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Touch Modality Interpretation for an EIT-Based Sensitive Skin

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Abstract— **During social interaction, humans extract important information from tactile stimuli that improves their understanding of the interaction. The development of a similar capacity in a robot will contribute to the future success of intuitive human-robot interaction. This paper presents a method of touch sensing based on the principle of electrical impedance tomography (EIT) that can be used to implement a large, flexible and stretchable artificial sensitive skin for robots. A classifier based on the "LogitBoost" algorithm is used to classify the modality of six different types of touch on an experimental EIT-based skin. Experiments showed that the modality of touch was correctly classified in approximately 80% of the trials. This is comparable with the experimental accuracy of a human touch recipient. The classification accuracies show significant improvements from previous classification algorithms applied to different artificial sensitive skins.**

I. Introduction

As interactions between humans and robots become more complex, there is increasing interest in building robots that can interact with humans in more intuitive and meaningful ways [1]. Robots such as the Fish-Bird wheelchairs [2] have demonstrated that people naturally seek interaction through touch and expect even inanimate robots to respond to tactile stimulus [3].

The interpretation of touch between humans is highly complex and is strongly influenced by the context of the interaction, along with the cultures, emotions, and beliefs of the people who are communicating. Early work on social interaction [4] demonstrated that humans extract certain characteristics from tactile stimuli that communicate different messages defined within somewhat overlapping categories, which reflect the level of physical contact, ranging from unintentional touch to intimate/sexual touch.

In robotics it is important to design a method for touch identification that can be active over all or most of the robot's body area; this could be done through an artificial "sensitive skin." The functional requirements for an artificial sensitive skin remain debatable, and are to some extent dependent on the application that the skin is intended for. In the literature, an artificial sensitive skin is usually considered to be a flexible and stretchable array of sensors that fits onto curved robot surfaces of substantial extent. In some cases, multiple layers of heterogeneous sensors are used in an attempt to more closely imitate the capabilities of human skin [5].

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From the first comprehensive elucidation of the concept of "sensitive skin" by Lumelsky *et al.* [6], researchers have contributed several prototypes of artificial skin. These usually consist of a number of discrete sensors connected individually or in a grid configuration [7], capable of responding to touch, temperature or other physical phenomena [8]. Approaches to sensing range from the use of organic field-effect transistors [9] or piezoresistive semiconductors [10] to transducers that use capacitive [11], magnetic [12], piezoelectric [13], optical [14] or other principles [15]. A recent, thorough review of the state-of-the-art in robot tactile sensing is given by Dahiya *et al.* [16].

The interpretation of touch on an artificial sensitive skin is a large and unresolved research area that will play a crucial role in the development of human-robot interaction. A robot that is able to "feel," "understand" and respond to touch in accord with human expectations could lead to more meaningful and intuitive human-robot interactions. This paper concentrates on the interpretation of touch through classification, with a supervised "LogitBoost" algorithm, of different modalities of touch applied to an artificial sensitive skin based on electrical impedance tomography (EIT) [17] and designed to cover the whole body of a robot for human robot interaction.

To our knowledge, this is the first time that touch interpretation via an EIT-based skin has been attempted, and that a boosting classifier has been used to classify touch modality. Experimental results show significant improvements over previous methods for touch modality interpretation applied to different artificial skins [18]–[20]. Accuracies are comparable to those achieved by humans when interpreting touch.

II. Tactile Communication

Skin is the largest of all human organs and the first one to develop. It protects the body from dehydration, physical injury, toxic substances and ultraviolet radiation. It is waterproof and helps regulate body temperature, water balance and salt metabolism. It can be touched, vibrated, stretched, compressed, sheared or indented, and without doubt it is critical for touch perception [21].

Touch is essential for healthy human development; it facilitates interpersonal closeness and provides physical well-being [21], reduces stress [22] and cardiovascular disease [23], improves self-exploration [24], state of mind, alertness and physical vitality [25]. It is almost impossible not to respond to touch; yet communication by touch is

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so powerful that misinterpreted intentions are potentially harmful.

Influencing the interpretation of touch are factors such as the modality of the touch (e.g. pat, push, scratch, etc.), the location of the touch on the body, the degree of "interpersonal involvement" [26] of the two people touching and the content and prosody of any concurrent speech [27].

The location of touch, for example, can be divided into two classes: "non-vulnerable" body parts such as hands, arms, shoulders, and upper back, and "vulnerable" body parts such as head, neck, torso, lower back, buttocks, legs, and feet [28]. The more a touch is seen as an invasion of privacy the less positive—loving, pleasant and friendly—it is.

Additionally, congruence between modality of touch, body location, context of the interaction and the social intimacy of the people involved in the interaction [29] are significant factors in the interpretation and psychological receptivity to touch. For example, a pat on the buttocks is acceptable between members of a sporting team after a good play, but is considered sexual in more intimate interactions [30]; a pat on the head is often interpreted as condescending, whereas a pat on the back is used to signify congratulations or condolence [31].

