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 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: sensor (1) stationary, varying *substrate* and *covering* (n=10); (2) 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.5.2 [**INFORMATION INTERFACES AND PRESENTATION**]: User Interfaces—*Haptic I/O*; I.5.2 [**PATTERN RECOGNITION**]: Design Methodology—*Classifier design and evaluation*

General Terms

Gesture, Touch and Haptics; Affective Computing and Interaction; Human-Robot Interaction; Non-verbal behaviors

Keywords

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

1. INTRODUCTION

A broad variety of interactive applications will be enabled by the capacity to recognize relevant nuances of social touch. In many cases, this requires a sensor with *high flexibility*, to support wearability on the body or embedding on curving, flexing surfaces of interactive objects; and sufficient resolution of *touch pressure* and *location* for a signal processing system to interpret its output in realtime as accurately as the application needs. Flexible pressure sensors have become affordable, and approaches have proliferated with the help of inexpensive electronics and Do-It-Yourself (DIY) guides [17]. However, simultaneously sensing location is more difficult, and wearable applications require that fidelity be balanced with cost. This balance will come through signal processing techniques as well as sensor technologies.

In this paper, we explore the potential of gesture recognition using a highly flexible fabric pressure sensor that also localizes input on a grid with fingerpad-scale taxels ($\sim$1 taxel per inch). The sensor's materials cost could be a few dollars when produced in volume [7]. To assess the extent to which interference due to movement and other factors interfere with gesture recognition, we first collected touch data for a set of 7 validated social gestures [28] on a stationary sensor with a variety of substrate stiffnesses and coverings. We then mounted the same sensor on an actuated robot skeleton and collected a similar dataset while varying the sensor's covering and motion. After performing signal recognition, we examined the degree to which these factors impacted our ability to distinguish both touch gesture, and identity of the toucher.

Accuracy needs will vary by application. Our recognition rates were within 80-95% for all conditions we tested (chance 14.2%), which will suffice for many purposes and are enough to merit empirical comparison to human recognition ability in future work. At the same time, we found enough idiosyncrasy in individuals' touch signatures to permit identification of toucher within this sample, at an accuracy rate similar to that of the gestures themselves.

1.1 Detailed Requirements

Our goal is to add social-touch recognition capability to surfaces that flex and move in a biological manner, such as human-worn garments that might be touched by others, or interactive robots with malleable, active, touch-inviting bodies and skins.

Movement and elasticity: These surfaces are neither static nor uniform. Therefore, an effective sensor for these environments must be highly flexible, somewhat elastic, and perform well while mounted on non-rigid and/or actuated surfaces.

Pressure range: To read gestures as non-verbal communications, we must accurately interpret a wide range of pressures. While the gestures we measured in the experiments were not delivered with communicative intent, they were chosen because in less constrained circumstances, they could be. Based on a preliminary survey of these touch pressures, we determined that our sensor needed to register touches between 0.005 and 1 kg.

Multitouch: Reading multiple points of contact at once expands the space of intent that can be read [28]; e.g., differentiating *constant* and *rub* from *tickle* and *scratch*.

Resolution and computational cost: Taxel resolution, sampling rate and computational cost must be traded off to achieve usable recognition accuracy. For real-time sensing and recognition, our computational cost is dominated by sensor polling and scales to the number of taxels per grid edge. Our recognition tasks and feature selection explicitly analyze the differences between frames. In this case, recognition accuracy plateaus with fingerpad-scale taxels, when sampled fast enough to capture voluntary movement (peaking at 10 Hz [21]. We must be able to recognize changes in pressure and localized hand and finger motions up to this frequency.

Single-fingerpad resolution ($\sim$2 taxels per inch) could capture small fluctuations; however, our gestures (not including *no touch*) either involved the flat or palm of hand, (*constant*, *pat*, *rub*, *stroke*) or tended towards quickly crossing many taxels (*tickle*, *scratch*). This suggests that using statistical features that emphasized the changes from frame to frame could be used to achieve reasonable classification rates even at 1-inch taxels[7].

