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Bayesian perception of touch for control of robot emotion

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Abstract—In this paper, we present a Bayesian approach for perception of touch and control of robot emotion. Touch is an important sensing modality for the development of social robots, and it is used in this work as stimulus through a human-robot interaction. A Bayesian framework is proposed for perception of various types of touch. This method together with a sequential analysis approach allow the robot to accumulate evidence from the interaction with humans to achieve accurate touch perception for adaptable control of robot emotions. Facial expressions are used to represent the emotions of the iCub humanoid. Emotions in the robotic platform, based on facial expressions, are handled by a control architecture that works with the output from the touch perception process. We validate the accuracy of our system with simulated and real robot touch experiments. Results from this work show that our method is suitable and accurate for perception of touch to control robot emotions, which is essential for the development of sociable robots.

I. INTRODUCTION

Sociable robots are designed with the purpose to be integrated in society to safely interact with humans, robots, objects and their surrounding environment. An important social aspect in human communication and interaction are emotions which are coupled to social context to determine behavioural reaction to social events, internal needs and goals [1, 2]. For that reason, integration and control of emotions in robots is essential to achieve robust socially interactive intelligent systems able to exhibit human social characteristics [3].

Investigation on methods for emotions in computers, robots, toys and software agents has rapidly increased in recent years given that people usually treat these systems as conscious agents [4, 5]. Psychology and neuroscience have inspired the development of architectures for control of artificial emotions in different robotic systems, emphasising the use of vision and speech modalities for human-robot interaction [6, 7, 8].

Touch not only plays a fundamental role to build a physical representation of the external world, identify and manipulate objects, but also serves as a non-verbal communication channel to feel and mediate social perceptions in various ways [9, 10]. A recent work has shown that humans are able to accurately recognise intended emotions through the perception of touch only [11]. Despite the importance of touch for social robotics and the advances in tactile sensor technology [12], only few works have paid attention for control of emotions in

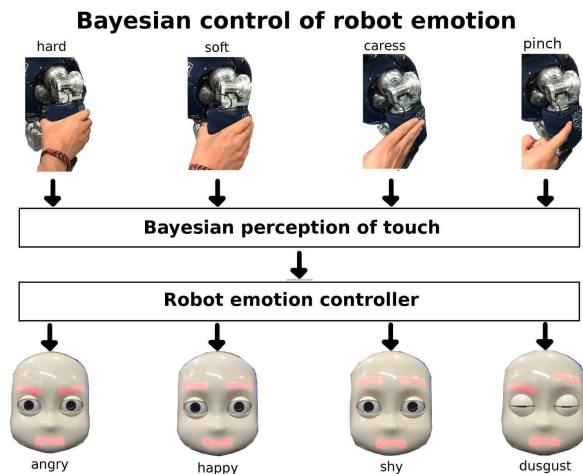


Fig. 1. Robot emotion control for social robots based on perception of touch. Tactile data is obtained from the artificial skin of the iCub humanoid robot. Emotions are represented by facial expressions and controlled by the touch perceived from a human-robot tactile interaction.

robotics using facial expressions, discrete tactile switches and emotional states based on human-robot interaction [13, 14].

We propose a control method for robot emotions using touch as stimulus during human-robot interaction. In this work, robot emotions are based on facial expressions with a discrete categories approach that implements various emotions such as *happiness*, *shyness*, *disgust* and *anger* [15]. This subset of emotions is drawn from the study of universal emotions generated from patterns of neural responses [16]. Facial expressions, commonly composed by eyebrows, eyelids and lips, have demonstrated to provide a good interface to display emotions with different robotic platforms [14, 17, 18, 19].

In this work, we defined four types of touch that can be perceived by the robot: *hard*, *soft*, *caress* and *pinch*. Thus, facial expressions, that display robot emotions, are controlled by the perceived touch applied by a human on the skin of the robotic system located in its torso, arms and hands.