For a robot to interpret touch during human-robot interaction, an artificial skin with touch sensing capabilities should cover most of the robot surface. This skin should provide sufficient information from the tactile stimulus to allow the classification of different types of touch. The following section briefly describes electrical impedance tomography [17], and how it is used to effect a touch-sensitive artificial skin.

III. EIT-based Sensitive Skin

Electrical impedance tomography (EIT) is an imaging technique used to estimate the internal conductivity distribution of an electrically conductive body by using measurements made only at the boundary of the body. If the conductivity in a region of the body changes, the current distribution also changes and EIT can be used to quantify these changes. The application of EIT to sensitive skin was previously described by Kato *et al.* [32], Nagakubo *et al.* [33] and Alirezaei *et al.* [34]. These researchers located electrodes on the border of a thin conductive sheet (made of one or more layers of conductive materials) that responded to applied pressure with local changes in resistivity. EIT then allowed changes in resistance—and therefore pressure—across the sheet to be determined.

Since most of the sensing area used in an EIT-based sensitive skin is made of an homogeneous thin material without any wiring, a large, flexible and stretchable "skin" suitable to cover small and large areas of variable three-dimensionally contoured bodies can be realised.

A. Mathematical Model

The EIT reconstruction problem is to find the distribution of conductivity inside an object when a set of injected currents and the resulting potentials are known. The starting point for EIT is Maxwell's equations for electromagnetics. For a conductive volume Ω enclosed by a boundary $\partial\Omega$, the forward problem is to find the potential on the boundary of an object with known conductivity distribution that is induced by given injected currents. The mathematical model can be derived by solving the Laplacian elliptic partial differential equation

$$\sigma\nabla^2 u = 0 \tag{1}$$

with a mixed Dirichlet and Neumann boundary condition. The resulting forward problem is

$$\sigma\frac{\partial u}{\partial n} = -J_s \cdot n \equiv j \,, \tag{2}$$

where σ is the electrical conductivity, u is the electric potential, n is the outward unit normal to the boundary $\partial\Omega$ and j is the negative normal component of injected current density J_s on the boundary. To ensure the uniqueness of the solution the conservation of charge theorem must hold

$$\int_{\partial\Omega} j = 0 \,, \tag{3}$$

together with a choice of an arbitrary ground or reference voltage.

A technique commonly used to solve equations (1–3) is the finite element method. The method is based on transforming the continuous form of the problem into a discrete approximation constructed as a finite collection of K elements with constant conductivity interconnected through N nodes. For more information the reader is referred to [35], [36] and [17].

B. Inverse Solution and Image Reconstruction

Difference imaging or dynamic imaging [37] is a fast, non-iterative method of imaging that reduces possible problems with unknown contact impedance and inaccurate electrode positions. The essence of the method is to first calculate the initial state of potentials $\mathbf{V}_l$ for an assumed *homogenous* body with "known" conductivity $\boldsymbol{\sigma}_0$. The discrete model is then replaced by a linear approximation used to compute only the difference $\delta\boldsymbol{\sigma}$ from the homogeneous case. Then, after calculating the Jacobian $\mathbf{J}$ between changes in boundary potential and internal conductivity, the discrete form of the linearised problem becomes

$$\delta\mathbf{V}_l \approx \mathbf{J}\delta\boldsymbol{\sigma} + \mathbf{w} \,, \tag{4}$$

where $\mathbf{w}$ is a noise vector and $\delta\mathbf{V}_l$ is the difference in potential between two measurements: the homogenous and inhomogeneous cases.

Since little current passes through most of the elements, many Jacobian elements will have values close to zero. Dividing by such small values causes numerical sensitivity in the solution so that small changes in measured potentials (e.g. electrical noise) can cause large changes in the reconstruction; this ill-conditioned problem has to be solved by regularisation. For this study, the generalised Tikhonov regularisation as presented in [37], [17] and [38] is used; this solution has the form

$$\delta\boldsymbol{\sigma} = (\mathbf{J}^T\mathbf{W}\mathbf{J} + \alpha^2\mathbf{R}^T\mathbf{R})^{-1}\mathbf{W}\mathbf{J}^T\delta\mathbf{V}_l\,, \qquad (5)$$

where $\mathbf{W}$ is a diagonal weighting matrix that models the system noise, α is a scalar hyperparameter that controls the amount of regularisation and $\mathbf{R}$ is a regularisation matrix that controls the smoothness of the solution. For a fixed initial $\boldsymbol{\sigma}$, the Jacobian $\mathbf{J}$ and $(\mathbf{J}^T\mathbf{W}\mathbf{J}+\alpha^2\mathbf{R}^T\mathbf{R})$ can be precalculated off-line, greatly speeding up the solution.