Versatility of sensor technology: The sensor must be able to access both the high-pressure surface gestures (as in *pat*) as well as the lighter touches (as in *tickle*) without being lost in the noise of various deformations. But it also must be durable and easy to construct, and withstand stretch under dynamic motion.

1.2 Questions, Contributions and Applications

We were interested in how accurate our flexible fabric sensor could be in predicting gesture and differentiating between users, determining how the sensor would perform under deformation due to curvature and motion such as that due to a zoomorphic social robot, and the computational viability of computational cost of real-time gesture recognition. With 20-fold cross validation on random forest models, we contribute:

- Initial results of deployable accuracy in gesture recognition (7 key gestures): 91.4% on a firm, flat surface, 90.3% on a foam, curved surface, and 88.4% on a foam, curved, moving surface
- And of differentiating toucher (with all 26 participants' data) at 88.8% accuracy.
- Investigation of factors underlying recognition performance including feature selection
- Discussion of feasibility of embedded real-time gesture recognition.

Our study compares gesture recognition performance across a variety of conditions which approach real-time dynamic gesture recognition. Toucher recognition accuracy shows promise for systems that incorporate personalized responses to an individual touch signature.

In context of social robots, a flexible sensor could present a way for robots and humans to effectively use gestural touch as a method of communication. Close proximity and direct contact is a requirement for many tasks, such as a robot attendant that engages in affective interaction via a touch on the arm.

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.

A robot capable of recognizing touch signatures may be able to predict or influence emotional state [10]. In a behavioural education context, a soft touch-sensing playmate may be able to aide students testing on the autism spectrum by responding to anxious or agitated strokes with slow, soothing, regulated breathing.

2. RELATED WORK

We situate our work in the context of social robots and affective tactile communication. Gestural touch has been identified as a key component of human-robot cooperation [2] wherein a communicative act emerges from nuances in touch data. Should one need to effectively communicate with a robot, naturally occurring non-verbal cues bring a depth to the interaction that are otherwise inarticulable. One could never teach a young potter how to throw clay without guiding their hands directly – each touch can either halt, contribute, or modify the behaviour execution [2]. The dimensions of touch-based communication lie in affect and predicting the intent behind a gesture [10].

2.1 Uses & Needs of Affective Touch Sensing

Human-Robot collaboration in an industrial or manufacturing setting presupposes a lexicon of social touch for operational interactions [8]. To ensure safe and effective communication, Gleeson et al indentifies the requirements of both a comprehensive gestural dictionary and lightweight sensing technology. Social touch could even extend beyond the factory floors to become collaborative household help as in a homecare assistant [1].

Correlations found between emotional and gestural touch [10] suggest that with sufficient gesture recognition accuracy and nuance, we can detect the toucher's emotional state by this route. With consistently higher accuracy results for within-subject classification than between-subject [7, 11], there is potential for touch behaviours to be used to identify individuals.

Much of the current work on affective touch recognition occurs on a sensor worn by either a human or robotic arm [10, 22, 11, 12]. The arm on an humanoid robot could be a primary source of communicative touch and offers a static surface onto which to affix a sensor. Sensors thus deployed must be flexible enough to wrap around an irregular, padded zoomorphic form.

Animals [6] and interactive robots in animal form (such as Sony's pet-dog AIBO [3, 24], the seal-shaped PARO [27, 9, 14, 20]) offer a potential of mental health benefits. Another notable therapy robot is the teddy bear-like Huggable [23]; and others that do not have a recognizable Earth animal analogue, e.g., Probo [19]. However, while real pets respond to complex touch commands anywhere on the body, this has been difficult to achieve before now.

2.2 Flexible Pressure–Location Sensors

Requirements of representing pressure and location despite deformations including stretching, curving, masking etc. restricted construction materials. While many highly accurate pressure-location sensors exist, such as those developed for robot grippers used in dextrous manipulation (e.g., [18, 26]), these tend to be insufficiently flexible, overkill in terms of performance, and considerably too expensive for the objectives outlined here.