A Bayesian approach was developed for perception of touch that allows to reduce uncertainty from measurements through the accumulation of evidence. This method has been used

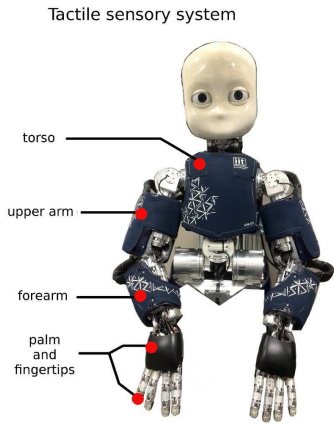


Fig. 2. Tactile sensory system of the iCub humanoid robot. The robot is covered by tactile sensor in its torso, upper arm, forearm, palm and fingertips. The sensors are based on capacitive technology that allow the robot to feel, perceive, interact and manipulate its surrounding environment.

in previous works for study of perception with vision, audio and touch sensing modalities obtaining accurate results for recognition of human emotion, object and shape discrimination [20, 21, 22]. We implemented our methods with a sequential analysis approach to give the robot the capability to make decisions once its confidence of the touch perceived has exceeded a belief threshold [23].

We developed a control architecture to integrate our proposed method for emotion control based on touch and activation of facial expression in the robotic platform. The architecture is composed of four processing layers named *sensation*, *perception*, *action* and *environment*. The input is the tactile data generated from the artificial skin of the iCub humanoid robot, whilst the output is the activation of a specific facial expression to display robot emotion. This architecture allows humans to interact with the robot and change in real-time its emotion based on tactile contact.

Validation of our method was made with experiments in simulated and real worlds. The experiment was to perceive a specific type of touch and activate the appropriate emotion based on facial expressions with the iCub humanoid robot. For the simulated world experiment, we trained and tested our method with various tactile datasets collected from the skin of the iCub humanoid robot. We simulated human-robot tactile interaction randomly drawing tactile data from the testing datasets. For the real world experiment, human participants interacted with the robot touching its skin. Thus, the robot was able to show different emotions, based on the activation of appropriate facial expressions, for each type of touch perceived.

Overall, results from the investigation undertaken in this work show that our method allows accurate perception of touch to control robot emotions from a human-robot tactile interaction, which provides a reliable framework for the development of intelligent sociable robots.

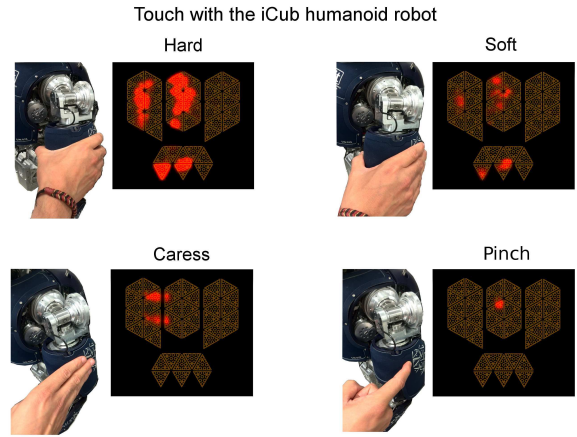


Fig. 3. Types of touch applied by a human on the skin of the iCub humanoid robot. The different tactile contacts were defined as *hard*, *soft*, *caress* and *pinch*. Each type of touch is characterised by pressure and duration features.

II. METHODS

A. Robotic platform

For investigation of emotion control for sociable robots we chose the iCub humanoid robot platform. This robot is an open platform designed for research on cognitive development, control and interaction with humans [24]. The iCub is a 53 degrees of freedom robot with a similar size of a four year old child. Its arms and hands allow dexterous manipulations and interaction with its surrounding environment, whilst its head and eyes are fully articulated. It is integrated with multiple sensory capabilities such as vision, touch and hearing that allow the robot to acquire information on different modalities from the environment. The iCub humanoid robot is also capable to produce facial expressions through arrays of LEDs (Light-Emitting Diodes) located in its face. This allows the robot to show emotional states for a more natural behaviour and interaction with humans.

We investigate on touch for control of robot behaviour and interaction with humans. For that reason, we use the tactile sensory system of the iCub humanoid robot, which is located on its arms, forearms, fingers, palms and torso (Figure 2). The artificial skin covering the iCub humanoid robot is based on a distributed pressure sensor built with a capacitive technology. The sensors are composed of flexible Printed Circuit Boards (PCB), where each PCB provides 12 measurements of capacitance that correspond to 12 round pads known as taxels. Tactile measurements are locally converted from capacitance to digital values with 8 bit resolution and sent to the main computer located in the head of the robot.

