
EmotiFactor: Emotional Expression of Robotic Physical Contact

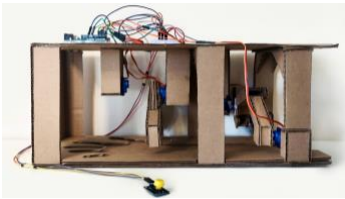


Figure 1: Robotic tactor interface

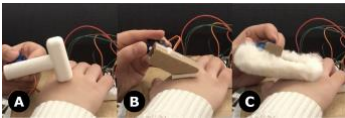


Figure 2: Touching by different materials (A) PLA Plastic (B) EPDM rubber (C) Fake fur

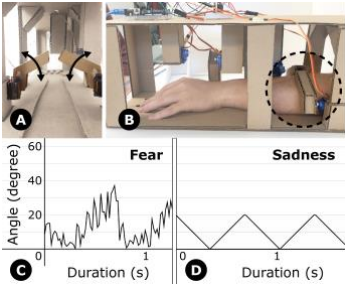


Figure 3: (A) Tactor 1: designed in the shape of two bending fingers driven by servo motors. (B) It can squeeze the human's forearm and behave as trembling and stroking. (C) Graph for fear (squeezing and trembling). The slightly random motion of the tactor gave people a tactile sensation of trembling. (D) Graph for sadness (stroking and squeezing). The frequency of the servo's motion was lowered.

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Abstract

The study of affective communication through robots has primarily been focused on facial expression and vocal interaction. However, communication between robots and humans can be significantly enriched through haptics. In being able to improve the relationships of robotic artifacts with humans, we posed a design question - What if the robots had the ability to express their emotions to humans via physical touch? We created a robotic tactor (tactile organ) interface that performs haptic stimulations on the forearm. We modified timing, movement, and touch of tactors on the forearm to create a palate of primary emotions. Through a preliminary case study, our results indicate a varied success in individuals being able to decode the primary emotions through robotic touch alone.

Author Keywords

Expressive Robotics; Haptics; Physical Contact; Human-Robot Interaction; Emotion Communication

CSS Concepts

• **Human-centered computing~Human computer interaction (HCI); Haptic devices; User studies;**

Introduction

In our speculative vision of the world, robots are poised to coexist with humans. The scenarios include daily

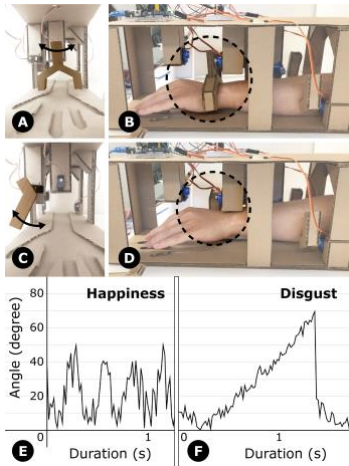


Figure 4: (A) Factor 2: designed in the shape of a grasping hand, controlled by a servo motor installed at the top. (B) Factor 2 can behave as swinging and shaking. In the test, participants needed to lift their wrists to let their hands move following the tactile behavior of the robot. (C) Factor 3: driven by a SO5NF STD servo motor with higher torque. (D) Factor 3 can push the hand from the side. (E) Graph for happiness (swinging and shaking). The function was applied to the factor 2. (F) Graph for disgust (pushing). We programmed the factor 3 with a higher range motion since disgust is a strong emotion.

activities, such as education, play, and commerce. In an effort to neutralize the “otherness” of these machines and to improve the emotional expressiveness of the robots, we hypothesize that touch could play a crucial role. To detangle the nontactile signals in affective communication, we designed a machine interface (Fig. 1) that performed touch stimuli on the forearm of an individual. We limited the form to a unit in which a user inserted their arm and the tactors (Fig. 3-5) were programmed to mimic human touch. We limited the scope to test primary emotions conveyed through touches, including fear, anger, disgust, happiness, sadness, and sympathy [3]. The tactors were driven by individual servo motors. Through careful design of the timing, we were able to program the grip and strength of tactor presses on the arm. Through our preliminary user studies, we found that an intuitive and realistic communication was indeed possible through these presses. Our contributions are:

- i. Discussion on primary emotions from human-human touches utilized in the context of HCI to create human-robot touches
- ii. A preliminary case study showing varied experiences of participants in being able to decode emotions through tactor presses

Related Work

Hernandez and Prescott [1] developed a “Bayesian method” to have an accurate recognition of touch applied by humans on the robotic skin to control the emotional facial expression of the robot. Willemse and Erp [2] claimed that “social touch” by robots enhances the intimate relationship between humans and robots. While studies have begun to explore emotional haptic interaction [6] [10] [11] between humans and robots, to our knowledge, there are no research projects that

focus on the specific emotions convey from robots to humans via touch. We are interested in active motion of robots, to let humans receive information via touch and decode the emotions. Our goal is to let robots express themselves through tactile behaviors.