C. Artificial Skin Fabrication

The artificial skin was constructed using two layers of inexpensive four-way knitted fabrics. The bottom layer was made of a rectangular piece of carbon-loaded resistive fabric (Eeonyx Corp.) of dimensions 320 × 200 × 0.6 mm. The surface conductivity ($\sigma \approx 12.5$ mS/sq) of this material changes as it is stretched in-plane or compressed normal to the plane of the fabric. Seventeen circular silver eyelets of 7 mm diameter were used as electrodes and fixed both near the edge and within this layer (Fig. 1).

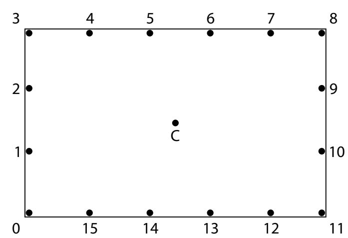

Fig. 1. Model of the experimental skin with 16 boundary electrodes and an internal (C)entre electrode.

Similar to the approach followed by [34], a second layer of thin, stretchable, highly conductive ($\sigma \approx 660$ mS/sq) fabric (Less EMF Inc.) was placed on top. To detect multiple simultaneous points of pressure over the skin, the second layer (Fig. 2) was made of discrete unconnected squares (15 × 15 ×0.5 mm). By applying the theory of area of contact between the two cloth layers, it was possible to improve the response to touch and minimise changes in resistivity due to fabric stretch. Finally, to provide a soft insulating surface, increase the contact area and give a more "pleasant" feel a non-conductive foam was used to cover the skin.

A user interface for experimentation was written in LabVIEW®, data acquisition was through an ADLINK Technology Inc. board and inverse solution and image reconstruction were done in Matlab®. EIDORS [38] was used for initial testing, although most of the experimental software was written and implemented by the authors.

IV. Proposed Method

Many different strategies of current injection and potential measurement can be applied. For this study a constant DC current (1.8 mA) was intermittently injected across adjacent pairs of boundary electrodes (adjacent injection pattern [39]) and potential measurements were taken from all other electrodes referenced to the centre electrode (centre measurement pattern [39]). The electrical potential was not measured at

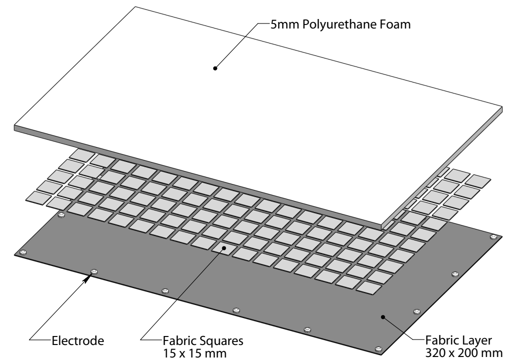

Fig. 2. Exploded 3D model of the experimental sensitive skin constructed from two layers of different conductive fabric covered with 5 mm thick, open-cell polyurethane foam. Squares on the second layer were stitched to the bottom layer with non-conductive cotton thread.

electrodes containing injected current, so that a total of 224 independent voltage measurements were obtained at each acquisition time step.

For simplicity the point electrode method, in which electrodes are considered to be single nodes in the mesh, was used and contact impedances between electrodes and the fabric body were ignored. Initial surface conductivity was assumed to be homogeneous ($\sigma \approx 12.5$ mS/sq). The Jacobian $\mathbf{J}$ was calculated by solving the forward model for each element and the generalised Tikhonov regularisation method in (5) was applied for the inverse solution with $\mathbf{W}$ replaced by the identity matrix $\mathbf{I}$. The value of the hyperparameter α was selected through an heuristic method [40] and $\mathbf{R}^T\mathbf{R}$ was modelled with the NOSER algorithm [41]. A total of 2,240 elements connected by 1,193 nodes were used for the forward solution. Data acquisition and image reconstruction were achieved at a maximum speed of 60Hz.

All the experiments presented in the remainder of this paper were conducted with the artificial skin fixed flat on a desk (Fig. 3). The EIT principle and its implementation, however, apply equally when the skin is used to cover three-dimensionally contoured bodies.

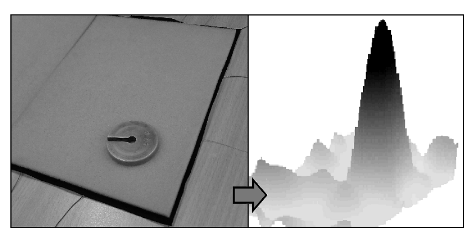

Fig. 3. 3D reconstruction (right) of pressure on the artificial skin caused by a 50 g weight (left). The diameter of the weight is 20 mm.

