# Categories of touch: Classifying human touch using a soft tactile sensor

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***Abstract*— Social touch plays an important role not only in human communication but also in human-robot interaction. We here report results from an ongoing study on affective human-robot interaction. In our previous research, touch type is shown to be informative for communicated emotion. Here, a soft matrix array sensor is used to capture the tactile interaction between human and robot and a method based on PCA and kNN is applied in the experiment to classify different touch types, constituting a pre-stage to recognizing emotional tactile interaction. Results show an average recognition rate for classified touch type of 71%, with a large variability between different types of touch. Results are discussed in relation to affective HRI and social robotics.**

***Keywords*— tactile interaction, social touch, affective HRI**

## I. Introduction

Social touch is important to the physical interactions between humans [1]. Communicating affect through social touch can increase social acceptance and bonding. While many types of emotions are communicated using other modalities than touch, e.g., face expressions, touch appears to be the preferred channel for communication of intimate emotions and critical for social bonding [2]. Affective tactile interaction is therefore likely to be critical for successful applications of social robotics.

Currently, social touch technology is being used to develop a more human-like interaction with robots. The goal is to achieve a greater social acceptance of the robots by humans [1] and to offer enhanced human-robot interaction functionality. This technology should therefore support different kinds of tactile/touch interactions between people and physically embodied artificial social agents. The further purpose of this technology is to decode emotions that are expressed in human-robot interaction scenarios.

Our contribution describes a soft array sensor that can be used to categorize different touch patterns that have been identified in studies of affective tactile interaction [3]. On the basis of previous results from a human-robot interaction study [3], we selected seven types of touches (stroke, scratch, poke, press, push, squeeze and grab) to classify. The results from this previous study showed that squeezing, stroking and pressing constituted more than half (59%) of all tactile interaction in the study.

Intensity, duration and location are key factors of tactile interaction that convey emotions. These factors served as the source of data that was used to determine the different categories of touch. In what follows, we present the accuracy of a machine-learning technique (kNN) that in a future step will be used to support emotion recognition in human-robot interaction.

## II. Experimental Setup and Methods

### A. Sensors and Electronics

An FSR (Force Sensitive Resistor) matrix array sensor MS9724 together with an Arduino Leonardo compatible board Snowboard from Kitronyx [4] are used, as shown in Fig 1. The matrix sensor has 160 force sensing nodes (16 rows × 10 columns) with 128mm × 80mm active sensing area and is designed for true force and multi-touch detection. The working sampling rate of the sensor is 30Hz. The matrix sensor is placed on a Pepper [5] robot's arm, as shown in Fig.1.

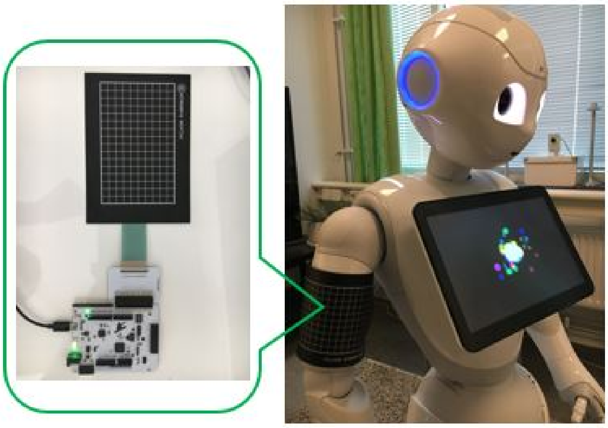

Fig. 1 Left: The Kitronyx matrix array sensor and the Snowboard microcontroller. Right: the sensor is placed on Pepper's arm.

### B. *Touch with emotions*

Seven different types of touch movements are adopted in the experiment. They are stroke, scratch, poke, press, push, squeeze and grab, as shown in Fig 2. The length of the movement is 60 samples, which equals to 2 seconds.