Human-Human Touch

Hertenstein et al. [3] proved that humans can decode emotions via touch alone. In their study, they divided participants into dyads and randomly assigned them to the role of encoder and decoder. The encoders needed to convey the emotion assigned to them by touching decoders’ forearm without visual or vocal interaction. The decoders needed to choose the emotion that they felt through the cutaneous stimuli on the “response sheet.” The results showed that anger, fear, disgust, love, gratitude, and sympathy could be decoded at above-chance levels. They also recorded the most commonly used tactile behaviors for each emotion. Our work was based on this study because study of human development has always been a great inspiration for the implementation of robotic systems [4].

EmotiTractor’s Design Process

To study the emotional expression of robotic contact, we replaced the role of the encoder with the touches of robotic tactor (tactile organ, Fig. 3-5). We hypothesized that humans could decode the emotions from the robotic tactile stimulation, similar to human-human touches. Out of the six primary facial and vocal communication emotions [5], we chose five for our test: anger, fear, happiness, sadness, and disgust. We did not choose surprise since it was not decoded via touch in Hertenstein et al.’s study [3]. In their study, humans were greatly inclined to “interpret attempts to communicate sadness as sympathy.” In order to verify

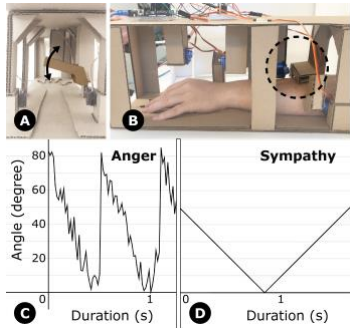


Figure 5: (A) Factor 4: designed in the shape of a palm, which has a larger contact area. (B) It can behave as hitting and patting (C) Graph for anger (hitting). We programmed the function with high frequency, large range, and randomness. (D) Graph for sympathy (patting). The gesture was gentle and regular.

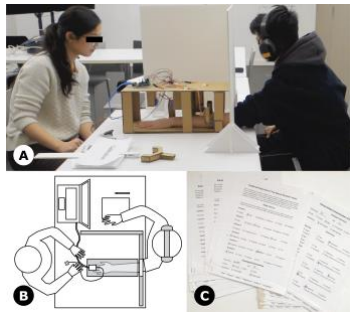


Figure 6: (A) Participant was taking the test. (B) Experimental scene. (C) Response sheets matched with function-order slips.

this result in robot-human touch interaction, we added the sympathy emotion in our study. We utilized the most frequent types of touch for each emotion provided by their research [3] and applied them to program the behaviors in our machine interface. We held a series of user tests to investigate whether humans can decode the emotions from the robotic tactile stimulations.

Prototype

The prototype is a structure (Fig. 1) that fits the length of the forearm (18 inches). At the bottom of the structure, there is a hand-shape groove acting as an affordance for the participants and helping them place their arms in the right position (Fig. 6). Inside the structure, there are four machine factors driven by servo motors (Fig. 3-5). Each factor aims to behave as one or two of the most frequent types of touch for each target emotion in Hertenstein et al.'s study [3] by the motion of the servo motor. The tactile behaviors recorded in their study [3] included: squeezing, trembling, patting, hitting, shaking, and stroking.

For the purpose of quick iterations, this prototype was made out of cardboard. To preclude nontactile clues like movement or gesture in the communication [12], the participants were kept from seeing the machine or the movement of factors during the testing by a foam board (Fig. 6). We also took textures of contact materials into consideration. We didn't use PLA plastic owing to its specific heat capacity that produces a noticeable stimuli to humans due to its lower than room temperature (Fig. 2(A)). In contrast, rubber and fake fur (Fig. 2(B), (C)) were soft and gave humans a sense of intimacy, which was not conducive to testing negative emotions like anger. To preserve the feeling of a robotic or a machine touch, we did not add any

silicone/skin-like texture to the ends of the factor. The factor contact points thus were also made of cardboard. We did so to be able to gauge the raw results from machine behaviors and a machine-like touch alone, rather than a furry, soft or squishy textured materials that have different associations for a user.

