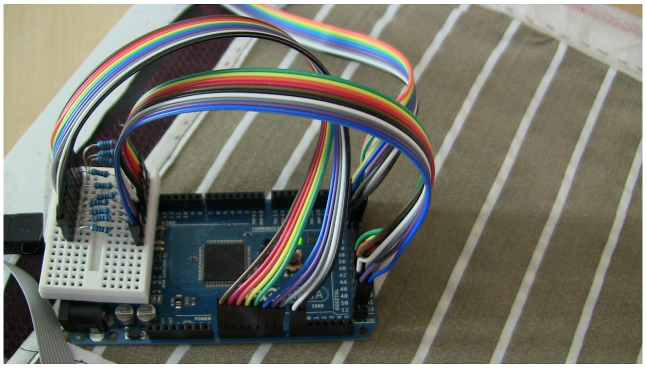

Figure 1: The fabric pressure sensor constructed out of EeonTex conductive fabric and an Arduino Mega microprocessor.

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3. STUDY

3.1 Methods

3.1.1

We constructed a sensor using 2 square sheets of EeonTex[1]Zebra fabric which has 21mm wide conductive strips separated by 4mm wide non-conductive strips. Each sheet was cut to include 10 strips and placed perpendicularly to one another, forming a 10x10 grid. Between the 2 sheets, we placed a sheet of Eeontex SLPA 20,000 Ohm resistive fabric. This grid size was chosen based on two main factors: the available input/output pins on an Arduino Mega microprocessor (see Figure 1), and the minimum size needed to identify sensor cross-talk for multiple touch points.

In order to poll the sensor, a circuit was constructed in which each strip of the conductive fabric was wired to either a digital output or a paralleled pair consisting of a digital output and analog input. The digital outputs were designed to sequentially send a 'high' voltage signal to each row and column, effectively polling each 'pixel' or 'square' of the sensor. The resistance value of each 'pixel' would then be read by the analog inputs in sequence. As seen in Figure 2, the digital output of the paralleled pair was connected in series to a resistor; this resistance value acted as a voltage divider and was chosen to optimize the sensitivity and range of the sensor readings.

[1]Fabric was purchased through Eeonyx at www.eeonyx.com

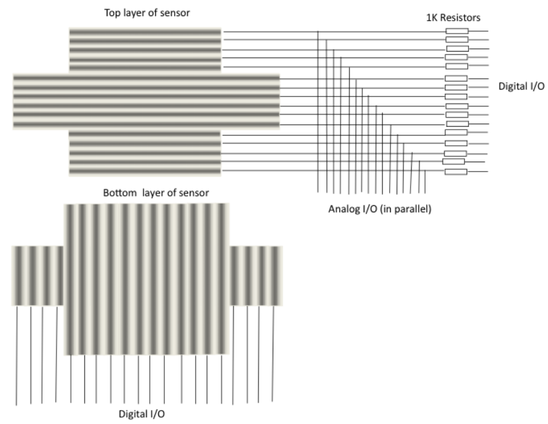

Figure 2: A diagrammatic look at the grid-sensor polling.

The same sensor and microprocessor set was used in all studies.

3.1.2

We selected gestures from a touch dictionary [9], we provided participants with a reference sheet including very general definitions on 7 selected gestures:

- **constant**: touch contact without movement
- **no touch**: no contact with the sensor
- **pat**: quickly and gently touching with the flat of the hand
- **rub**: moving the hand to and fro with firm pressure
- **scratch**: rubbing with the fingertips
- **stroke**: moving hand repeatedly
- **tickle**: touching with light finger movements

At 54 frames per second where each frame consists of pressure data from all 100 pixels in the 10x10 grid, we collected 10 seconds of continuous hand touch data for each combination of gesture and condition, randomizing gestures and conditions wherever possible.

3.1.3 Study 1 - Cover and substrate on Static Robot

This was a factorial design of 4x3x7 ([fur] x [substrate] x [gesture]) study. The *fur* condition varied pile or density from no cover (direct contact with the sensor) at all to a very long, very thick synthetic fur. In between, we had a short furry minkee fabric generally used for baby blankets, and longer minkee fabric with long, sparse fibers.