B. Data collection

For classification of touch we collected tactile data applying different pressures by humans using their hands over the artificial skin of the iCub humanoid. These pressures or types of touch are labelled as *hard*, *soft*, *caress* and *pinch*. The parts of the iCub humanoid robot covered with artificial skin; torso, arms and hands are shown in Figure 2. The artificial skin

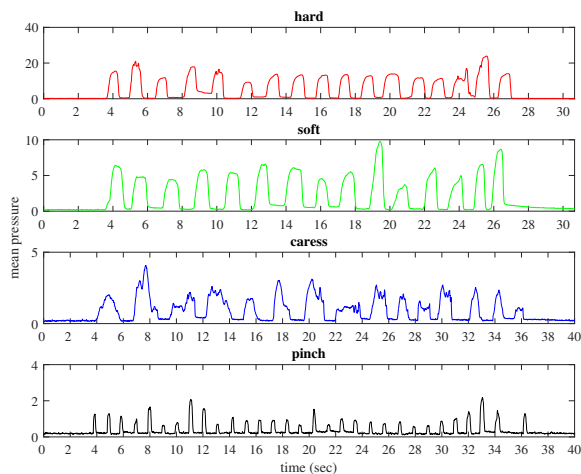


Fig. 4. Data collected from the four types of touch applied by a human on the artificial skin of the iCub humanoid robot. The tactile contacts are characterised by pressure and duration features, which allowed to define *hard*, *soft*, *caress* and *pinch* contacts shown in red, green, blue and black colours.

on the left upper arm of the robot was arbitrarily chosen for data collection. The four types of touch used for tactile data collection and their visualisation with a GUI (Graphical User Interface) are shown in Figure 3.

We collected a total of ten tactile datasets from the artificial skin of the iCub humanoid robot. On the one hand, five tactile datasets were collected from the left upper arm and used for training our methods. On the other hand, different areas of the tactile sensory system, e.g., arms and torso were used to collect five tactile datasets for testing our methods. Samples of data collected for each type of touch are shown in Figure 4.

The data collected is processed before using it as input of our modules. First, we normalised the data for all the types of touch. Next, the data is separated to obtain individual tactile contacts (see Figure 5). Then, the processed data is used to train our methods for perception of touch (see Section II-C).

C. Bayesian framework for touch

Our work is focused on emotion control in robots based on touch to show a more natural behaviour in human-robot interaction. Integration of touch in robotics requires the development of methods for perception and understanding of the changing environment in the presence of uncertainty.

In this work, we propose a probabilistic method with a Bayesian approach that uses past and present observations from the environment. Tactile data from human-robot interaction is used as input for recognition of touch and control of robot emotion. Four types of touch (*hard*, *soft*, *caress* and *pinch*) are used in this work for recognition of touch, which are characterised by pressure and duration features. Figure 5 shows the plots containing these features for each type of touch applied on the iCub humanoid robot.

The proposed probabilistic approach for touch recognition implements the Bayes' rule which combines prior probabilities and the likelihoods obtained from a measurement model. Our approach also uses a sequential analysis method that estimates

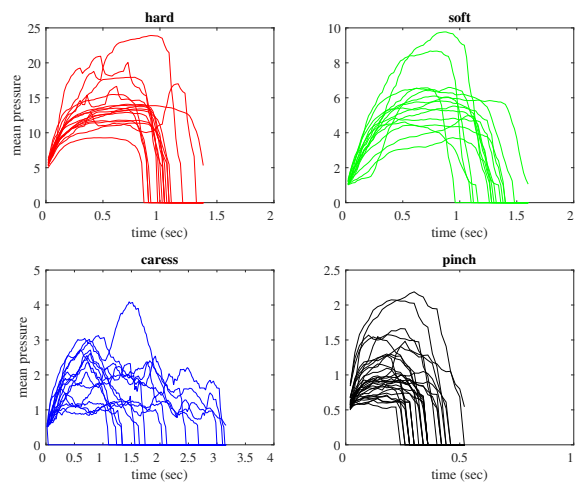


Fig. 5. Tactile data collected from the right forearm of the iCub robot. The complete dataset from each type of touch is segmented in individual contacts and used as input for our Bayesian framework for perception of touch.

the posterior probability based on recursively updating of observations. The sequential analysis allows to make decisions once the belief threshold is exceeded, improving the accuracy of the robotic system. The benefits of sequential analysis have been studied for classification of objects and shapes with touch sensors in robotics [25, 26].