A. Feature Extraction

One important factor for touch interpretation is the human ability to (subconsciously) extract features and use them to classify different touch modalities. In a sensitive skin, it

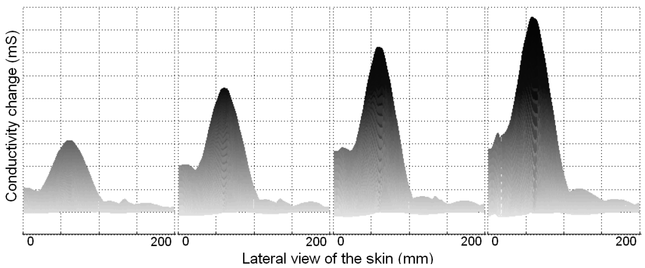

Fig. 4. Lateral slices of 3D reconstruction of four different circular weights (from left to right: 10 g, 20 g, 40 g and 50 g) applied to the same location of the artificial skin.

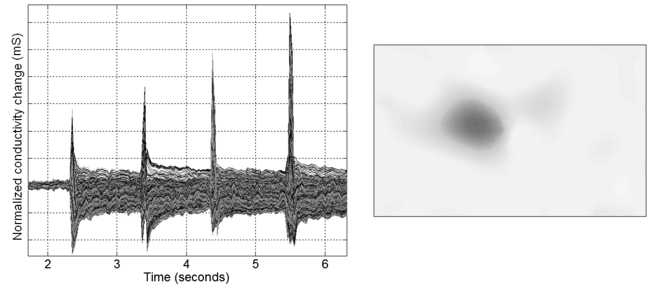

Fig. 5. Instantaneous 2D reconstruction of a "tap" (right), and amplitude of all elements in the reconstructed image during a sequence of 4 taps (left).

is sensible to use features analogous to those used when evaluating the human sense of touch. Five attributes are proposed as a foundation for the features needed to classify different touch modalities.

1. *Intensity Change.* Weber [42] observed that in human touch there is a required intensity before a small change in intensity can be detected, the *Weber ratio.* Discrimination as a result of both touch and muscular effort is twice more precise than discrimination on the basis of touch alone. In the artificial skin currently described, intensity changes are not linear with pressure; this is due to the non-linearity of EIT and the characteristics of the materials used. Fig. 4 shows a set of lateral 2D slices of reconstructed pressures generated by sequentially placing four circular weights on top of the skin.

2. *Point Localisation.* Evaluates the capacity of a person to locate the position of a tactile stimulus [5]. Human sensitivity to touch location varies considerably—from 2 mm to 20 mm—as a function of body location; the face, torso and fingers are the most sensitive areas. In the sensitive skin, point localisation is equivalent to the system's ability to locate accurately the centroid of a stimulus. A value of zero would represent perfect performance by this measure.

3. *Two Point Discrimination Threshold.* Represents the capacity of a person to discriminate between two simultaneous stimuli. Human two point discrimination accuracy—2 mm to 45 mm—also changes as a function of body location [5]. Stronger pressures mask weaker pressures, and it is easier to discriminate between two touches that do not occur at exactly the same time [42].

In the artificial skin, the two point discrimination threshold is calculated by evaluating the absolute spatial resolution of a single stimulus; as the spatial resolution increases, so does the capability of the system to discriminate between two different stimuli. The absolute spatial resolution was evaluated by calculating the ratio of the number of elements in the reconstructed image containing at least 50% of the maximum amplitude when a single stimulus is applied. Spatial resolution in EIT is strongly affected by the number of boundary [43], and internal [39] electrodes.

4. *Area of Contact.* Refers to the fraction of the area in contact between two objects and provides information about pressure distributions on the surface of the skin. For a sensitive skin, contact area is evaluated by calculating the number of elements in the reconstructed image that belong to an individual stimulus.

5. *Temporal Information.* Temporal information refers to changes caused by a stimulus applied to the skin over the time of contact. Some examples are: touch duration, frequency of repetition, rate of intensity change, and displacement of a touch through the surface of the skin. Repetition frequency can easily be seen in Fig. 5 where four "taps" were applied sequentially to different locations of the artificial skin.

B. Classification with Boosting

The objective of a supervised machine learning algorithm for classification is to build an hypothesis from a set of "labelled" features or instances (the training set), which then can be used to make predictions about future unlabelled instances (the testing set). The simplest case is the binary, as opposed to the multi-class, classification problem. Formally, let $\mathcal{X}$ be a finite set of training instances $\mathcal{X} = \{(x_1, y_1), ..., (x_N, y_N)\}$ used to produce an hypothesis $h : \mathcal{X} \rightarrow \mathcal{Y}$ that can be used to generalise any future instances $x_i \in \mathcal{X}$ and map them onto their true label $y_i \in \mathcal{Y} = \{-1, +1\}$.

Boosting [44] is an algorithm for supervised learning designed as a method for constructing a "strong" learning algorithm from an iterative combination of simple "weak" algorithms which, by themselves, perform slightly better than random guessing. This algorithm was first introduced by Schapire [45] and subsequently evolved into the more commonly used "AdaBoost" algorithm [46].

