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Expressive touch: control of robot emotional expression by touch

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***Abstract*— In this paper, we present a work on control of robot emotional expression using touch sensing. A tactile Bayesian framework is proposed for recognition of different types of touch gestures. We include a sequential analysis method that, based on the accumulation of evidence from tactile interaction, allows to achieve accurate results for recognition of touch. Input data to our method is obtained from touch sensing, which is an important modality for social robotics. Here, emotion in the robot platform are represented by facial expressions, that are handled by a developed control architecture. We validate our method with experiments on tactile interaction in simulated and real robot environments. Results demonstrate that our proposed method is suitable and accurate for control of robot emotions through interaction with humans using touch sensing. Furthermore, it is demonstrated the potential that touch provides as a non-verbal communication channel for the development of social robots capable to interact with humans.**

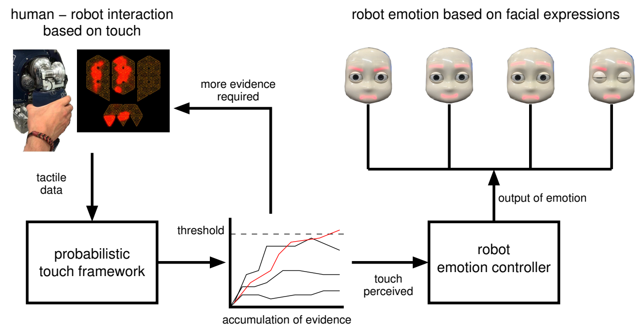

Fig. 1. Robot emotion control based on perception of human touch. Tactile data is obtained from the artificial skin of the iCub humanoid robot. Emotions are represented by facial expressions controlled by human touch.

I. INTRODUCTION

Integration of robots in society, which represents an exciting and challenging goal for scientists and engineers, requires of reliable methods for control, perception, learning and interaction with humans. An important role in human communication and interaction is played by emotions, which coupled to social context, determine behavioural reaction to social events, internal needs and goals [1], [2]. This drives the necessity to integrate emotional representation and control methods in robotic platform to achieve socially interactive robots that mimic human social characteristics [3]. Inspiration from psychology, neuroscience and ethology has motivated some works on the investigation and design of software architectures, focusing on vision and speech stimuli, for control of artificial emotions [4], [5], [6].

Touch plays an important role to build a physical representation of the external world, identify and manipulate objects. This sensing modality also serves as a non-verbal communication channel in human interaction to feel and mediate social perceptions in various ways [7], [8]. Recently, it has been observed that perception of touch sensing allows humans to accurately recognise intended emotions [9]. For these reasons, rapid advances in tactile sensor technology have been observed in the last decade, opening a wide repertoire for applications for robot touch [10]. Surprisingly, only few works have focused their research on touch for control of robot emotions using facial expressions, discrete tactile switches and emotional states approaches [11], [12].

We propose a probabilistic framework for control of robot emotions using touch as stimulus during a human-robot interaction process. Here, robot emotions are based on facial expressions with a discrete categories approach that implements happiness, shyness, disgust and anger, which are drawn from the set of emotions identified from patterns of neural responses [13], [14]. Facial expressions have demonstrated to provide a good interface to display emotions in robotic platforms [15], [16], [17].

A Bayesian approach was developed together with a sequential analysis method for perception of touch. This method has been used in previous works for study of perception with vision, audio and touch sensing modalities providing accurate recognition of human emotion and object discrimination [18], [19], [20]. Our method gives the robot the capability to accumulate tactile evidence and make decisions once a belief threshold is exceeded.

We developed a control architecture for emotion control based on touch and activation of facial expressions in the robotic platform. This architecture composed of five processing layers named sensation, perception, decision, action and world, allows humans to change the emotional state of the robot based on real-time tactile interaction.

Validation of our method was made with experiments in simulated and real worlds. The experiment was to perceive a specific type of touch (*hard, soft, caress* and *pinch*), based on human-robot tactile interaction, and activate the appropriate emotional expression in the iCub humanoid robot. Furthermore, we investigated how the use of individual and combination of features extracted from tactile data affect the accuracy and reaction time of perception of touch.