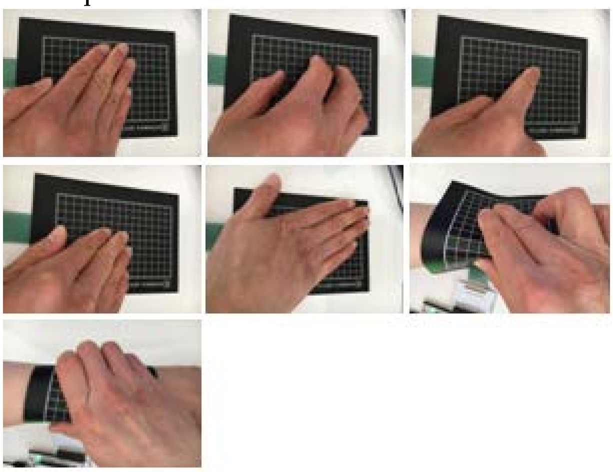

Fig. 2 7 types of touch movements adopted in the experiment. Row 1, from left to right: stroke, scratch, poke; Row 2: press, push, squeeze, Row 3: grab.

### C. *Feature extraction*

A touch movement is represented by a time series of sensor observations. Each observation at a time interval defined by the sampling rate contains the magnitudes of all the nodes on the sensor. The sensor used in this experiment has a dimension of 16 rows and 10 columns and as a result each sample constitutes a 2D vector of size 16×10. The temporal properties of touch can be characterized by a 1D vector describing the sum of values of all active nodes within a specific time window. Fig. 3 shows a stroke movement with its sum of values over the duration of the interaction. These vectors are normalized with respect to the mean and a Principal Component Analysis (PCA) [6] is applied, from which eigenvalues, eigenvectors and the eigenspace are calculated. Finally, the Eigenvector matrix is applied to individual touch interactions to obtain features for classification.

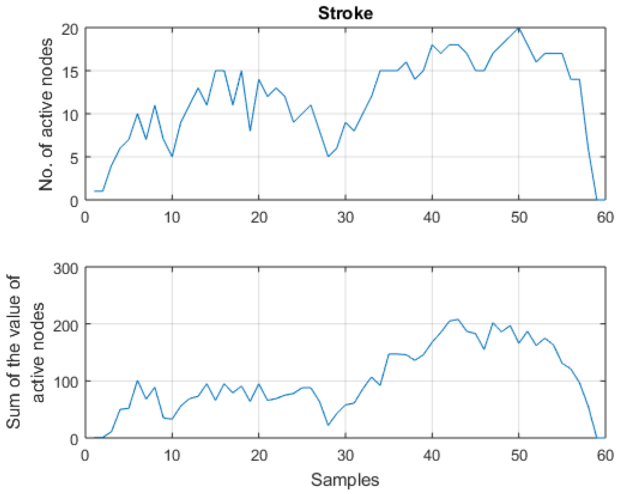


Fig. 3 An example of stroke interaction at 30Hz.

### D. *Classification*

140 touch interactions from one person (7 types of touches, 20 for each) are collected from the Kitronyx matrix sensor and used as training data and transformed into features following the feature extraction process described in Sec. C.

For classification a k-NN [7] classifier was implemented using a single neighbor based on Euclidean distance in the feature space.

## III. EXPERIMENTAL RESULTS

Table I shows descriptive statistics of the training set. Grab and Push have the largest number of pressed nodes and magnitude. Poke and Scratch have the least number of nodes activated, while Scratch has a smaller magnitude.

Eighty-four interactions (7 types, 12 for each) are used for testing. Table II shows the recognition rate of each touch type and Fig. 4 shows the confusion matrix. It can be seen that Stroke, Scratch and Poke are the easiest to recognize but Squeeze is very often misinterpreted. The accuracy can be improved by adopting more training samples and also combining with other classification techniques.

TABLE I
CHARACTERISTICS OF DIFFERENT TOUCHES USED IN THE TRAINING

| Touch type | Active nodes | Magnitude | Avg. magnitude | Duration (samples@30Hz) |
|---|---|---|---|---|
| Stroke | 7-28 | 42-367 | 6-13 | 44-60 |
| Scratch | 2-4 | 16-55 | 10-18 | 21-46 |
| Poke | 1-4 | 27-114 | 15-55 | 20-43 |
| Press | 10-20 | 131-364 | 12-22 | 30-60 |
| Push | 17-41 | 183-438 | 7-13 | 32-60 |
| Squeeze | 10-18 | 102-210 | 9-14 | 35-51 |
| Grab | 17-39 | 164-477 | 6-12 | 32-60 |