Fundamentally, let $\mathcal{H}(x) = \{h_1(x), h_2(x)...h_T(x)\}$ be a set of weak hypotheses which, when combined, produce a new hypothesis

$$f(x) = \sum_{t=1}^{T} \alpha_t h_t(x),$$

where α_t are constants selected by AdaBoost to measure the importance assigned to $h_t(x)$. By training the hypothesis $f(x)$ in an iterative manner and providing higher weights in the next iteration to any misclassified instances, the combined classifier $f(x)$ is a weighted function of T classifiers $h_t(x)$ with weights assigned by α_t.

For this work, the "LogitBoost" classifier as presented in [47] is used. LogitBoost is a version of the AdaBoost

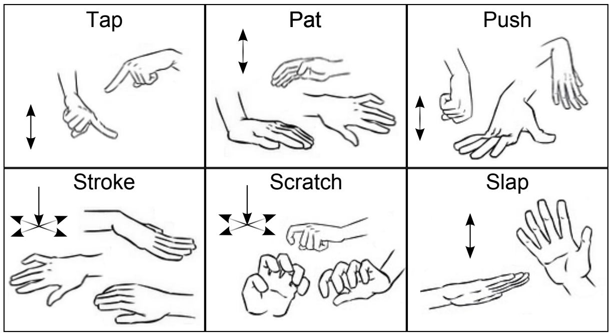

Fig. 6. Several examples of each touch modality. (Images from http://gr8ball.blogspot.com/2007/12/today-is-my-first-day-of-work-back-at.html, accessed 11 Jan. 2011.)

algorithm, with the main difference being that it minimises the log-likelihood error instead of the exponential loss, thereby showing less sensitivity when dealing with noisy data.

V. Touch Interpretation

This section describes the experiments performed to classify the modality of different touch gestures applied to the sensitive skin described in section III-C. Six widely used modalities of touch, described to the participants as "tap," "pat," "push," "stroke," "scratch," and "slap," were studied. These six were selected from a preliminary list of about 30 touch modalities and were selected to span a wide variety of commonly-used touches. For all experiments, the experimenter gave a demonstration of each touch modality on the artificial skin (Fig. 6), in addition to naming the gesture. The expected characteristics of each touch modality (not provided to the participants) are shown in Table I. Three experiments were performed and are described below.

TABLE I
Main characteristics of each touch modality.

	Contact area	Intensity	In-plane displacement	Duration
Tap	small	low	no	short
Pat	med-large	low-med	no	short
Push	sm-large	high	no	med-long
Stroke	med-large	low-med	yes	med-long
Scratch	sm-large	med-high	yes	med-long
Slap	med-large	high	no	short

A. Experiment 1

The objective of the first experiment was to determine the accuracy of classifying different modalities of touch from a single individual.

One male participant was instructed to convey each touch modality to the artificial skin 120 times, giving a total of 720 touch samples. The participant was encouraged to vary the characteristics of touch (e.g. location, intensity, contact area, etc.) without changing the modality.

Data mining software (WEKA [48]) with the LogitBoost classifier were used for classification. Samples were labelled manually. A total of seven features (Table II) based on the attributes presented in Sec. IV-A were used. To reduce variability in the results, a 15-fold cross-validation technique was used to assess the classification.

TABLE II
List of features.

Maximum intensity value
Minimum intensity value
Spatial resolution at 50% of maximum intensity
Mean of intensities within the area of contact
Touch duration
Rate of intensity change
Displacement from initial to final location

To evaluate the accuracy of the classification, the results are presented as an averaged confusion matrix in Table III. The first column in the matrix lists the actual class while the first row lists the predicted class. In this experiment the lowest accuracy was for the modality "pat" (83%), in which up to 15% of the samples are confused with a "tap". The average classification accuracy (average of main diagonal) is 91%.

TABLE III
Confusion matrix, single experimental participant.

	Tap	Pat	Push	Stroke	Scratch	Slap
Tap	**85%**	14%	0%	0%	1%	0%
Pat	15%	**83%**	0%	0%	0%	2%
Push	0%	0%	**97%**	1%	2%	0%
Stroke	0%	0%	0%	**93%**	7%	0%
Scratch	0%	0%	0%	7%	**93%**	0%
Slap	0%	3%	0%	0%	0%	**97%**

B. Experiment 2

The second experiment aimed to determine the accuracy of the classifier for different touch modalities across a diverse range of individuals. A total of 35 participants (28 male and 7 female, aged between 22 and 52 years old) from the Engineering Faculty at the University of Sydney volunteered for the experiment. Volunteers originated from 16 different countries within Australasia, Europe, Latin America, the Middle East and North America, and identified with seven different religions.

Participants, one by one, were instructed to convey each touch modality to the artificial skin five times, giving a total of 1,050 samples. Participants were encouraged to vary the characteristics of touch without changing the modality.

