Real-time Social Touch Gesture Recognition for Sensate Robots

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***Abstract*—This paper describes the hardware and algorithms for a realtime social touch gesture recognition system. Early experiments involve a Sensate Bear test-rig with full body touch sensing, sensor visualization and gesture recognition capabilities. Algorithms are based on real humans interacting with a plush bear. In developing a preliminary gesture library with thirteen Symbolic Gestures and eight Touch Subtypes, we have taken the first steps toward a Robotic Touch API, showing that the Huggable robot behavior system will be able to stream currently active sensors to detect regional social gestures and local sub-gestures in realtime. The system demonstrates the infrastructure to detect three types of touching: social touch, local touch, and sensor-level touch.**

I. Introduction

The physical nature of robots necessarily dictates that detecting different levels of touch is an important area of research. We define *sensor-level touch* as the robot's knowledge of the activation and location of each individual sensor. This helps the robot be aware of its physical boundaries. Sensor-level touch enables functional tasks such as robot grippers to operate safely by allowing the robot to sense when and where it had made contact with something.

As robots become social actors with the ability to physically engage human bodies, we must develop a social touch taxonomy to describe the new realms of interaction. *Social touch* is defined as touch that contains social value. Prior work has demonstrated the detection of *local touch* sub-gestures with increased tactile resolution and gesture profiles, for detection of affective content. *Local touch* allows discrimination of a tickle from a poke. In this work, we attach a social value to touch at different body locations to determine *symbolic touch*, which posits that there is a locational significance to touch, in particular that of an anthropomorphic robot's body.

Our hypothesis is that a body-awareness of touch, combined with the gesture profile of the touch, can allow a robot to detect the difference between a socially laden gesture (like a hug) and a local gesture (like a poke). This work unites the sensor level touch with the profiling of affective touch, to create a system that can infer social meaning from the contact between a human and a teddy-bear body.

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This paper describes our development of a system of real-time touch classification for full body touch sensors. We track gestures across the geometry of a teddy bear using an initial touch gesture library gleaned from behavioral studies with adults. In ongoing work, the sensor system and architecture presented in this paper are being incorporated into the Huggable robotic teddy bear [1], [2].

II. Background

A. The Huggable

The immediate application for this research is to equip the Huggable personal robot platform with sensate touch, so that it can better perform its role in healthcare, social communication [3], education and entertainment applications. In prior work with the Huggable, we classified a diverse set of affective touch interactions for a paw segment with pressure, temperature and capacitive sensors using off-line techniques [1]. In order to further develop the tactile taxonomy, we distilled the system into a stand-alone touch processing sensor system by creating a separate hardware test system, called the Sensate Bear, which has a lower-density of electric field sensors spread throughout a teddy bear body [4].

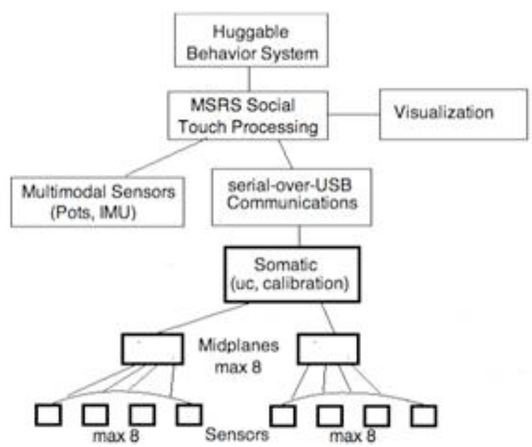

Fig. 1. Target System for Huggable: The Social Touch Processing developed on the Sensate Bear will be used in conjunction with multimodal sensors to feed information and take commands from the Huggable Behavior system. A visualization of sensor and gesture activity is also available

The creation of a separating testing platform allowed us to make our somatic processing system full-body and real time while the current 3rd generation Huggable robot was still being developed and built. The goal of this work is to apply the lessons learned using the Sensate Bear test system back to the 3rd generation Huggable robot for real time affective and social touch processing. Figure 1 shows a diagram of where the social touch processing system outlined in this paper will be placed in the larger Huggable robot context.