Results from this work show that our tactile Bayesian approach allows robots to perceive various types of touch and control its emotional expressions. Overall, we provide an accurate method using touch as a non-verbal communication channel for control of emotions in social robotics.

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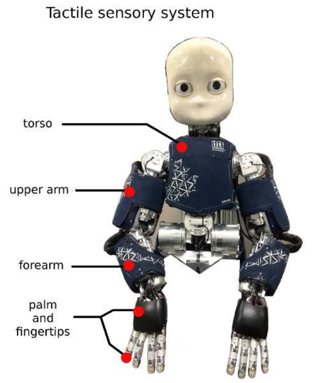

Fig. 2. Tactile sensory system of the iCub humanoid robot composed of artificial skin in its torso, upper arm, forearm, palm and fingertips.

A. Robotic platform

We chose the iCub humanoid robot platform for our investigation on human-robot interaction for emotion control. The iCub robot is an open platform designed for research on cognitive development, control and human-robot interaction [21]. This robotic platform with a similar size of a four year old child has 53 degrees of freedom. Its arms and hands allow dexterous manipulations and interaction with its surrounding environment, whilst its head and eyes are fully articulated. Multiple sensory capabilities integrated in the iCub robot, e.g., vision, touch and hearing, allow it to receive rich sensory information from the environment in different modalities [22]. The open robotic platform is also capable to produce facial expressions through arrays of LEDs (Light-Emitting Diodes) located in its face, which allow the robot to show emotional states important to reach a more natural behaviour and interaction with humans.

In this work, we focus on perception and emotion control using data from tactile human-robot interaction. The iCub humanoid has one of the most advanced tactile sensory technologies, which covering its torso, arms, palms and fingers, offers a great opportunity for investigation on perception, control and interaction in robotics (Figure 2). The artificial skin of the iCub humanoid robot is based on a distributed pressure sensor built with a capacitive technology. The sensors are composed of flexible PCBs (Printed Circuit Board), where each one 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.

II. Methods

A. Data collection

For the analysis and development of our method on perception of touch we collected tactile data from the iCub humanoid robot. The data collection was based on the interaction of humans with the robot by applying different types of touch on its artificial skin. The artificial skin on the left upper arm of the robot was arbitrarily chosen for data collection. The types of touch used by humans were labelled as *hard, soft, caress* and *pinch*. The four types of touch used for tactile data collection and their visualisation with the Skin GUI (Graphical User Interface) application provided in the iCub software repository are shown in Figure 3.

We collected a total of ten tactile datasets from the artificial skin of the iCub humanoid robot; five datasets collected from the left upper arm were used for training our method, while data from different areas of the tactile sensory system, e.g., arms and torso were used to collect five datasets for testing in a simulated world. Samples of data collected for each type of touch are shown in Figure 3.

The data collected is preprocessed before using it as input of our modules. First, we normalised between 0 and 1 the data from all the types of touch. Next, the data is separated to obtain individual contacts, which are used for training our methods for perception of touch described in Section II-B.

B. Bayesian framework

Our work is focused on emotion control in robots based on touch. Integration of touch in robotics requires the development of methods for perception and understanding of the changing environment in the presence of uncertainty.

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 then used as input for recognition of touch and control of robot emotion. Four types of touch defined as *hard, soft, caress* and *pinch* (see Figure 3) are used in this work