The *substrates* used included a firm, flat surface which was the sensor affixed by velcro to a table; a spongy foam, flat surface (the sensor over medium density foam); and a spongy foam, curved

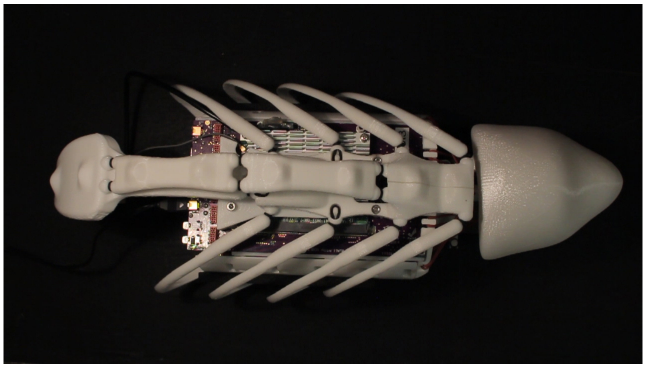

Figure 3: Top view of the CuddleBot skeleton.

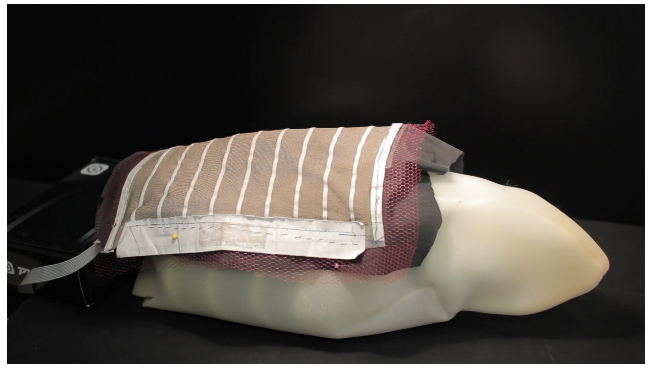

Figure 4: Image illustrating the sensor attached to the CuddleBot. The sensor was pinned to a foam substrate that was wrapped around the CuddleBot skeleton. This corresponds to a *No touch* x *No motion* x *No cover* condition.

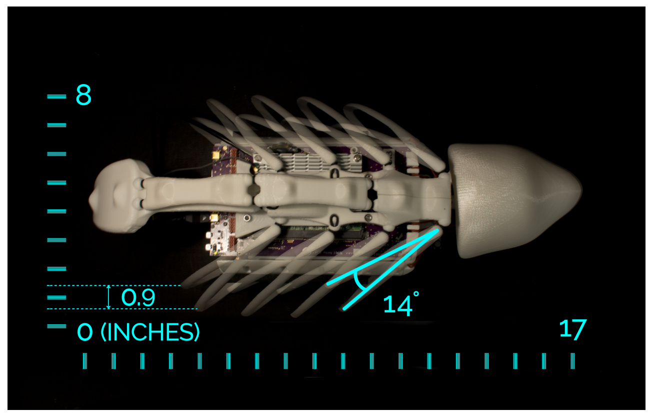

Figure 5: Image illustrating the CuddleBot's full range of breathing motion that was used in this study. Ruler markings are for scale.

Figure 6: Image illustrating a fully-covered CuddleBot. In our study, we draped a cover of nearly identical material to facilitate changing conditions quickly.

surface (sensor is pinned to foam that covers a curved styrofoam form).

In order to minimize the disturbance of moving and masking the sensor, we had to block collection on the fur x substrate conditions. Condition order, however, was randomly generated per participant and gesture order was further randomized over each condition set. For instance, we randomly generated a masking condition set (ex. fur x flat foam) and ran all 7 gestures in a randomly generated order before changing the masking condition and again running all 7 gestures. The study continued until all participants ran through all 12 conditions.

3.1.4 Study 2 - Stationary vs Moving Robot

Similar to Study 1, using standard Machine Learning algorithms and a known set of gestures, we want to quantify how well we can predict the user interaction with the sensor. We seek to answer the following questions: How accurate are our gesture predictions? What is the degradation effect of motion and deformation due to application to a more ecologically valid object (such a small robot)? Could we differentiate participants by how they touch the sensor? Do individuals have a 'touch signature'?