The Bayes' rule used in our approach recursively updates the posterior probability $P(c_k|\mathbf{x}_t)$ by the product of the prior probability $P(c_k|\mathbf{x}_{t-1})$ and likelihood $P(\mathbf{x}_t|c_k)$. These values are normalised by $P(\mathbf{x}_t|\mathbf{x}_{t-1})$ to obtain probabilities in $[0, 1]$. This process is defined as follows:

$$P(c_k|\mathbf{x}_t) = \frac{P(\mathbf{x}_t|c_k)P(c_k|\mathbf{x}_{t-1})}{P(\mathbf{x}_t|\mathbf{x}_{t-1})} \quad (1)$$

where $c_k \in C = \{hard, soft, caress, touch\}$ are the perceptual touch classes to be estimated with $k = 1, 2, \dots, K$. Observations over time t are represented by the vector \mathbf{x} .

Prior: an initial prior probability $P(c_k)$ is assumed as uniform for all the classes of touch C , where \mathbf{x}_0 are the observations at time $t = 0$ and $K = 4$ is the number of classes used in the task.

$$P(c_k) = P(c_k|\mathbf{x}_0) = \frac{1}{K} \quad (2)$$

Likelihood: the measurement model to estimate the likelihood is based on a multivariate normal distribution of a 2-dimensional vector $\mathbf{x}_t = \{x_1 = pressure, x_2 = duration\}$ at time t as follows:

$$P(\mathbf{x}_t|c_k) = \frac{1}{2\pi|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(\mathbf{x}_t, \mu)^T \Sigma^{-1} (\mathbf{x}_t, \mu)\right) \quad (3)$$

where the multivariate normal distribution is characterised by the mean vector μ and covariance Σ values from pressure and duration measurements from tactile contact.

The product from the prior probability and likelihood are normalised by the marginal probabilities conditioned on previous tactile interactions as follows:

$$P(\mathbf{x}_t|\mathbf{x}_{t-1}) = \sum_{k=1}^K P(\mathbf{x}_t|c_k)P(c_k|\mathbf{x}_{t-1}) \quad (4)$$

Decision making: sequential analysis allows to accumulate evidence and make a decision once one of the hypotheses from the perceived touch exceeds a belief threshold. This method provides a decision making approach inspired by the *competing accumulators* model proposed from studies in neuroscience and psychology [27]. Thus, the perceptual class is obtained using the *maximum a posteriori* (MAP) estimate as follows:

$$\begin{aligned} &\text{if any } P(c_k|\mathbf{x}_t) > \theta_{\text{threshold}} \text{ then} \\ &\hat{c} = \arg \max_{c_k} P(c_k|\mathbf{x}_t) \end{aligned} \quad (5)$$

where \hat{c} is the estimated class of touch at time t . The belief threshold θ_{decision} allows to adjust the confidence level, which affects the required amount of accumulation of evidence and the accuracy of the decision making process. To observe the effects on the perception accuracy, we defined the belief threshold to the set of values $\{0.0, 0.05, \dots, 0.99\}$. Thus, the estimated class of touch \hat{c} is used to control the emotions, based on facial expressions, of the iCub humanoid robot (see Section II-D). The flowchart of the process described in this section for recognition of touch that implements our probabilistic approach is shown in Figure 6.

D. Robot emotion control

We developed an architecture that integrates our probabilistic approach for the control of emotions based on touch and activation of facial expressions with the iCub humanoid robot. This architecture, that receives tactile data and controls facial expressions, is composed of *sensation*, *perception*, *action* and *environment* layers as shown in Figure 6.

Collection and preparation of tactile data as described in Section II-B are performed in the *sensation* layer. Our probabilistic method described in Section II-C is implemented on the modules located in the *perception* layer. The decision-making process from the posterior probability distribution, emotion controller and memory, which stores the actions observed along the interaction with humans, are performed in the *action* layer. Finally, the human-robot interaction process and display of emotions with the iCub humanoid robot are located in the *environment* layer.

The *emotion controller* module receives the decision made from our probabilistic method, which activates specific patterns of LEDs (Light-Emitter Diodes) to show the corresponding facial expression. The set of facial expressions used in this work is *facial_expressions(happiness, shyness, disgust, anger)*, and each of them is selected as follows:

$$S_{\text{emotional}} = \text{facial_expressions}(\hat{c}) \quad (6)$$

where \hat{c} is the output from the *action* layer and $S_{\text{emotional}}$ is the emotion selected and sent to the iCub humanoid robot for activation of the facial expression. Examples of facial expressions activated from the perceived touch during human-robot interaction are shown in Figure 7.