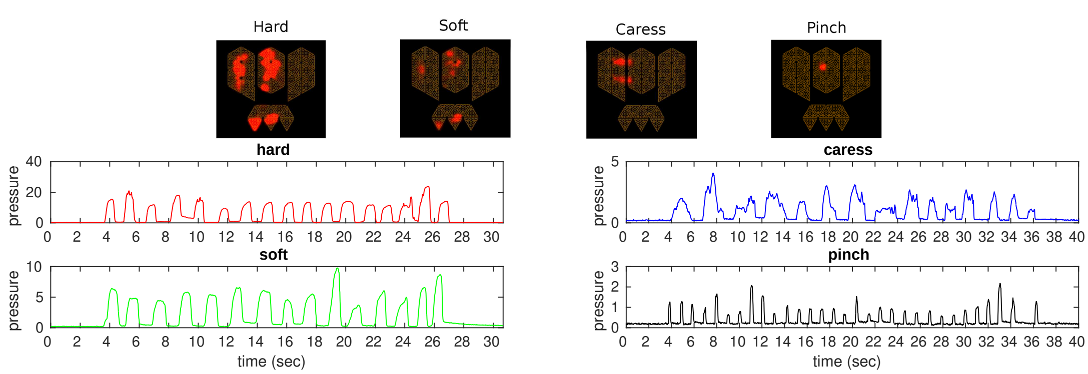

Fig. 3. (top) Activation of tactile sensors for each type of touch applied by a human on the skin of the iCub humanoid and defined as *hard, soft, caress* and *pinch*. (bottom) Data collected from each types of touch and characterised by *pressure* and *duration* features.

for recognition of touch, which are characterised by their *pressure* and *duration* features.

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 the posterior probability based on recursively updating of observations. The benefits offered by our approach have been studied for classification of various stimuli in robotics [20], [23], [24].

For our method we used tactile observations, composed of *pressure* and *duration* features ($\mathbf{x} = \{pressure, duration\}$), to estimate the most probable type of contact ($C = \{hard, soft, caress, pinch\}$) applied on the tactile sensors of the robotic platform. 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 obtained probabilities that sum to 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 $c_k \in C$ is the perceptual class to be estimated with $k = 1, 2, \ldots, K$ and $\mathbf{x}_t$ observations over time t.

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 $\mathbf{x}_t$ at time t with *pressure* and *duration* features as follows:

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

where the multivariate normal distribution is characterised by the mean vector μ and covariance Σ values from *pressure* and *duration* features from tactile contact. Figure 4 shows the likelihood for each type of 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 [25]. Thus, the perceptual class is obtained using the *maximum a posteriori* (MAP) estimate as follows:

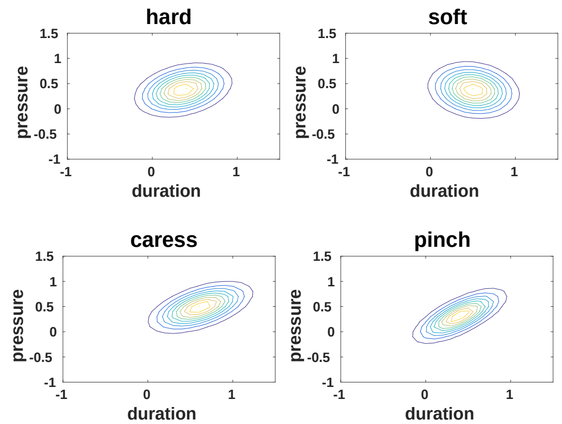

Fig. 4. Likelihood for each type of touch based on multivariate normal distributions composed of *duration* and *pressure* features.

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

where $\hat{c}$ is the estimated class of touch at time t. The belief threshold $\theta_{\text{threshold}}$ 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 $\{0.0, 0.05, \ldots, 0.99\}$. 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-C). The flowchart of the process described in this section for recognition of touch that implements our probabilistic approach is shown in Figure 5.

C. 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*, *decision* and *action* layers as shown in Figure 5.

Collection and preparation of tactile data as described in Section II-A are performed in the *sensation* layer. Our probabilistic method described in Section II-B is implemented on the modules located in the *perception* layer. The decision-making process from the posterior probability distribution is performed in the *decision* layer. Finally, the emotion controller and memory module located in the *action* layer are responsible for representing emotions, based on facial expressions, and storing the set of emotions observed along the interaction of a human with the iCub humanoid robot.

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. In this work, the set of facial expressions is defined by $F_{expression}$, and implemented as follows:

$$S_{\text{emotional}} = F_{expression}(\hat{c}) \tag{6}$$

where $\hat{c}$ is the output from the *decision* 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 6.

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 developed for robust control of robotic systems.

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-A. The task was to randomly drawn different types of touch from the testing datasets with 5,000 iterations for each belief threshold in $\{0.0, 0.05, \ldots, 0.99\}$, and used them as input in our probabilistic approach for perception of touch.