Stretch sensors designed for medical purposes by Vista Medical[1] inspired much of our implementation. Vista's sensors recognized only pressure, however, without localization. Further, gesture recognitions require multi-touch capacity.

Using Force-Sensing Resistors (FSRs) affixed to a hard shell restricts the need to account for recalibration of sensor movement; however, the trade-off is difficulty in detecting touch between sensors, limits in rendered motion, and non-aesthetic tactility [5, 2].

Several multitouch, flexible fabric sensors are available [12]. However, flexibility alone does not afford a full range of motion; it must be able to stretch and deform to approximate animal skin.

The design and sensing capabilities described by Flagg et al [7] informed many of our requirements and suggested that the bulk of the recognition accuracy could be achieved by the "below surface" sensor alone. However, this study did not consider the full design space of a robot in motion including a non-sensing cover and a variety of configurations. To evaluate how much information is compromised under these conditions, we applied to a variety of realistic use noise sources to the sensor, both directly and indirectly.

Still more comprehensive is the collection of touch sensor projects developed by Perner-Wilson [17]. The demonstrations depicted on the Plusea site[2]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.

3. STUDY

We hypothesized that:

- gesture recognition rates decrease with increased noise factors and we wish to determine a rank of these factors with respect to performance degradation.
- higher variability exists between subjects than within suggesting that individuals may exhibit an identifiable touch signature allowing us to between differentiate them.

3.1 Apparatus

We constructed a sensor using two squares of conductive EeonTex[3] Zebra fabric, layered at 90 degrees. Between them are layers of a plastic standoff mesh separator and a sheet of Eeontex SLPA 20K Ω resistive fabric (Figure 1. A circuit is constructed wiring each strip as an analog input to a digital output. An Arduino Mega microprocessor polls the sensor by sending a 'high' voltage signal to each row and column, reading the resistance value of each taxel determines the pressure and location where the top layer makes contact with the bottom (where pressure is placed).

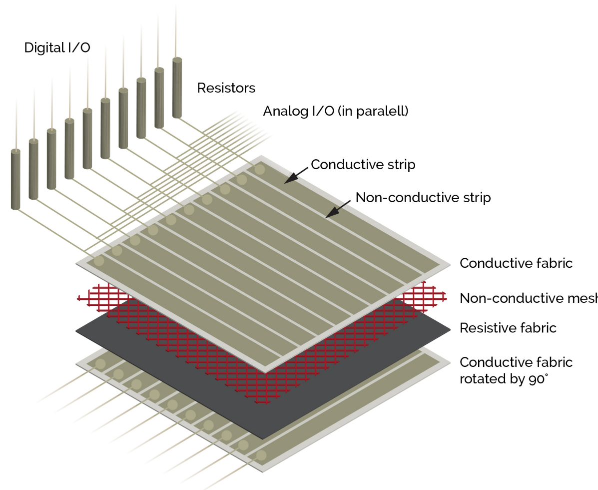

Figure 1: The fabric pressure sensor constructed out of EeonTex conductive fabric and wired to an Arduino Mega microprocessor.

Preliminary testing of our sensor using stationary weights showed that under ideal conditions, we were easily able to achieve a touch weight range of 0.005 to 1 kg using 1K Ω resistors. Under the most severe conditions (In Study 1, this was the curved-foam substrate + thick fur cover; for Study 2, the cover condition + bot in motion), the lighter touches were lost in the dense fur cover and the heavier end equalized by the yielding foam substrate.

We also found that using resistors much greater than 1K Ω allowed our sensor to register much greater forces but would lose a lot of the finer variations as one increment of our 1024 grade scale represented a much greater change in pressure. Conversely, while lower valued resistors gave us greater granularity in recognizing very fine touches, they caused the sensors to be overloaded too quickly to recognize more the forceful pressures.

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

3.2 Methods

While the two studies aimed to assess different masking conditions, we kept the gestures and data collection method consistent.