This study varied [cover] x [motion] x [gesture] giving a 2x2x7 factorial design where [motion] = *breathing*, *not breathing* and [cover] = *cover*, *no cover*. Each participant performed each gesture x condition combination twice in randomly generated order.

The sensor was attached to the CuddleBot (Figure 3), a small robot designed for use in therapy (Figure 4). The CuddleBot employed a 'breathing' motion by extending and contracting its ribs (Figure 5). To simulate a full fur jacket (Figure 6), we used a draped piece of nearly identical fabric. This allowed us to completely randomize our conditions. For example, a participant might perform *Tickle* x *Cover* x *Breathing* immediately proceeding *Scratch* x *No cover* x *Not breathing*.

Each session began by asking the participant to interact 'freely' with the covered, moving CuddleBot to mitigate any novelty effects. Then each condition was presented randomly twice, for a total of ((2x2x7) + 1) = 57 trials. As with the earlier study, we provided participants with a reference page describing each gesture though they were asked to interpret each gesture as they saw fit.

3.2 Analysis and Results

To keep consistency, we discarded the first and last second of each 10 second gesture capture and divided the remaining 8 seconds into 4 two-second windows in both studies. The 2 second window was so chosen as each gesture has some periodicity and all can be completely performed within 1 second [2]. Further, it is unlikely that we would be capturing the one exactly complete gesture in a realistic setting. The 2 second window ensures that we are able the capture *at least* 1 complete gesture cycle as well as the end of a previous gesture and/or the beginning of another.

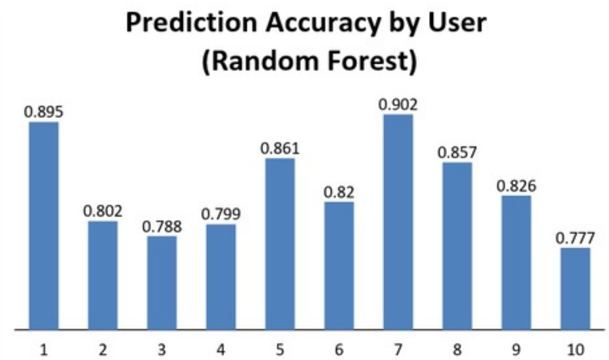

Figure 7: Prediction accuracy when trained and tested using 200 fold cross-validation Random Forest on the same individual.

In order to account for changes in position we also calculated a centroid, or average geometric centre, weighted based on the measured pressure reading for each frame. Each centroid contributed 2 dimensions: a row-position (1) and a column-position (2) and was calculated as follows:

$$C_x = \frac{\sum_{i=1}^{10}\sum_{j=1}^{10} i * pressure(i,j)}{\sum_{i=1}^{10}\sum_{j=1}^{10} pressure(i,j)} \quad (1)$$

$$C_y = \frac{\sum_{i=1}^{10}\sum_{j=1}^{10} j * pressure(i,j)}{\sum_{i=1}^{10}\sum_{j=1}^{10} pressure(i,j)} \quad (2)$$

Here C_x represents the x or row position of the centroid (Eqn 1). We found the weighted pressure reading across the rows and divided by the total frame sum. The C_y or column position of the centroid (Eqn 2) is found similarly with the *j* and *i* indices reversed.

We then calculated 7 features across these 3 dimensions (frame value, centroid row-position, centroid column-position) for each 2 second window (or 108 frames) for a total of 21 features. For each dimension, these were: maximum, minimum, mean, median, variance across all frames, total variance within the 2 second window, area under the curve (window sum). Condition variables (*curvature*, *fur*) or (*cover*, *motion*) made up the other features. The *subject* labels were included for *gesture* predictions and vice versa.

3.2.1 Study 1

After building a Random Forest model using Weka, we perform a 200-fold cross-validation training on the entire numerical data set. The overall accuracy rate for gesture prediction was 76.67%.

As with other studies [2], we were curious how such a predictor would perform when training and testing over the same individual. Mirroring our overall predictive model, we again performed 200-fold cross-validation using Random Forest but training and testing on the same individual and found that our gesture prediction did indeed improve (Figure 7) with an accuracy range of [77.7%, 90.2%].