First, we analysed the performance in accuracy and reaction time for perception of touch using individual *duration* and *pressure* features, to compare them with the performance achieved by combination of both features. Results from these experiments were averaged over all trials and for each belief threshold. Figure 7a shows the results for perception accuracy for each belief threshold. Red colour curve shows that the *duration* feature was not able to provide accurate touch perception, obtaining a maximum accuracy of 53.15% for a belief threshold of 0.99. Conversely, the *pressure* feature shows an improvement in perception of touch with a maximum accuracy of 87.20% for a belief threshold of 0.99 (purple colour curve). The combination of both *duration* and *pressure* features allowed to achieve better perception of touch over the use of individual features (green colour curve). This result shows an increment in perception accuracy for increasing belief thresholds, obtaining a 95% accuracy for a belief threshold of 0.99. We observed that for the cases of individual *pressure* and combination of features, the perception accuracy was gradually improved for increasing values of belief threshold.

Results in Figure 7b shows the reaction time required to make a decision for each belief threshold. On the one hand, individual *duration* and *pressure* features presented a similar behaviour (red and purple curves), where both features required a mean of 6 tactile contacts to make a decision with a belief threshold of 0.99. On the other hand, combination of both *duration* and *pressure* features interestingly improved the performance of reaction time, requiring only a mean of 4 contacts from the human-robot interaction to achieve the highest perception accuracy using a belief threshold of 0.99. These experiments show that our proposed method not only allows to perform accurate perception of touch, but also to

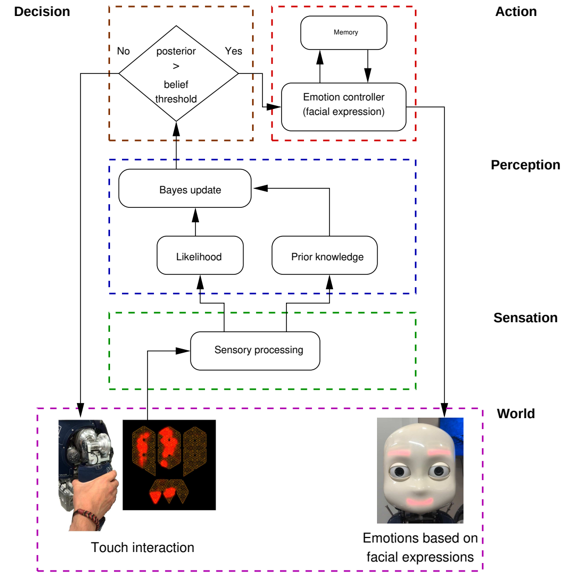

Fig. 5. Architecture for control of robot emotions. Five layers compose the proposed architecture: *Sensation, Perception, Decision, Action* and *World*. Tactile data is acquired and preprocessed in the *Sensation* layer. Our probabilistic method for perception of touch is implemented in the *Perception* layer. *Decision* layer is responsible for the decision making process once a hypothesis has exceeded the belief threshold. Activation of appropriate facial expressions in the robot is performed in the *Action* layer. *World* layer contains the human-robot tactile interaction process.

reduce the number of tactile contacts to make a decision. Both perception accuracy and reaction time are plotted in Figure 7c for comparison of performances.

The confusion matrices for the *duration* feature, *pressure* feature and the combination of them, show the accuracy for recognition of each type of touch in a simulated environment (Figures 8a,b,c). The confusion matrix with *duration* feature results shows that *caress* and *pinch* were successfully recognised (100% and 99.6%), whilst for *hard* and *soft* the recognition accuracy was very low (12% and 0.9%). The confusion matrix with *pressure* feature results shows the achievement of accurate recognition of *hard, caress* and *pinch* (99.3%, 81.73% and 95.5%), and a less accurate recognition of *soft* touch (72.2%). Finally, the confusion matrix with results from the combination of features, clearly presents the improvement for recognition of the four types of tactile contact (*hard, soft, caress, pinch*), achieving high accurate perception of touch (99.4%, 83%, 99.9% and 97.6%).