The same classifier and features used in the first experiment were used for classification. Classification results were assessed with 15-fold cross-validation. Averaged results are presented in the confusion matrix in Table IV. The average classification accuracy is 74%.

C. Experiment 3

A third experiment was conducted to assess the ability of an individual to identify the modality of touch administered

TABLE IV

CONFUSION MATRIX, MULTIPLE EXPERIMENTAL PARTICIPANTS.

	Tap	Pat	Push	Stroke	Scratch	Slap
Tap	**84%**	15%	0%	0%	0%	1%
Pat	27%	**61%**	6%	1%	0%	5%
Push	0%	5%	**89%**	4%	1%	1%
Stroke	0%	1%	4%	**58%**	37%	0%
Scratch	0%	1%	0%	34%	**65%**	0%
Slap	2%	10%	1%	0%	0%	**87%**

to his back by a second individual. Participants administering the touches were the same subjects from Experiment 2.

Immediately after each participant completed Experiment 2, the names of ten randomly-selected touch modalities were provided to each participant. The set of ten modalities was adjusted to include at least one instance of each modality. The experimenter took the place of the touch recipient while the 35 participants were instructed to touch him on his (clothed) upper back or shoulder. A total of 350 samples were acquired in the following distribution: 60 pats, 52 taps, 53 pushes, 60 strokes, 62 scratches and 63 slaps. Touch classification was performed by the recipient immediately after each touch; averaged results are presented in the confusion matrix in Table V. The average performance of the human classification was 86%.

TABLE V

CONFUSION MATRIX, SINGLE HUMAN CLASSIFIER.

	Tap	Pat	Push	Stroke	Scratch	Slap
Tap	**85%**	10%	5%	0%	0%	0%
Pat	17%	**70%**	9%	0%	0%	4%
Push	7%	0%	**93%**	0%	0%	0%
Stroke	0%	0%	0%	**97%**	3%	0%
Scratch	0%	0%	0%	19%	**81%**	0%
Slap	3%	8%	2%	2%	0%	**85%**

VI. DISCUSSION

It is clear that a number of factors affect the interpretation that humans have of touch, and most of these factors are related to touch only in an indirect way. In other words, touch interpretation for human-robot interaction cannot depend purely on the skin; interpretation should be adjusted depending on factors such as context and location (i.e. cultural setting) of the robot. Touch interpretation should work in a harmonious balance with other system sensory modalities (e.g. sound/speech recognition, vision, etc.) that will provide more information about the people touching the robot (e.g. gender, behaviour, etc.) and the environment.

If we scrutinise into the modality of touch, we notice that human interpretation of different modalities can be very broad and this effect is even more pronounced when people from different countries and language backgrounds are involved. As shown in Table V, a human can make up to 30% error when classifying different touch modalities. In Experiment 3, the experimenter noted that, since every participant touches differently, his best strategy for interpretation was to compare touches of different modalities administered by the same person. This suggests that higher efficiencies should be expected when touch from a single person is evaluated, as is confirmed by the results shown in Table III.

As presented in section I, robotics researchers are working with several different technologies in an effort to improve the sensing capabilities of artificial skin. But is a high-performance artificial skin necessarily a key factor in improving human-robot interaction? First we have to appreciate that the purpose of touch during human-to-human interaction—and hence, by extension, to intuitive human-robot interaction—is not to transmit different modalities of touch, but to convey a message or an intention to the touch recipient. If the same modality of touch is used on different body locations, or in a different social context, the receiver may differentially interpret touch as open and friendly, condescending or even sexual.

As presented in Tables III–V, similar touch modalities (i.e. tap and pat) were easily confused by both the classification algorithm and the human receiver. We know, however, that during social interaction, and regardless of errors in modality classification, humans are capable of understanding to some degree the different messages that are transmitted through touch. Is accurate classification of touch modality then really a key factor in effective communication through touch? If humans confuse different modalities of touch, yet are still capable of making a sound interpretation of transmitted messages, is it possible to achieve effective interpretation through an artificial skin regardless of the classification "errors" presented in this paper?

We believe that an artificial skin with similar capabilities to the one presented here, which has the ability to extract features such as intensity, location, duration, displacement and area of contact, is sufficient for effective touch interpretation when factors such as the location of the touch on the robot's "body," behaviour of the person touching, social context, etc., are considered.

VII. CONCLUSIONS

This paper presented a thin, flexible and stretchable sensitive skin based on the principle of electrical impedance tomography. This sensitive skin is suitable to cover large areas of a robot and has the ability to extract information such as location, duration, displacement and intensity of touch. This information was successfully used to classify six different modalities of touch using a LogitBoost algorithm. Classification of the modality of touch from a single participant was performed with up to 91% accuracy. This accuracy was higher than the accuracy of a human in classifying the modality of touch administered to his upper back by 35 participants. The accuracy of the LogitBoost classification decreased to 74% when classifying the modality of touch from 35 participants. The diminished accuracy is due to the increase in variation of touch between individual participants. These results show significant improvements from previous skin technologies and interpretation algorithms.