3.2.1 Gestures and Sampling

We selected gestures from an available touch dictionary [28] based on the most appropriate for human-animal interactions as determined by Flagg et al [7]. In all cases, the sensor was placed on a table in front of a seated participant. A reference sheet with very general definitions on 7 selected gestures was provided as seen in Table 1. Participants were asked to interpret each gesture as they saw fit; there were no further directions on how to perform.

At 54 frames per second where each frame consists of pressure data from all 100 taxels 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.

3.2.2 Study 1 - Cover and substrate on Static Robot

[1]Stretch based sensors can be purchased commercially from Vista Medical http://www.vista-medical.com/subsite/stretch.php

[2]Many wearable sensors are displayed at http://www.plusea.at/

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

Gesture	Suggested Definition
constant	touch contact without movement
no touch	no contact with the sensor
pat	quick & gentle touches 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

Table 1: General suggested guideline for touch gestures shown as reference.

This was a factorial design of 4×3×7 (*covering* × *substrate* × *gesture*) study. The *covering* 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 fabric generally used for baby blankets, and longer-furred fabric.

The *substrates* used included a firm, flat surface which was the sensor affixed by velcro to a table; a spongy foam, flat surface; and a spongy foam, curved surface. In cases with foam, the sensor was pinned directly to foam substrate.

In order to minimize the disturbance of moving and masking the sensor, we had to block collection on the *covering* × *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 with 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. From each participant, each gesture generated 48 2-second window samples.

This study had 10 participants (4 female, 6 male) with cultural backgrounds from Canada, England, Southeast Asia, and the Middle East.

3.2.3 Study 2 - Stationary vs Moving Robot

This study varied *cover* × *motion* × *gesture* giving a 2×2×7 factorial design where *motion* = {breathing, not breathing} and *cover* = {cover, no cover}. Each participant performed each *gesture* and condition combination twice in randomly generated order.

In order to create the in-motion condition, the sensor was attached to the CuddleBot (Figure 2(a)), a small robot designed for use in therapy (Figure 2(b)). The CuddleBot employed a 'breathing' motion by extending and contracting its ribs (Figure 2(c)). To simulate a full fur jacket (Figure 2(d)), we used a draped piece of nearly identical fabric. This allowed us to completely randomize our conditions. For example, a participant might perform *tickle, with a cover, while breathing*, then be asked to perform *scratch, no cover, while 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 ((2×2×7) + 1) = 57 trials. We ran 16 participants (10 female, 6 male) where each participant provided 32 2-second samples of each gesture across all conditions.

3.3 Analysis and Results

From the raw data, 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 (or 108 frames) was so chosen as each gesture has some periodicity and all can be completely performed within 1 second [7]. Further,

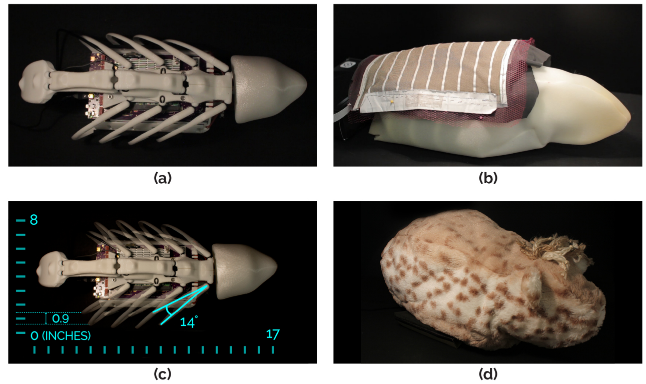

Figure 2: (a) Top view of the CuddleBot skeleton. (b) The sensor was pinned to a foam substrate that was wrapped around the CuddleBot skeleton. This corresponds to a *No touch* × *No motion* × *No cover* condition. (c) CuddleBot's full range of breathing motion as used in this study. Ruler markings are for scale. (d) The fully-covered CuddleBot; a cover of nearly identical material was used in the study to facilitate changing conditions quickly.

it is unlikely that we would be able to determine gesture boundaries in a realistic setting. The 2 second window ensures that we are able the capture *at least* 1 complete gesture cycle.