Another research question we investigated was the degradation by the substrate-cover condition variable. Again using 200-fold cross-validation and Random Forest, we conditioned our training and testing on the same condition set (Figure 8) and was able to achieve a gesture prediction accuracy rate in the range of [73.05%, 84.10%]. It's also interesting to note that condition across our Substrate conditions Curve, Foam, None, the prediction accuracy rate is 74.84%,79.38%,79.71% respectively (Figure 9); conditioning over the Cover conditions Fur, Long, None, Short, 76.19%, 75.65%, 83.01%, 76.41% respectively (Figure 10).

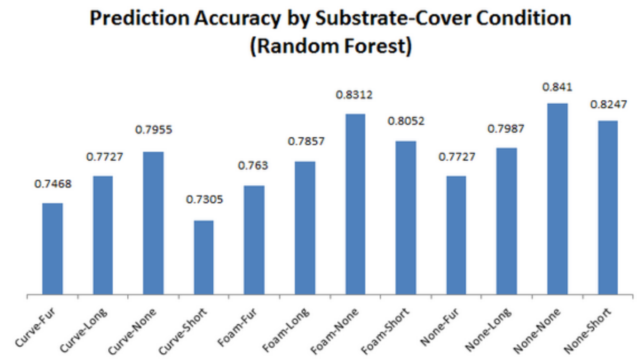

Figure 8: Prediction Accuracy when trained and tested using 200 fold cross-validation Random Forest on the same substrate-cover combined condition.

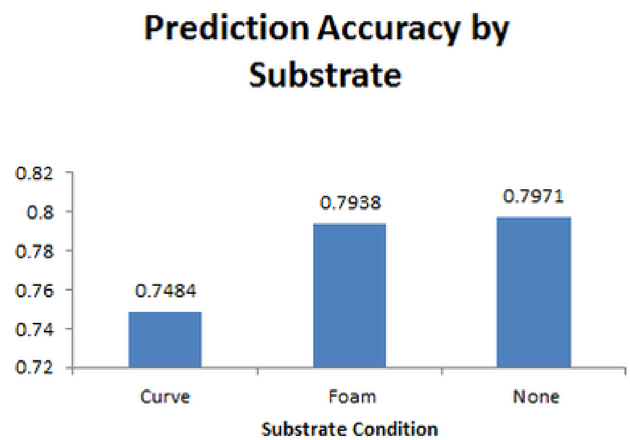

Figure 9: Prediction Accuracy when trained and tested using 200 fold cross-validation Random Forest across the same Substrate Condition.

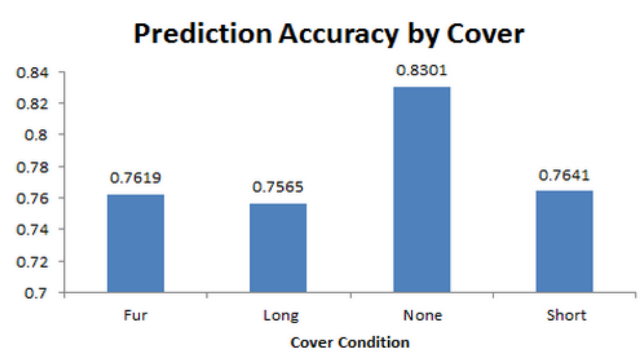

Figure 10: Prediction Accuracy when trained and tested using 200 fold cross-validation Random Forest across the same Cover condition.

We find that when trained and tested on the same individual, the accuracy rate increases significantly; so much so that our overall accuracy rate lies below the [77.7%, 90.2%] individual prediction range. This implies that individual differences in gesture behaviour may play a significant part in the predictor performance. As such, we could expect to see a significant improvement in our on-the-fly prediction mechanisms should we calibrate our prediction models to particular individuals.