The experimental results presented here show that good algorithmic classification of touch modality can be achieved by the artificial skin. The experimental and observed data suggest that interpretation of the "meaning" of touch will require the integration of factors such as location of touch on the robot's "body," intensity, degree of contact, etc., together with external influences such as social context and culture. Future work should investigate these factors.

References

[1] C. Breazeal, "Toward sociable robots," *Robotics and Autonomous Systems*, vol. 42, pp. 167–175, 2003.

[2] M. Velonaki, D. Rye, S. Scheding, and S. Williams, "Fish-bird: Autonomous interactions in a new media arts setting," in *Proc. Vital Signs*, 2005.

[3] K. Wada, T. Shibata, T. Saito, and K. Tanie, "Analysis of factors that bring mental effects to elderly people in robot assisted activity," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots and Systems*, vol. 2, 2002, pp. 1152–1157.

[4] R. Heslin, "Steps toward a taxomony of touching," Presented at the annual meeting of the Midwestern Psychological Association, Chicago, IL., 1974.

[5] S. J. Lederman, "Skin and touch," in *Encyclopedia of Human Biology*, R. Dulbecco, Ed. San Diego: Academic Press, 1991, vol. 7, pp. 51–63.

[6] V. J. Lumelsky, M. Shur, and S. Wagner, "Sensitive skin," *IEEE Sensors J.*, vol. 1, pp. 41–51, 2001.

[7] T. Papakostas, J. Lima, and M. Lowe, "A large area force sensor for smart skin applications," in *Proc. IEEE Sensors*, vol. 2, 2002, pp. 1620–1624.

[8] W. D. Stiehl and C. Breazeal, "A sensitive skin for robotic companions featuring temperature, force, and electric field sensors," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots and Systems*, 2006, pp. 1952–1959.

[9] T. Someya, T. Sakurai, and T. Sekitani, "Large-area electronics based on organic transistors," in *64th Device Research Conference*, 2006, pp. 209–210.

[10] T. Mukai, M. Onishi, T. Odashima, S. Hirano, and Z. Luo, "Development of the tactile sensor system of a human-interactive robot RI-MAN," *IEEE Trans. Robot.*, vol. 24, pp. 505–512, 2008.

[11] G. Cannata, M. Maggiali, G. Metta, and G. Sandini, "An embedded artificial skin for humanoid robots," in *IEEE Int. Conf. Multisensor Fusion and Integration for Intelligent Systems*, 2008, pp. 434–438.

[12] M. Goka, H. Nakamoto, and S. Takenawa, "A magnetic type tactile sensor by GMR elements and inductors," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots and Systems*, 2010.

[13] S. Takamuku, G. Gomez, K. Hosoda, and R. Pfeifer, "Haptic discrimination of material properties by a robotic hand," in *Proc. 6th IEEE Int. Conf. Development and Learning*, 2007, pp. 1–6.

[14] H. Nicholls, "Tactile sensing for robotics," in *Proc. IEE Colloq. Robot Sensors*, 1991, pp. 5/1 – 5/3.

[15] B. Hutchings, A. Grahn, and R. Petersen, "Multiple-layer cross-field ultrasonic tactile sensor," in *Proc. IEEE Int. Conf. Robotics and Automation*, vol. 3, 1994, pp. 2522–2528.

[16] R. S. Dahiya, G. Metta, M. Valle, and G. Sandini, "Tactile sensing—from humans to humanoids," *IEEE Trans. Robot.*, vol. 26:1, pp. 1–20, 2010.

[17] W. Lionheart, N. Polydorides, and A. Borsic, "The reconstruction problem," in *Electrical Impedance Tomography: Methods, History and Applications*, D. S. Holder, Ed. Bristol and Philadelphia: Institute of Physics Publishing, 2005, pp. 3–63.

[18] F. Naya, J. Yamato, and K. Shinozawa, "Recognizing human touching behaviors using a haptic interface for a pet-robot," in *Proc. IEEE Int. Conf. Systems, Man, and Cybernetics*, vol. 2, 1999, pp. 1030–1034.

[19] H. Iwata and S. Sugano, "Human-robot-contact-state identification based on tactile recognition," *IEEE Trans. Ind. Electron.*, vol. 52, pp. 1468–1477, 2005.

[20] W. D. Stiehl and C. Breazeal, "Affective touch for robotic companions," in *Proc. Affective Computing and Intelligent Interaction*, 2005.

[21] T. Field, *Touch*. Cambridge, USA: MIT Press, 2001.

[22] J. Triplett and S. Arneson, "The use of verbal and tactile comfort to alliviate distress in young hospitalized children," *Research in Nursing and Health*, vol. 2, p. 22, 1979.