TABLE II
RECOGNITION ACCURACY BASED ON PCA AND KNN

| Touch type | Accuracy (total tested / successful recognition) |
|---|---|
| Stroke | 91.7% (11/12) |
| Scratch | 83.3% (10/12) |
| Poke | 100% (12/12) |
| Press | 66.7% (8/12) |
| Push | 58.3% (7/12) |
| Squeeze | 33.3% (4/12) |
| Grab | 66.7% (8/12) |
| **Total** | **71.4% (60/84)** |

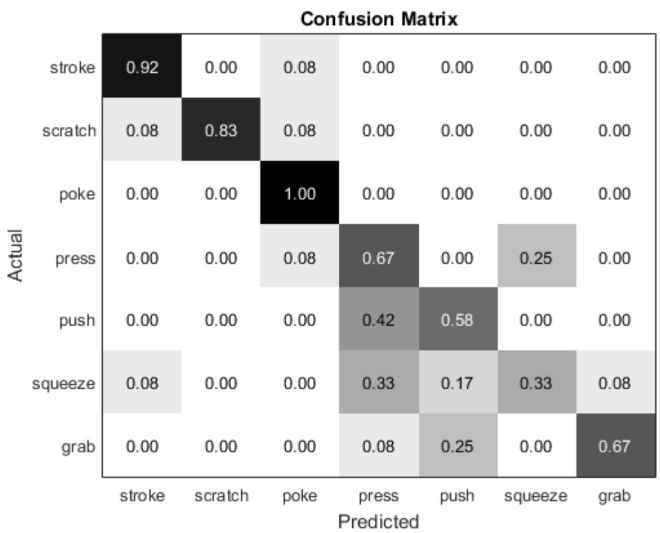


Fig. 4 The confusion matrix for touch recognition.

## IV. CONCLUSIONS

In this paper, seven most commonly used touches that occur in the expression of different emotions in human-robot interaction were selected to illustrate how touch categorization could be achieved by using input from a soft array sensor to categorize different types of touch. Using a classifier based on PCA and kNN, an overall recognition accuracy of 71.4% is achieved.

The results show large variability in recognition rate between different touch types, ranging from 100% for poke to 33.3% for squeeze. This could be understood as some touch types, e.g. squeeze and push, land close to each other in feature space, reducing recognition rate, while other touch types, e.g., stroke and poke, appears well separated from other types of touch.

One interesting connection could be made to human-human tactile interaction, where different types of touch have been shown to carry varying degrees of emotional information [8]. For example, push is indicative for anti-social emotions such as anger and disgust, while other touch types, e.g., squeeze, appears when communicating a variety of emotions and as a consequence carries less information. We therefore hypothesize that the more similar two emotions are to each other, the less distinct communicated touches are from each other, and therefore more difficult to classify. This is in line with conceptual space theory [9], predicting that the distance between categories, such as different emotions, should be reflected in their physical expressions.

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## REFERENCES

[1] G. Huisman, “Social touch technology: A survey of haptic technology for social touch,” IEEE Transactions on Haptics, 09 January, 2017.
[2] App, B., McIntosh, D. N., Reed, C. L., & Hertenstein, M. J. (2011). Nonverbal channel use in communication of emotion: how may depend on why. Emotion, 11(3), 603–617.
[3] Andreasson, R., Alenljung, B., Billing, E., & Lowe, R. (2016). Affective Touch in Human-Robot Interaction: Conveying Emotion to the Nao Robot. Submitted to International Journal of Social Robotics.
[4] Kitronyx Inc. http://www.kitronyx.com
[5] Pepper robot, https://www.ald.softbankrobotics.com/en/cool-robots
[6] I.T., Jolliffe, Principal Component Analysis, Springer, 2002.
[7] L. Kozma, “k Nearest Neighbors algorithm (kNN),” Helsinki University of Technology, Tech. Rep., 2008
[8] Hertenstein, M. J., Holmes, R., McCullough, M., & Keltner, D. (2009). The communication of emotion via touch. Emotion, 9(4), 566–573.
[9] Gärdenfors, P. (2004). Conceptual spaces as a framework for knowledge representation. Mind and Matter, 2(2), 9–27.