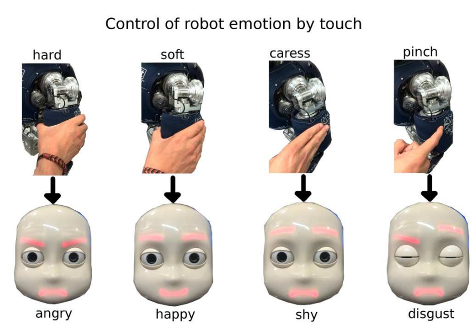

Fig. 6. Emotional expressions based on the activation patterns of eyebrows, eyelids and mouth observed from the experiment of human-robot tactile interaction in real environment.

Results not only show that our probabilistic method allows the accurate recognition of touch from the skin of the iCub robot, but also the improvement of perception accuracy and reaction time based on the accumulation of evidence through an iterative human-robot tactile interaction.

B. Real robot touch

For the second experiment, we performed recognition of touch and control of emotions using the iCub humanoid robot with human-robot interaction. For training our method, we used the training datasets previously collected from the robotic platform, whilst for testing, we collected tactile data in real-time with human participants touching the artificial skin of the iCub humanoid robot. In this experiment we used the belief thresholds of 0.3 and 0.9.

The scenario for this experiment was the following: First, the iCub humanoid robot started the task with a flat prior knowledge about perception of touch from its skin, showing a neutral facial expression. Second, the robot waited for a tactile interaction by a human 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 probabilistic approach. Then, if for the current touch interaction the belief threshold was not exceeded by the posterior probability, the robot showed the same facial expression, which means that its current emotional state did not change. Thus, the current posterior probability is used to update the prior probability for the next tactile interaction to allow the accumulation of evidence along the human-robot interaction process. Otherwise, once the posterior probability exceeded the belief threshold, a decision was made to select the corresponding emotional state from the set of facial expressions. The complete interaction task was performed 20 times, to allow the robot to display different emotions by the application of different types of touch.

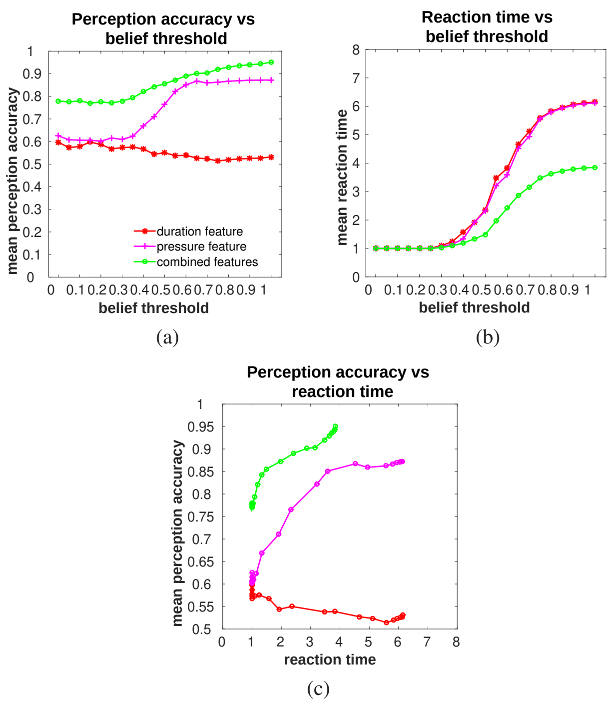

Fig. 7. (a) Perception accuracy versus belief threshold. (b) Reaction time versus belief threshold. (c) Perception accuracy versus reaction time. These results show the improvement in perception accuracy and reaction time for the combination of features and increasing values of belied thresholds.

Figures 8d and 8e show the recognition accuracy achieved for each type of touch and for both 0.3 and 0.9 belief thresholds using real data from the iCub robot. For this experiment we used combination of both *duration* and *pressure* features extracted from tactile data. 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. On the one hand, for the belief threshold of 0.3 (Figure 8d), 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%. On the other hand, for the belief threshold of 0.9 (Figure 8e), our probabilistic method allowed the robot to accumulate more evidence from the human-robot interaction, reducing uncertainty and making reliable decisions to improve the perception of touch 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 recognition process was used to control different emotions in the iCub humanoid robot. The final control and activation of robot emotions were based on the *emotion controller* module included in our architecture presented in Figure 5. Thus, the iCub humanoid robot was able to display *happiness, shyness, disgust* and *anger* emotions in real-time, based on the perceived human touch as observed in Figure 6.