Implementation of Factors

The factors in the machine were driven by micro servo motors. Four of them were SD 90 (torque: 2.5 kg-cm), one was SO5NF STD (torque: 3.2 kg-cm). We used an Arduino UNO to control them. We also developed a graphic interface to visualize how the degree of angle of the servo motors changed along with the time (Fig. 3(C), (D), 4(E), (F), 5(C), (D)).

Study 1

On arrival, the participant sat at a table and was asked to wear earplugs to mask the distraction of the external noise and motor's sound (Fig. 6). Then, participants placed their forearm into the machine through a hole at the bottom of the opaque foam board (18 x 18 inches) which separated them from the EmotiFactor on the other side. Calibration is manually carried out before running the test to guarantee that the factors indeed touch their arms. The machines then cycle through the functions according to a random order of the six emotions. After each function, participants were asked to make a choice on a response sheet. For each round, the participants had the option to select one of seven response options: anger, fear, happiness, sadness, disgust, sympathy, and N/A.

Participants

The first-round study had 10 participants (2 Male, 8 Female) with an average age of 24.6 (SD = 2.5). Each

Emotion	Accuracy (%)
Fear	40
Disgust	40 (<i>Anger, 60</i>)
Happiness	60
Sadness	10 (<i>Sympathy, 70</i>)
Anger	10
Sympathy	40

Table 1: percentage of decoding accuracy and the most frequently chosen emotion for target emotion in study 1

Emotion	Accuracy (%)
Fear	70
Disgust	70
Happiness	100
Sadness	20 (<i>Sympathy, 70</i>)
Anger	70
Sympathy	40 (<i>Sadness, 40</i>)

Table 2: percentage of decoding accuracy and the most frequently chosen emotion for target emotion in study 2

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participant was been explained the protocol mentioned above before starting the self-running program that does the sequence of the functions for emotions.

Results

Table 1 shows the decoding accuracy for each target emotion as well as the emotion that was most frequently chosen by participants. In Hertenstein et al.'s study [3], they set a chance guessing rate of 25% by following Frank and Stennett [7]. The accuracy rate in study 1 shows that fear, disgust, happiness, and sympathy were decoded at above-chance levels. It was hard for participants to distinguish disgust and anger since both of them are strong emotions. As for sadness, participants were confused about it with sympathy, which was consistent with the previous study [3].

Study 2

In a follow-up study, options were arranged in a randomized order on the response sheet. It was designed to exclude the influence of human judgment due to the order in which people saw emotion options. We redesigned the function for anger by programming it with hitting behavior for tactor 4. It was expressed by tactor 1 with strong squeezing and trembling in study 1, but results came out that it was hard to decode. These three types of touch were typical for anger in the former study [3]. In study 1, we found that many individuals had no previous experience of being touched through a machine. Their understanding of the emotions was affected a lot by the emotions' order. To avoid this interference factor, we added a process called overview to familiarize participants with the interface. The machine cycled through all of the haptic functions, but the participants were not needed to make responses during this routine. We also used noise

reduction earphones instead of the earplugs for more effective noise cancellation.

Participants

10 participants completed the study (4 Male, 5 Female, 1 Other) with an average age of 24.1 (SD = 1.1).

Results

Table 2 shows that the accuracy was much higher than of study 1. Fear, disgust, happiness, and anger were decoded at significantly higher (from 70% to 100%) above-chance levels. It was still confusing for participants to regard sadness as sympathy. During the participants' interviews, however, we also observed that it was hard for individuals to tell the differences between these two emotions, at the subjective level.

Conclusion & Future Application

Our results indicate that, given the accurate design of gestures, humans can decode at least five emotions through robotic tactile behaviors (fear, disgust, happiness, anger, and sympathy). This decoding accuracy ranged from 40% to 100%. Future work could explore refining the parameters by further comparative experiment for each emotion to improve the replicability of the study. We also plan to hold a future workshop that allows participants to program their own EmotiFactor by using a dashboard interface and analyze their parameter settings. EmotiFactor has the potential to be implemented in smart toy design [8] and applied to the remote social touch while humans communicate remotely through VR devices [9]. It can also provoke communication between medical robots with humans, especially people with hearing and vision disorders.

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