B. Relation to prior work

Touch plays a key role in human interaction [5], [6]. Prior work demonstrates that a robot should respond to affective displays, such as petting in pet therapy [7], [8] or in playing with children [9], [10]. We note that much of the prior work falls into detecting sensor-level touch, rather than detecting the symbolic value of touch [11]. A penguin robot with full-body capacitive sensing was used to detect the on-off presence of a human along with other multimodal sensors in [12].

Pressure-based robotic skin systems include [11] and [13]. We apply a similar algorithmic strategies to capacitive sensing, which senses both human contact and close proximity touch. However, we also incorporate body-awareness into the Symbolic Gesture recognition pathway. Touch researchers have demonstrated that the social value of touch varies depending on the body location and various other factors (duration, relationship of people) [14].

Our work looks to populate the social touch taxonomy by observing social gestures demonstrated by humans, and implementing pattern recognition. The closest algorithmic match is [15], which uses both region and manner of touch to automatically group common clusters of touch. These techniques could be used to further populate our touch gesture library, but should incorporate interactivity to gain more representative results for our target social situations.

III. System Overview

Our algorithms mirror the structure and connotations of human touch, and we developed a simplified hardware to implement our system as compared with the previous Huggable experimentation. The advantages of full-body social touch are differentiation of regionally significant gestures at the expense of heavier computational load.

Real-time recognition requires tiered processing and rapid sensing. We selected capacitive sensors because they are fast, sense proximity in addition to contact and differentiate people from most objects. The Sensate Bear uses a capacitive sensor circuit design based upon [16], and is configured into a network of 56 modular sensors covering the entire bear. Figure 2 depicts the system components and flow.

The sensors connect through *Midplane boards* to a central *Somatic processing board* for calibration. From there, signals pass via USB to the computer where gesture recognition takes place. The microcontroller can stream signal data with 10-bit resolution. Even when treated as on-off sensors, however, our studies showed high correlation for the tested subset of Symbolic Gestures.

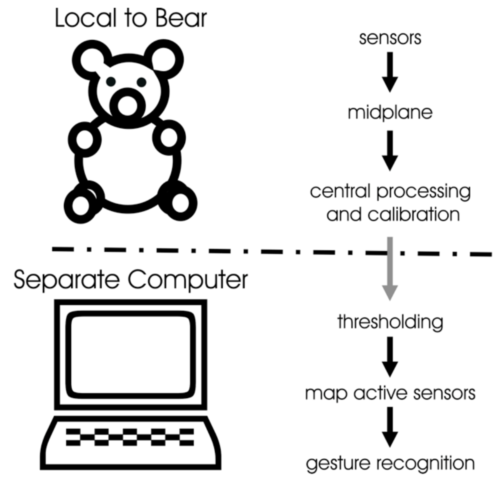

Fig. 2. System Overview: Subcomponents include sensors and electronics on the Sensate Bear, followed by on-computer processing and classification

Once on the computer, the Sensate Bear software, created with Microsoft Robotic Developers Studio in C#, reads the associated COM port data and performs thresholding, gesture recognition, and processing then displays active sensors and gesture classifications on a locally hosted website visualization.

During processing, we track *social touch gestures*, i.e. tactile communication or affective gestures between the human and bear. These gestures play a key role in *robot social touch*, which contrasts traditional *robot functional touch* research, e.g. object manipulation. In particular we identify *Symbolic Gestures* that have social significance across individuals and associated regional touch distributions (e.g. hug, footrub), and *touch subgestures*, which are smaller scale and are independent of location (e.g. pat, poke).

IV. Hardware Design

A. Tiered Hardware Architecture

Within the bear, all communication and calibration takes place on a centralized *Somatic processing board*. It gathers data in a tree structure from eight *Midplane board* channels, each of which processes the signal from up to eight capacitive sensors, Figure 3. We tune our sensing circuits to detect human touch to a height of approximately 1 inch.