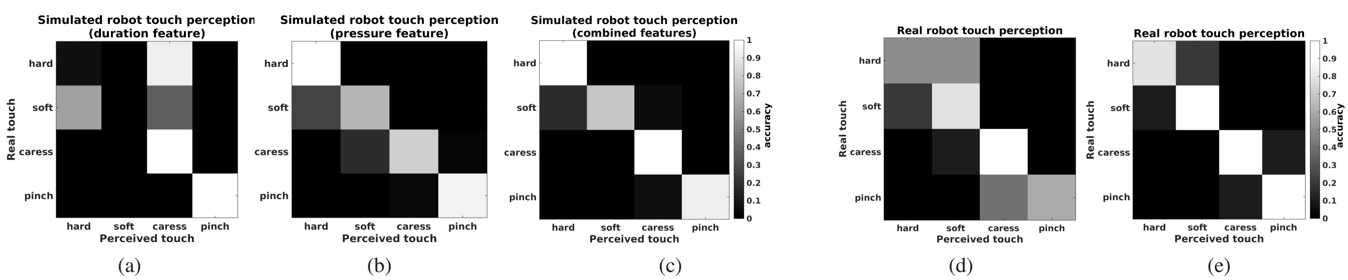

Fig. 8. Confusion matrices for perception of touch in simulated and real robot touch. (a,b,c) Confusion matrices from simulated robot touch with perception results for individual *duration* feature, *pressure* feature and combination of them achieving an accuracy of 53.15%, 87.20% and 95% for a belief threshold of 0.99. (d,e) Confusion matrices from real robot touch using the combination of features, which achieved a perception accuracy of 70% and 89.50% for belief thresholds of 0.3 and 0.9 respectively.

Overall, the results from the experiments demonstrate that our probabilistic method is suitable for accurate perception of touch and control of emotional expressions in robotics with a human-robot interaction process.

IV. Conclusion

We presented a method for emotion control in robotics though a human-robot tactile interaction. Robot emotions were represented by facial expressions with the iCub humanoid robot. Our method was able to accurately recognise different types of touch, applied by humans on the skin of a robotic platform, for control of robot emotion in real-time.

A Bayesian methods was developed for control of robot emotional expression based on the perception of touch. Our approach, together with a sequential analysis method, provided accurate decisions. The robot was able to perceive touch from humans by the accumulation of evidence through a human-robot tactile interaction process. Accurate perception permitted to develop a robust control of robot emotional expressions. Emotions in the iCub robot were represented by facial expressions such as *happiness, shyness, disgust* and *anger* controlled by different types of perceived touch such as *hard, soft, caress* and *pinch*.

Our method was validated in simulated and real robot touch environments. For the simulated robot touch we used the testing and training datasets from the data collection process. The simulated robot touch experiment was performed using individual and combination of tactile features for a set of belief thresholds. We achieved a maximum accuracy of 95% and mean reaction time of 4 tactile contacts with a belief threshold of 0.99 and combination of tactile features. These results outperformed the 53.15% and 87.20% accuracy, and the mean reaction time of 6 tactile contacts achieved for the use of individual *duration* and *pressure* features.

For the validation with real robot touch, a human-robot tactile interaction was performed by human participants and 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 skin of the robot. For each decision made by the robot, its emotional state was controlled according to the perceived touch. The mean perception accuracy achieved from all the trials was 70% and 89.50% for belief threshold of 0.3 and 0.9 respectively. The results also showed an accurate control of robot emotions, based on the activation and control of eyebrows, eyelids and mouth in the robotic platform.

Touch plays an important role as a non-verbal channel for human-robot interaction. This sensing modality is also essential for the control of emotions and the development of intelligent social robots. For future work, we plan to investigate on the integration of multiple sensing modalities such as vision, hearing and touch, for the control of robot emotions using data from the environment in various formats and achieve robust and intelligent systems for society.

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