All the modules in the control architecture were developed in C/C++ language, whilst communication and synchronisation of modules were handled with the YARP (Yet Another Robot Platform) library [28], which has demonstrated to provide robust control in multiple robotic platforms and applications [29, 30, 31, 32].

III. RESULTS

A. Simulated robot touch

Our first experiment is the analysis of perception accuracy for recognition of touch in a simulated environment. For this task we used the five datasets for training and five datasets for testing previously collected in Section II-B. The task was to randomly drawn different types of touch from the testing datasets with 5,000 iterations for each belief threshold in the set of values $\{0.0, 0.05, \dots, 0.99\}$. The drawn data was used as input for our Bayesian framework for perception of touch described in Section II-C.

We analysed the accuracy of touch perception using individual duration and pressure features to compare their performances to the accuracy achieved by the combination of both features. Results from these experiments were averaged over all trials and for each belief threshold (see Figure 8). Red colour curve shows that the duration feature was not able to provide accurate touch perception for low and high belief thresholds. An accuracy of 53.15% was obtained using the duration feature for a belief threshold of 0.99. Conversely, the pressure feature used for perception of touch provided high

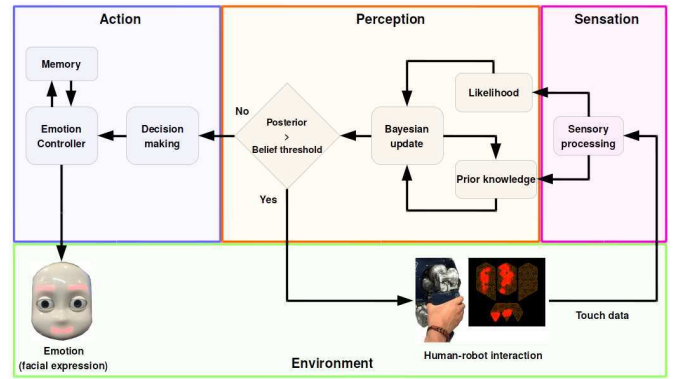


Fig. 6. Architecture for control of robot emotions. Four layers compose the proposed architecture: *sensation*, *perception*, *action* and *environment*. Tactile data is read and preprocessed in the *sensation* layer. Our probabilistic method for perception of touch is implemented in the *perception* layer. The *action* layer is responsible for the decision making process and activation of facial expressions, in the robotic platform, for representation of emotions. The human-robot interaction process is performed in the *environment* layer.

Emotion control based on touch

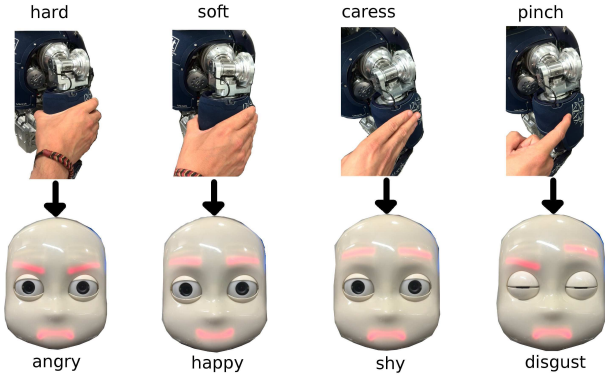


Fig. 7. Set of facial expressions used to show emotions for validation of our proposed method with real robot touch and the iCub humanoid robot. Facial expressions are activated by perception of touch during a human-robot interaction process.

accurate results, with a maximum accuracy of 87.20% for a belief threshold of 0.99 (purple colour curve). Also, it was observed that pressure feature was able to improve the perception accuracy for increasing belief thresholds. The combination of both duration and perception features allowed to achieve better perception of touch over the use of individual features (green colour curve). This result also shows an increment in perception accuracy for increasing belief thresholds obtaining a 95% accuracy for a belief threshold of 0.99.

The confusion matrices for the duration feature, pressure feature and the combination of them present in Figure 9, show the accuracy for recognition of each type of touch used in this work (*hard*, *soft*, *caress*, *pinch*). These results were obtained randomly drawing touch data from the test dataset with 5,000 iterations and for a belief thresholds of 0.99. The confusion matrix with duration feature shows that *caress* and *pinch* were successfully recognised with 100% and 99% accuracy, whilst for *hard* and *soft* the recognition accuracy was of 12% and 0.9%. The confusion matrix with pressure feature shows an improvement in the recognition of *hard* and *pinch* with an accuracy of 99.3% and 95.5%, and a slightly reduction for *soft* and *caress* achieving a 72.2% and 81.7% accuracy. Finally, the confusion matrix with the combination of features presents

improved recognition results for *hard*, *soft*, *caress*, and *pinch* with accuracies of 99.4%, 83%, 99.9% and 97.66%.