The micro-controller on the Somatic processing board streams data using serial over USB. It gathers information by iterating through the eight Midplanes. A more detailed description of the electronics design can be found in [16].

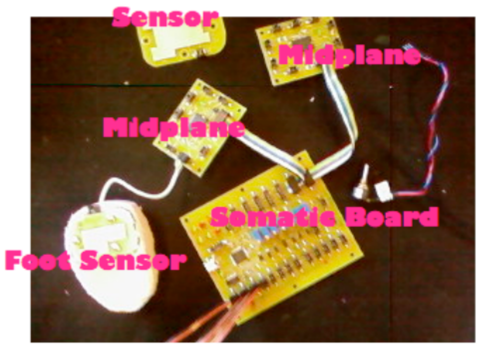

Fig. 3. Bear Electronics: Sensor board attached to foam 'foot' connects to an 8-channel Midplane, which itself plugs into one of the eight Midplane connectors on the Somatic board.

B. Physical Structure

The Sensate Bear has a rigid foam body, constructed to house the sensors under the fur of a commercial teddy bear. Its 56 sensors are installed on the surface of a foam superstructure with body segments and shapes that mirror the physical structure of the Huggable, as shown in Figure 4. The electronics for processing are inside the head and torso.

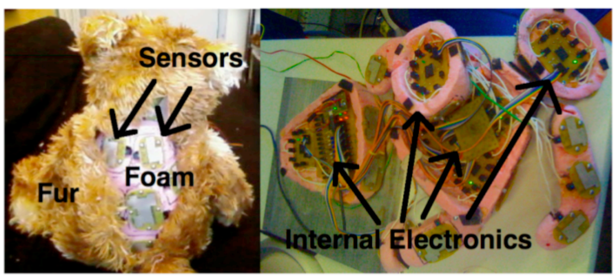

Fig. 4. The passive test-rig *Sensate Bear* has a foam superstructure that fits under a Teddy Bear's fur. Capacitive sensors span the surface of the foam and signal/communication electronics are mounted inside.

C. Capacitive Sensing for Social Touch

Capacitive sensors are well suited to social gestures as they are fast, inexpensive and can use conductivity to differentiate human from object-based touch. Additionally, if the sensing area is sufficiently large, physical contact is not required. On the other hand, if a person is wearing many layers, their body signal will be attenuated. To capture these edge cases, calibration is necessary.

To detect the presence of a person near the Sensate Bear sensing electrodes, we selected the Motorola/Freescale Semiconductor 33794 integrated circuit, which converts a touch's net effect on the electric field to an output voltage at a rate of five milliseconds per channel. This chip is located on the Midplane board, and we wire up to eight of its sensing channels. Thus, all sensors on the bear can be read in 40 milliseconds. The change in signal level increases with proximity, contact area and person/object conductivity. Direct touch results in the maximum change, saturating detection.

The sensor itself is a shielded electrode, essentially two metal plates, separated by a nonconductor. Because of this simple construction, capacitive sensors can be soft or hard and will ultimately be used to sense non-direct touch through the fur of the Huggable.

D. Optimizing Sensor Density

The identification of salient locations was based on a behavioral study where subjects role-played social interactions with a teddybear on videotape. The initial Huggable sensate skin design called for 1200 sensors of three different types, however, this bear simplifies the hardware design.

The previous Huggable paw had 2"x1" boards, each equipped with eight QTC pressure sensors, four temperature sensors and one electrode, which was tied to the electrodes of three other boards for region sensing. Thus, the total area that each capacitive sensing was about ~2"x4". Each of these sensors was tuned to detect proximity of the human hand from ~ 1 inch above the surface of the electrode. Because proximity is detected instead of force, they could detect very light touch, such as brushing the top surface of the fur.

In the Sensate Bear design there are two capacitive sensor sizes, 1.5"x2" and 3"x2", and layout is designed for social touch. The sensor boards have electrode plates on both sides, signal and shield, and a connector. The shield faces inward, directing sensitivity to the outward, amplifying the signal and decreasing sensor cross-triggering and electronics interference.