[23] J. Jorgenson, "Therapeutic use of companion animals in health care," *J. Nursing Scolarship*, vol. 29, pp. 249–254, 1996.

[24] J. E. Pattison, "Effects of touch on self-exploration and the therapeutic relationship," *J. Consulting and Clinical Psychology*, vol. 40, pp. 170–175, 1973.

[25] P. O'Neil and K. Calhoun, "Deficits and behavioral deterioration in senescence," *J. Abnormal Psychology*, vol. 84, pp. 579–582, 1975.

[26] E. McDaniel and P. A. Andersen, "International patterns of interpersonal tactile communication: A field of study," *Nonverbal Behavior*, vol. 22, p. 1, 1998.

[27] S. Jones, *The Right Touch: Understanding and Using the Language of Physical Contact*. Hampton Press, 1993.

[28] S. E. Jones and E. Yarbrough, "A naturalistic study of the meaning of touch," *Communication Monographs*, vol. 52, pp. 19–56, 1985.

[29] R. Heslin, T. D. Nguyen, and M. L. Nguyen, "The case of touch from a stranger or same sex person," *J. Nonverbal Behavior*, vol. 7, pp. 147–157, 1983.

[30] O. Zur and Nordmarken. (2010) To touch or not to touch: Exploring the myth of prohibition on touch in psychotherapy and counseling. Retrieved 20 April 2010 from http://www.zurinstitute.com/ touchintherapy.html.

[31] M. Hunter and J. Struve, *The Ethical Use of Touch in Psycotherapy*, C. T. Hendrix, Ed. SAGE Publications, 1998.

[32] Y. Kato, T. Mukai, T. Hayakawa, and T. Shibata, "Tactile sensor without wire and sensing element in the tactile region based on EIT method," *IEEE Sensors J.*, vol. 2, pp. 792–795, 2007.

[33] A. Nagakubo, H. Alirezaei, and Y. Kuniyoshi, "A deformable and deformation sensitive tactile distribution sensor," in *Proc. IEEE Int. Conf. Robotics and Biomimetics*, 2007, pp. 1301–1308.

[34] H. Alirezaei, A. Nagakubo, and Y. Kuniyoshi, "A tactile distribution sensor which enables stable measurement under high and dynamic stretch," *IEEE Symp. 3D User Interfaces*, pp. 87–93, 2009.

[35] P. Silvester and R. Ferrary, *Finite Elements for Electrical Engineers*, 3rd ed. Cambridge University Press, 1996.

[36] M. Vauhkonen, "Electrical impedance tomography and prior information," Ph.D. dissertation, Kuopio University, 1997, pp. 37-49.

[37] A. Adler and R. Guardo, "Electrical impedance tomography: regularized imaging and contrast detection," *IEEE Trans. Med. Imag.*, vol. 15, no. 2, pp. 170–179, 1996.

[38] A. Adler and W. R. B. Lionheart, "Uses and abuses of EIDORS: An extensible software base for EIT," *Physiol. Meas.*, vol. 27, pp. S25–S42, 2006.

[39] D. Silvera Tawil, D. Rye, and M. Velonaki, "Improved EIT drive patterns for a robotics sensitive skin," in *Proc. 2009 Australasian Conf. Robotics and Automation*, 2009.

[40] B. M. Graham and A. Adler, "Objective selection of hyperparameter for EIT," *Physiol. Meas.*, vol. 27, pp. S65–S79, 2006.

[41] M. Cheney, D. Isaacson, J. C. Newell, S. Simske, and J. Goble, "NOSER: An algorithm for solving the inverse conductivity problem," *Int. J. Imaging Systems and Technology*, vol. 2, pp. 66–75, 1990.

[42] E. Weber, *On the Tactile Senses*, D. J. Murray, H. E. Ross, and E. Weber, Eds. Academic Press, 1978.

[43] E. Woo, P. Hua, J. Webster, and W. Tompkins, "A robust image reconstruction algorithm and its parallel implementation in electrical impedance tomography," *IEEE Trans. Med. Imag.*, vol. 12, no. 2, pp. 137–146, 1993.

[44] R. E. Schapire, "The boosting approach to machine learning an overview," in *MSRI Workshop on Nonlinear Estimation and Classification*, 2002.

[45] ——, "The strength of weak learnability," *Machine Learning*, vol. 5, pp. 28–33, 1990.

[46] Y. Freund and R. E. Schapire, "A decision-theoretic generalization of on-line learning and an application to boosting," *Computer and System Sciences*, vol. 55, pp. 119–139, 1997.

[47] J. Friedman, T. hastie, and R. Tibshirani, "Additive logistic regression: A statistical veiew of boosting," *The Annals of Statistics*, vol. 28, no. 2, pp. 337–407, 2000.

[48] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, "The WEKA data mining software: An update," *SIGKDD Explorations*, vol. 11, no. 1, pp. 10–18, 2009.