Results from these experiments not only show that our method allows the recognition of different types of touch from the artificial skin of the iCub humanoid robot, but also the improvement of perception accuracy based on the accumulation of evidence through an iterative human-robot tactile interaction.

B. Real robot touch

For the second experiment, we repeated the task for recognition of touch but using the iCub humanoid robot. Also we included the control of emotions in the robot based on the perceived touch. For training our method, we used the training datasets previously collected from the robotic platform (see Section II-B), whilst for testing, we collected tactile data in real-time with human participants touching different parts of the artificial skin of the iCub humanoid robot. In this experiment the decision making process for recognition of touch was triggered by the belief thresholds of 0.3 and to 0.9 to observed the improvement in perception accuracy.

The scenario for this experiment was the following: First, the iCub humanoid robot started the task with a flat knowledge about touch perception from its skin, showing a neutral facial expression. Second, the robot waited for a touch interaction by a human participant in any part of its tactile sensory systems (torso, upper arms, forearms). Next, once the human touched the robot, it performed a data collection and perception process based on our Bayesian framework. Then, if the posterior probability, obtained for the current touch interaction, did not exceed the belief threshold, the robot showed the same emotion based on facial expression, which means that its current emotional state was not affected. Thus, the current posterior probability is updated as the prior probability for the next touch interaction, allowing to accumulate evidence along the human-robot interaction process. Otherwise, if the posterior probability exceeded the belief threshold, a decision was made selecting the corresponding emotional state from the set of facial expressions. The complete human-robot tactile interaction was performed 20 times for each type of touch and for both 0.3 and 0.9 belief thresholds.

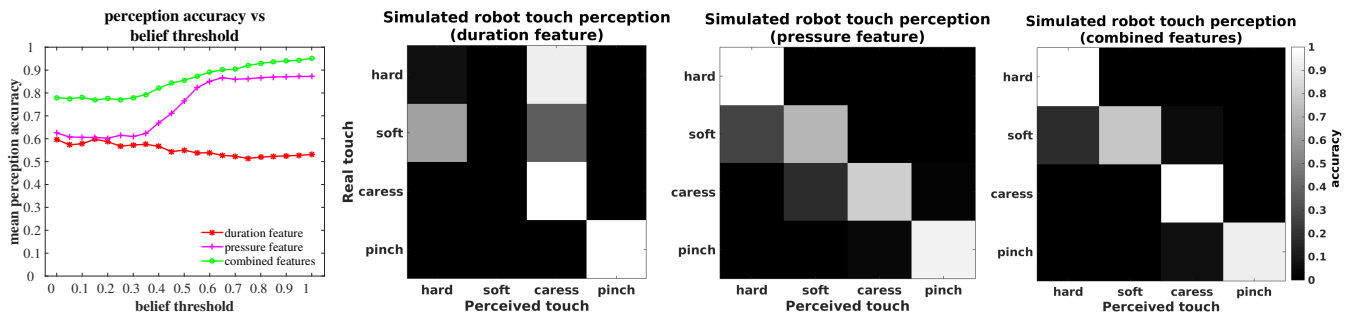


Fig. 8. Perception accuracy vs belief threshold with simulated robot touch. (left) Perception results from perception of touch using individual duration (red colour curve) and pressure (purple colour curve), and combination of both features (green colour curve). Perception accuracy results for each type of touch with belief threshold of 0.99 are shown in the confusion matrices obtained with (left matrix) duration feature (53.15% accuracy), (middle matrix) pressure feature (87.20% accuracy) and (right matrix) combination of both features (95% accuracy).