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 were calculated as follows:

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

Here C_x represents the x or row position of the centroid (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 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. Condition variables (*curvature*, *fur*) or (*cover*, *motion*) made up the other features. The *subject* labels were included for *gesture* predictions and vice versa.

We used Weka, an open-source application that applies common machine learning algorithms to our classification problem. We ran a small subset of our data through k-fold cross validation for k= 5, 10, 20, 100, 200) and found that improvement between 20- and 100- folds was within 1% on average with some decreasing performance. All reported classification performance is based on 20-fold cross validation of random forest models. A previously made comparison of results between random forest and a number of other algorithms ranked random forest on top consistently in gesture recognition of this type [7]. Accuracy is defined as the percentage of data instances that are correctly classified.

3.3.1 Gesture Classification by Condition

We compare the classification of the various conditions and we see that the best condition appears to occur without cover and on

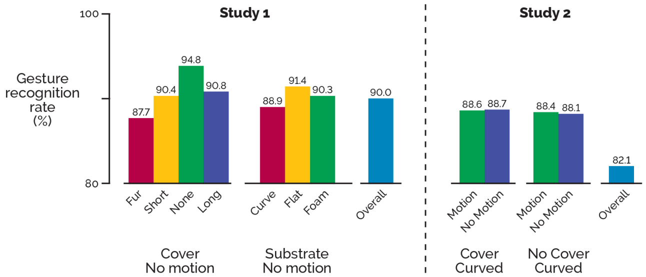

Figure 3: Gesture recognition accuracy breakdown by condition for Study 1 and Study 2, respectively.

the firm, flat substrate case whereas the worst performers occur in the dense fur and curved foam substrate. When looking at Study 2 and comparing how motion and cover effect our recognition, we notice that there is very little difference between all cases.

When we consider training across all participants, we can see that there is quite a bit of variance in the accuracies in Study 1. However, Study 2 demonstrates similar findings from other studies [12, 7, 16, 25]

cover-substrate-motion: Figure 3 shows overall gesture recognition accuracy for each study when compared to the respective condition sets.

participant: We performed gesture classification training by participant. In Study 1, we saw that the mean rate achieved was 89.1% with the greatest accuracy rate at 94.6% [4], though training overall was within a percentage point of the mean rate at 90.0%.

For Study 2, a greater effect was seen by training over participants. Training across all data gives 82.1% accuracy while by participant gave a mean of 86.5% with a max at 95.5% [5].

However, we are most interested in the motion × cover condition which had an overall 79.4% recognition rate but increased to a mean of 85.7% when trained on participants[6].

3.3.2 Subject Recognition

Being able to recognize the 'toucher' may have great impact on reading emotional state. We compare the subject classification performance of models that are trained across the entire dataset and those trained on particular gestures. We also look at accuracy rates when considering only the in-motion, with-cover condition.

recognition rate by gesture:
Overall recognition rate when classifying 'toucher' by pooling data in both studies is 88.8% where chance is 3.8% ($n = n_1 + n_2 = 10 + 16$)

Breaking it down by study, we see that Study 1 achieves an accuracy rate of 78.5% (chance 10%) but when we train on each gesture we see an improvement with mean = 87.9%[7], where the highest contributing gesture is *constant* at 92.7%.

Training on all data from Study 2, participant recognition rate is 80.3% (chance 6.3%). Training by gesture again sees an improvement with the highest performer as *constant* at 93.8%, mean is 85.4%[8].

Conditioning on only the *in-motion, with cover* condition in Study 2, recognition rates of participants are 89.8% (chance 6.3%). Conditioning another level to split training data by gesture, does not provide a mean improvement at 85.2%[9]; however, *constant* again is the highest performer at 90.6%.

4. DISCUSSION

We compared our classification performance under a variety of conditions and found that the effect of having a cover is significant; even more so than the underlying motion. The pressure applied by a denser, heavier fur cover may have masked differences in touch weight and/or distribution, causing particular pairs of gestures to be confused. This could provide insight into the key features of gesture recognition (Figure 4).