V. Algorithms and Software

A. Detection Modes for Social Touch

We define three classes of touch for social touch recognition; *sensor level touch* includes localization and activation levels, *Touch Subtypes* involve detection of base forms of local touch (e.g. poke, pat) and *Symbolic Gestures,* which represent common body-wide social gestures with typical regional distributions (e.g. hug, handshake). These processing paths are depicted in Figure 5.

In sensor level touch, we read in the sensors, then process and scale their signals in calibration to use the full ground to supply voltage range. Next we convert the analog to a 10-bit digital signal and send it over USB to software, which uses a XML lookup table to map incoming sensor ID's to sensor locations.

Our detection of Touch Subtypes and Symbolic Gesture analyzed sensor activation patterns using a pre-defined touch gesture library, developed based on human studies and target behaviors of the bear. We present early examples of what these libraries should include.

The software creates an object for each sensor that consists of a Sensor name, a Buffer of sensor values reflecting the last twenty cycles, an Activation state Boolean that indicates whether the signal is over 30% on, and a Location. Buffer size and activation thresholds are configurable.

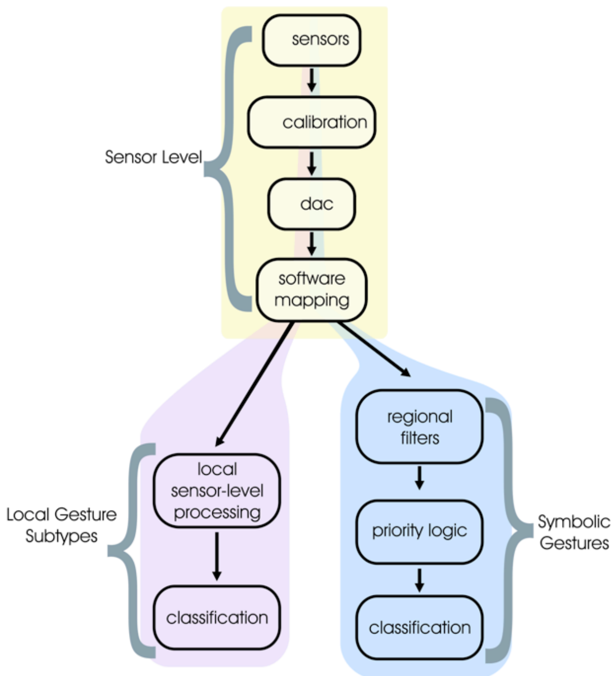

Fig. 5. Processing Pathways: The Sensor Level outputs calibrated, localized signals, which are then processed into local Touch Subtypes (time dependent) and body-wide Symbolic Gestures (not time dependent).

The local touch subtype pathway uses the buffer of signal values for a single sensor to calculate features, then iteratively checks for a matching subtype in the gesture library. Only one subtype can be active on each single sensor board and the detection speed for new gestures is inversely proportional to the size of the buffer.

The Symbolic Gesture Pathway utilizes the location information of multiple sensors, passing those patterns through locational filters at each timestep, using a simple priority logic to constrain which features can be active at the same time, and updating the classification in real time.

B. *Touch Gesture Library*

Observed gestures during adult behavioral study with nine subjects (mixed gender) and user study with eleven children (age 4-11) appear in Table I. Study details and procedure are published in [4], [17]. As in Figure 5, the processing path for Symbolic Gestures is:

Locational Filters ⇒ Priority Logic ⇒ Classification

While the Touch Subtypes path is:

Fill Data Buffer ⇒ Extract Features ⇒ Classification

Noted gestures were used to verify the techniques that follow for local and body-wide gesture recognition. This list is a starting point meant to motivate further exploration into touch gestures, and should be updated for different robotic form factors and applications. Tickle appears in both categories because people tend to associate particular regions with being ticklish, but there also exists a distinct tickle subgesture that can use to refine final classifications.