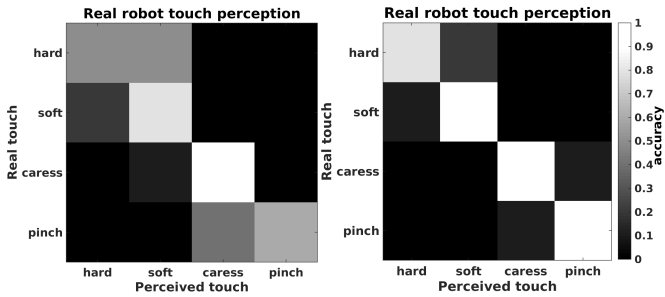


Fig. 9. Confusion matrices for perception with real robot touch. The experiment was performed with a human-robot tactile interaction using belief thresholds of 0.3 and 0.9. Results for perception of touch with belief threshold of 0.3 (left matrix) achieved an accuracy of 70.0%, whilst for the belief threshold of 0.9 (right matrix) the robot achieved an accuracy of 89.50%.

The confusion matrices in Figure 9 show the recognition accuracy achieved for each type of touch and for both belief thresholds using real data from the iCub robot through a human-robot tactile interaction. For the experiment with the real robot, we used the combination of both duration and pressure features. The confusion matrices were built with the decisions made for each type of touch iteratively applied by the human on the skin of the robot. For the belief threshold of 0.3 (left matrix), the robot was able to achieve accurate results for *soft* and *caress*, whilst a low recognition accuracy was obtained for *hard* and *pinch*. This confusion matrix shows a total accuracy of 70%. For the belief threshold of 0.9 (right matrix), our method allowed the robot to accumulate more evidence from the human-robot interaction, making reliable decisions and improve the touch perception for *hard*, *soft*, *caress* and *pinch*. The confusion matrix shows that the robot was able to achieve a total accuracy of 89.50%.

The output from the touch perception process was used to control the different emotions in the iCub humanoid robot. The final control and display of robot emotions was based on the *emotion controller* module included in our architecture shown in Figure 6. Thus, the iCub humanoid was able to show different emotions in real-time, based on facial expressions for *happiness*, *shyness*, *disgust* and *anger*, according to the perceived human touch applied on the artificial skin on the robotic platform as observed in Figure 7. Overall, the results from the experiments presented in this work demonstrate that our method is reliable for perception of touch and emotion control in robotics.

IV. CONCLUSION

In this work we presented a Bayesian method for emotion control in robotics based on perception of touch. Emotions in the robotic platform were represented with facial expressions. Our method was able to accurately recognise different types of touch applied by human participants on the artificial skin of a robotic platform.

We collected tactile data from the skin of the iCub humanoid robot, applying four types of touch based on a human-robot interaction process. The data collection process provided ten datasets; five datasets for training and five datasets for testing.

The tactile data was preprocessed and used as input for our method for perception of touch and control of robot emotions.

A Bayesian framework for perception of touch was developed including a sequential analysis method to make confident decisions. Our proposed method allowed the iCub humanoid robot to accurately perceive different types of touch based on the accumulation of evidence through human-robot tactile interaction. The accurate perception of touch permitted a better control of robot emotions. Emotions with the iCub humanoid robot were represented by a set of facial expressions (*happiness*, *shyness*, *disgust*, *anger*) that corresponds to different types of touch (*hard*, *soft*, *caress*, *pinch*). The facial expressions were controlled by our architecture composed by the *sensation*, *perception*, *action* and *environment* layers.

We validated our proposed method in simulated and real robot touch environments. For the validation with simulated robot touch, we used the training datasets from the data collection process. The testing was performed randomly drawing tactile data from the testing datasets, accumulating evidence and making a decision once the belief threshold was exceeded. This task was performed using individual and combination of features extracted from touch data. The experiment was repeated 5,000 times for a set of belief thresholds, achieving a maximum perception accuracy of 95% with a belief threshold of 0.99. Our method demonstrated accurate recognition for different types of touch applied to the robot.

For the validation with real robot touch, a human-robot interaction task was performed by human participants applying different types of touch on the skin of the iCub humanoid robot. Similar to the simulated robot touch, we trained our method using the training datasets from the data collection process. The experiment was repeated 20 times for each type of touch applied to the robot. For each decision made by the robot, its emotions were controlled according to the type touch perceived. The mean perception accuracy achieved from all the trials was 89.50% for a belief threshold of 0.9, showing accurate robot emotions by the activation of facial expressions.

Touch plays an important role in control of emotions to achieve safe and reliable social robots. We have demonstrated that robot emotions can be controlled by accurate perception of touch in robotics. For future work, we plan to investigate the integration of multiple sensing modalities such as vision, hearing and touch, which are essential to provide robust and socially intelligent systems for society.

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