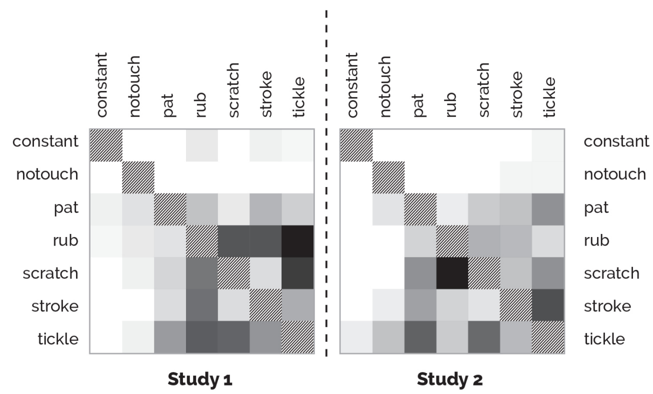

Figure 4: Confusion matrices for gesture classification. More black is more instances of confusion, max=32 for Study 1, max=25 for Study 2.

Figure 3 Study 2 demonstrates the effect of the cover. Regardless of whether we partition our data by cover; no cover or motion; no motion, we achieve a 6% increase in gesture recognition accuracy as compared to training on all data. A comparison between the *cover* and *motion* conditions doesn't appear significant. To determine the magnitude of the difference between the 'in-motion' and the 'at-rest' conditions, we ran a t-test on frames where no touches are made (See Table 2). Pressure values were higher on average in the 'in-motion' case (*M*=206.2, *SD*=61.1) than when the robot base was still (*M*=202.6, *SD*=59.7) with statistical significance but negligible effect size (t=7.7, *p*<0.001, *d*=0.06). For the 'with-fur' case (*M*=229.8, *SD*=59.3) as compared to the 'no-cover' case (*M*=178.2, *SD*=49.3), there is also a significant difference with a large effect size (t=123.59, *p*<0.001, *d*=0.95).

The relatively small effect of motion in raw frame data is unexpected, especially when considering the recognition improvement when conditioning over motion. One possible explanation could be that the periodic nature of robot breathing produced a similar effect

[4] Study 1 gesture recognition accuracy by participant: P1-93.0%, P2-83.8%, P3-85.0%, P4-92.6%, P5-93.2%, P6-88.0%, P7-94.6%, P8-91.7%, P9-86.0%, P10-83.4%

[5] Study 2 gesture prediction accuracy by participant: S1-90.2%, S2-86.6%, S3-86.6%, S4-91.1%, S5-81.3%, S6-86.1%, S7-84.8%, S8-79.5%, S8-79.5%, S9-95.5%, S10-79.5%, S11-90.2%, S12-93.8%, S13-97.3%, S14-83.0%, S15-79.5%, S16-79.5%.

[6] Study 2 using *motion* × *cover* data by participant: S1-80.9%, S2-86.2%, S3-86.2%, S4-91.6%, S5-80.9%, S6-73.7%, S7-88.0%, S8-88.0%, S9-95.1%, S10-86.2%, S11-89.8%, S12-95.1%, S13-93.4%, S14-91.6%, S15-64.8%, S16-79.1%.

[7] Participant recognition rates by gesture in Study 1: constant-92.7%, pat-88.9%, tickle-88.4%, scratch-88.2%, rub-85.0%, stroke-84.2%.

[8] Participant recognition rates by gesture for Study 2: constant-93.8%, pat-89.8%, scratch-84.8%, rub-82.8%, tickle-80.9%, stroke-80.1%.

[9] Participant recognition rates by gesture for Study 2, conditioned on *in motion, with cover*: constant - 90.6%, pat - 93.8%, rub - 81.3%, scratch - 82.8%, stroke - 84.4%, tickle - 78.1%.

to that of the cover. For example, an average over a noisy window could appear similar to a constant interference; motion and cover respectively.