TABLE I
INITIAL GESTURE LIBRARY FOR ROBOTIC TEDDY BEARS

Symbolic Gesture	Touch Subtype
Tickle	Pet*
Footrub*	Poke*
Handshake	Tickle*
Head-pat*	Pat
Shoulder-tap	Hold*
Belly-tickle	Tap
Side-tickle*	Shake
Foot-tickle	Rub
Go-to-sleep	
Wakeup	
Feeding	
Rocking	
Dance	

*Gesture implemented

C. *Sensor Level Touch*

Sensor level touch occurs mainly within the Sensate Bear electronics, which scale and condition the analog sensor signals before digital conversion. Data is passed into software as a list of sensor IDs and 10-bit amplitude levels. Each sensor ID is mapped in software to its respective on-bear location, so this format is sufficient to identify or interpolate touch locations.

Although the sensor IDs coming from the microcontroller mirror the Somatic to Midplane to sensor wiring, our software uses an XML document that delineates body regions and remaps data into human-readable labels, e.g. ‘head2’.

Direct access to sensor locations enables social behaviors, such as ‘Look At’ in which the bear’s gaze might track a touch location, as posited in [2].

D. *Touch Subtype Processing*

In this implementation, the recognition of local gestures, or *Touch Subtypes*, predicts the likelihood of predefined Touch Subtypes for a single sensor based on several seconds of data history. Sensor signals have 10-bit resolution. The challenge of classifying time dependent gestures is making them real time, thus trading-off ‘perfect characterization’ for reasonable but realtime accuracy.

Similar classifiers have been used for the paw segment [1] and in pressure-based skins [11]. Features in the first (paw segment) include: direction of motion, average sensor value, change in sensor value, number of sensors active; and in the second (pressure sensors): absolute values, spatial distributions and temporal difference.

Both use the absolute and derivative of signal amplitude. As Symbolic Gestures capture locational information, number and special distribution of sensors is less relevant. Direction of motion may be added in the future to the Sensate Bear’s processing, but we decided to first hone subgesture tracking on individual sensors.

In keeping with our observation-based design, we selected and added to these heuristics based on a single subject's demonstration of tickle, poke, and pet. Figure 6 shows the raw oscilloscope traces of these Touch Subtypes

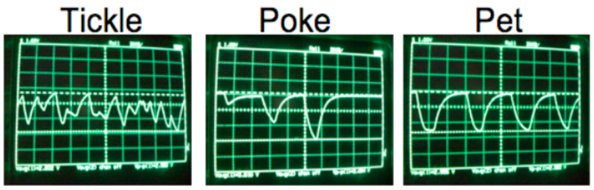

Fig. 6. Typical Touch Subtypes: Raw oscilloscope captures of subject demonstrating tickle, poke and pet on a single 3x2" sensor board. Testing physical touch, not proximity, duration is ~5 seconds.

By inspection, one can see that signal amplitudes vary with the different subtypes. The change in signal value is important, but one notes that the signal derivatives at a point overlap much more than the signal frequency spectrum over a few seconds. In taking the Fourier transform of those signals, there is variation in the dominant base frequency, e.g. the tickle signal has a much shorter average period than pet. Further, the distribution of frequencies (noise level) is much wider in tickle than pet. Thus, for each subtype, we evaluated feature values for peak amplitude, base frequency, frequency spectrum and duration (see Results).

As part of the touch subtype processing, a variable in the sensor class stores the last several cycles of values for its activation level as an array. We calculate feature values from that history. The peak amplitude is the maximum value in the set, base frequency can be calculated from lowest frequency value in the Fourier Transform, noise level reflects frequency spread, and duration is incremented for each cycle. Pseudocode for this process follows:

```
If (amplitude < 30%) {
  set_current_class = NoTouch
}
Else{
  Increment duration;
    If (duration < 3 sec)
      Set  current_class = Poke;
    Else{
      Update baseFreq, noiseLevel;
      ref_var = Alpha x baseFreq + Beta x noiseLevel
      If (ref_var > tickle_cutoff)
           set_current_class = Tickle;
      else if (ref_var > pet_cutoff)
           set_current_class = Pet;
      else
           set_current_class = Hold;
     }
}
```

E. *Symbolic Gesture Processing*

Symbolic Gestures recognized predominantly from location, so recognition can happen in realtime. Touch location on a body is highly tied to social intention, as found in [15], particularly given the anthropomorphic profile of the robot. Thus, our algorithms use a *locational filter* for each Symbolic Gesture (see Figure 7) gleaned from human pattern recognition of the adult behavioral study.