It was also important to consider the degradation of our prediction under a variety of conditions. This accuracy range under the 12 masking conditions lay within 11.05%, with the highest performance as that of No Substrate-No Cover at 84.10% accuracy as compared to Curved-Foam - Short Minkee at 73.05%. We expected our none-none condition to have the greatest predictive accuracy (as there would be the least amount of interference). Looking further into predictions when conditioning across different substrates and covers, we see that there may be more variable range [75.65%-long, 83.01%-none] on Cover as compared to that of Substrate [74.84%-curve,79.71%-none].

With respect to our application possibilities, this is encouraging. As we are trying to impart that our sensor behaves well under deformation, as long as the substrate used is also that substrate being trained on, it offers consistent sensor behaviour. In the case of a curved body, having a sub-5% difference in accuracy rate between that and no deformation at all is an interesting result as it suggests that we may very well be able to have relatively high confidence in our prediction performance with only minor adjustments. Further, in many of the potential applications that we have considered, we are likely to have more control over the cover conditions than that of the substrate. This result means that we are able to focus our attentions on ensuring that our cover minimizes the interference of user-enacted contact as there is relatively minor data-loss due to the substrate.

3.2.2 Study 2

We found similar accuracy ranges in all conditions, which suggests that deformation due to motion and object shape does not significantly influence sensor performance. This is promising, since it suggests that we should be able to apply the sensor in a variety of shapes and environments without performance degradation. (some stuff about numbers, Laura?)

More interestingly, though, was the sensor's ability to differentiate participants with X% accuracy. This highly suggests that individuals do indeed have a discernable 'touch signature'. We believe that this is the first step towards making a more emotionally-aware sensor, and more 'affectively-enabled' personal technologies.

4. DISCUSSION

Our gesture data houses a large amount of relatively robust information. Despite the added noise due to deformation from curvature and the introduction of motion, the accuracy rate of our prediction does not decrease by more than a few percentage points. It raises some interesting questions about how far that deformation can be taken, as well as about how our machine learning algorithm can be improved. For example, we quickly ignore the pressure on our skin due to sitting in a chair; could the algorithm be modified to be reactive only to large changes in pressure?

However, we are wary of the term "accuracy" to evaluate the efficacy of our recognition system may be problematic due the following reasons:

- There does not exist a viable benchmark.
- Gestures in the real-world context will not be as well-defined

Where and how the sensor is applied may also have significant effects. One might want a higher rate of accuracy as a touch interface where gestures are mapped explicitly to commands than in a social robot where a single error in interpretation could be easily rectified.

In our opinion, the most interesting result is that we could differentiate participants by their touch signature. The exact constituent dimensions of this signature are yet to be determined, but it heavily suggests that this sensor has a wide enough expressive range to develop a personalization scheme.

4.1 Limitations of study

4.2 ->Future Work? 'next steps' in discussion?

5. CONCLUSIONS

Generally conclusions go after discussion, and draws out the implications therein. Comparisons from the two studies - value from each study This could go within Discussion, or be part of the suggested combined Analysis & results section above.

6. FUTURE WORK

real-time gesture recognition on dynamic motion Any suggestions for improving results?

We believe that there is a lot of room for further investigation, not the least of which involves the differences between user gesture behaviour. At the least, a sensor that can differentiate between users could provide a personalized set of experiences or controls, which has the potential to create a very powerful application for a very low-resolution, low-cost sensor hardware.

Although it is important to confirm that the sensor can reliably and accurately identify gestures as a base, in isolation, the semantics of recognizing individual gestures is limited. An explicit symbolic abstraction of gestures can be mapped into a command-action paradigm, which has applications for control interfaces, but of much more interest to us is the emotional content of those gestures. It doesn't matter whether you pat or scratch your catâĂŤwhat matters is the feeling communicated through whichever gesture you choose.

With a sensor that can identify both the type of gesture and the individual who makes that gesture, it's reasonable to believe that differentiating affective intent is not a far leap. For example, a sensor could build a personal touch profile for you, determine how far you are deviating from that profile on a particular day, and infer your current emotional status from the difference. To properly build such a profile, it will be important to determine what dimensions constitute a 'touch signature'.

Last, training the sensor can only benefit from more data. It may be possible to attempt a field test for one of the less complex sensor applications. (I'm kinda like, OK, what would happen if I just used a touch-sensitive pillow at home for a week? What about a quilt? Is this the right spot for this?)

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