	No motion - No cover	No motion - Yes cover	Yes motion - No cover	Yes motion - Yes cover
No motion - No cover		t=-74.2 Large	t=6.9 Negligible	t=-89.5 Large
No motion - Yes cover			t=85.7 Large	t=-16.7 Negligible
Yes motion - No cover				t=-101 Large
Yes motion - Yes cover				

Table 2: T statistics and Cohen's d effect sizes on raw framesum values under all variations of the *motion* $\times$ *cover* condition. p-values «0.001 in all cases.

	No cover	yes cover	
No motion	88.7%	88.6%	87.7%
Yes motion	88.2%	88.4%	85.4%
	88.7%	85.8%	82.1%

Table 3: Gesture prediction accuracy rates when condition combinations of *cover* $\times$ *motion*.

Comparing effect sizes and recognition rates, we notice that while there is negligible effect due to changes in cover condition in Table 2, there exists an interaction effect between *motion* and *cover*. Training using data that is conditioned on combinations of motion and cover gives higher accuracy predictions ($\sim$ 88%) than training across the whole dataset (82.1%), as seen in Table 3.

A second explanation could be from the variability in ecological validity that the cover affords. One participant said
"When it had the fur on, I had a more pleasant experience...Without the fur, I found it difficult to touch it." - S7 This opinion is echoed by 10 of the 16 participants. More research is needed to determine if the fur caused more naturalistic touches.

We tested the sensor in a variety of conditions to determine the effects of various deformations on classification accuracy. However, in a realistic setting we aim to be able to perform real-time recognition on a furry, moving robot. This requires that we be as economical as possible in our computations. Prioritized feature selection allows us to focus on high-performing dimensions.

Using Weka's Attribute Evaluator function, we picked the highest-weighted features for the Random Forest model. The feature set which offers the largest differentiation abilities in gesture recognition tasks is in pressure variance while location variance dominates that of subject recognition. People's touch signature may vary more in spread, however, a gesture may be better characterized using pressure.

- *For Gesture Recognition (in decreasing order from left to right):*
  Study 1 - pressure features: variance; total variance row features: variance; total variance; median col features: total variance

  Study 2 - pressure features: max; variance; total variance; median; min row features: max; variance; mean col features: variance, total variance

- *For Subject Recognition:*
  Study 1 - pressure features: max; variance row features: min; median; variance; max col features: min; max; mediam; mean; variance

  Study 2 - pressure features: max; min; variance; median; total variance row features: min; median; variance; mean col features: max; min; mean, median, total variance

Evaluating a reduced feature set is difficult due to the lack of a benchmark for comparing accuracy rates [11]. Furthermore, we don't know how this would generalize to a real-world context as people are unlikely to perform distinct, discrete gestures with well-defined boundaries.

5. FUTURE WORK

Continuous gestures: Our participants made single gestures, sparing us the need to segment our data in pre-processing. In reality, an algorithm will not know a priori of gesture boundaries or length, and will also need to handle the case of different gestures that are seamlessly connected.

We have implemented a limited real-time gesture recognition engine. However, as our model is built on 2-second windows of the same gesture, we are missing the nuances that might expose differentiating characteristics. One approach is to run several different sampling windows of different length, to search for touch activations of varying extents (but at the cost of increased computational load). Future work needs to explore efficient architectures.

Pragmatic gestures: In this study, participants *were* instructed as to gesture, but not in communicative intent or emotion context. The semantics of a "natural" touch will be dependent on context of situation and the user's own state; to determine communicative intent, it may be necessary to observe other factors as well.

Participants often varied in how they interpreted a given gesture, both between-participants for a given condition, and within-participant between conditions. For example of the latter, we suspect that users may have performed more authentic gestures on the zoomorphic robot covered with fur and moving compared to a surface that was flat, stationary and/or uncovered; but our sensing mechanisms are unable to distinguish between differences in the actual gesture, and our ability to accurately sense whatever gesture was made due to experiment condition.

A longitudinal study where we collect data over long-term interactions with a sensor in a natural setting may be required.

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.

With a sensor that can identify both the 'touch' and 'toucher', it's reasonable to believe that differentiating affective intent is not a far leap [10]. 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 clarify the dimensions that constitute a 'touch signature'.

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