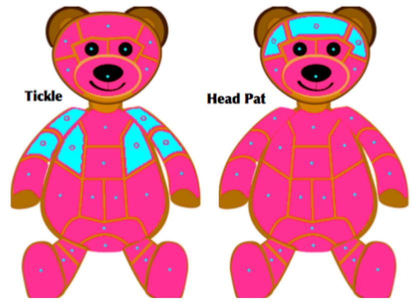

Fig. 7. Locational filter examples for Symbolic Touch: The programmed side-tickle and head pat filters are visualized here.

At each cycle, the software tests for any matching activation patterns, displaying active gestures on screen. The processing is probabilistic, a minimum number of sensors in within the locational filter must be active for at least two seconds, an increment informally chosen to parallel human recognition time.

Next, the algorithm enters its *priority logic*. It is possible to have multiple gestures, but we must capture the cases were classifications conflict. For example, the tickle distribution involves many of the same sensors as hug. However, hug involves various other unique sensors. Thus, if hug is active, tickle is unlikely to be happening, so hug supersedes Tickle. Priority logic must be based on human behavior and recalculated when adding new gestures.

Labeled interactions for the initial implementation are headpat, hug, tickle, and footrub. These classifications were approximations of user behavior from the behavioral study and represented the most used expressive gestures therein. The logic for each is as follows:

Tickle: (not Hug) && (active >= two of four sensors)
Headpat: (active >=one of the three sensors)
Hug: (both sides)&& (active >= four of ten sensors)
Footrub: (active => one of two sensors)

If needed, the robot can also evaluate the subtypes present within any active distribution.

At a higher level, the robot behavior system will eventually associate affective and communication content with Touch Subtypes (poke always gets attention) and Symbolic Gestures (hug has a positive reassuring effect).

VI. Results

A. *Timing Results*

Figure 8 depicts the timing delays during data flow from sensors over serial then in the software classification paths. The total per program cycle time is about 42 milliseconds including communications delay – thus locational filters can be processed ~20 times a second and subtypes are assessed about every second. Based on the observed gesture lengths in the study (see Table II), that is likely to be similar to human recognition time.

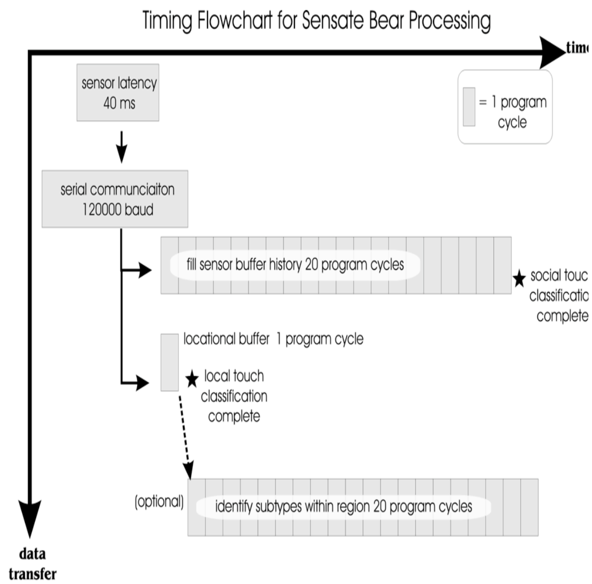

Fig. 8. Timing Flowchart for Processing: Each program cycle has a sensor latency, communication delay, and runtime which limits to minimum time before categorization complete.

B. Touch Subtype Results

Our experiments informed the touch subtype classification features, whose averaged values for four subtypes is depicted in Figure 8. We used observed data to craft an algorithm and verify it piecewise.

TABLE II
TRIAL SUBGESTURE FEATURE RESULTS

AVERAGE	**Tickle**	**Poke**	**Pet**	**Hold**	**No Touch**
Peak Amplitude	60%	>30%	100%	100%	0%
Base Frequency	5-10Hz	0-1Hz	0.5-2Hz	0 Hz	0 Hz
Freq Spectrum	high noise	blip	low noise	no noise	no noise
Duration	3-20 sec	1 sec	>4 sec	>4 sec	n/a

VARIANCE	**Tickle**	**Poke**	**Pet**	**Hold**	**No Touch**
Peak Amplitude	0.3	0.8	0.1	0.1	0
Base Frequency	0.5	0.1	0.3	0.1	0
Freq Spectrum	0	0.3	0.2	0	0
Duration	0.8	0.2	0.7	0.8	n/a

STD DEV	**Tickle**	**Poke**	**Pet**	**Hold**	**No Touch**
Base Frequency	3	0.5	1	n/a	n/a
Duration	5	0.2	7	11	n/a

Based on ten iterations with a single user.

Because the capacitive sensing mux requires time to acquire signal after switching channels, all sensors are queried in turn with a 5-millisecond delay between each one. Thus the true data rate is (58 sensors) x (.005 seconds) = 0.29 sec or 3.4 Hz, which will eliminate some of the higher frequency information, by the Nyquist rate, to a maximum of about 7 Hz. This has the risk, in particular cases of high frequency tickle of being misclassified as constant touch.

Classification of subtypes has been done in prior work [1], so this is a just for training of the test rig. What is novel is that we implement this for the first time exclusively with capacitive sensing. We believe that from the data presented in Table II that with a larger data set and more users, it may be possible that larger sensors and lower overall sensor density can be sufficient for detection of these touch sub-types.

C. Locational Filter Results

We selected a few Symbolic Gestures to verify that our probabilistic locational filters would correctly reflect a user's touch. We instructed subjects to demonstrate these gestures, in the context of a social interaction, for example, requesting a head pat because the bear was "doing a good job." The results are shown in Table III.

TABLE III
FIRST TEST OF REGIONAL FILTERS

	Activated on first try	**Activated with explanation**	**Regional Accuracy**
Headpat	100%	100%	100%
Tickle	20%	60%	20%
Hug	40%	80%	80%
Footrub	100%	100%	100%

Subjects instructed to demonstrate labeled gestures. High activation rate is due to the lack of crossover between locations of touch and the highlighted gestures.

Although our code did not test to distinguish between different subtypes, we observed, in confirmation with [15], that particular regions of the bear tended to have associated social content, regardless of subgesture. Thus, anthropomorphic profiling may already provide a higher than chance likelihood that particular social gestures are present.

VII. CONCLUSIONS

This paper is about developing a real time system for social and affective touch. Key contributions are, first, that our algorithms are based on real humans interacting with a plush bear. Secondly, research with the Sensate Bear test rig that will ultimately be incorporated into the Huggable personal robot system. Thirdly, we utilize the full-body sensing and anthropomorphic nature of the bear to motivate regional symbolic touch research.

We present our approach for realtime classification, currently in development, and some early results.
Table II demonstrates how the data looks for affective touch sub-types. We also posit that much of social touch is regionally dependant. Table III describes a study to demonstrate the regional nature of the touch.

Our next step is to focus on the classification of the robot. We have outlined an approach to real time social and affective touch, so the next step is to do a more in depth study with a large set of training data and evaluate our algorithms against that.

The preliminary timing results indicate that our system will be able to successfully execute real-time touch classification for a full-body sensate robot, demonstrating a tiered approach to touch recognition.

Our taxonomy of touch includes Symbolic Gestures that have associated locational distributions, and Touch Subtypes that are locationally-independent. Each of those can be accessed in software in addition to sensor-level data.

Thus, we have also created the software base for a Robotic Touch API, showing that the Huggable behavior system will be able to query currently active sensors and values, gestures and subgestures.

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