Using Skin Texture Change to Design Emotion Expression in Social Robots

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***Abstract*—We evaluate the emotional expression capacity of skin texture change, a new design modality for social robots. In contrast to the majority of robots that use gestures and facial movements to express internal states, we developed an emotionally expressive robot that communicates using dynamically changing skin textures. The robot's shell is covered in actuated goosebumps and spikes, with programmable frequency and amplitude patterns. In a controlled study ($n = 139$) we presented eight texture patterns to participants in three interaction modes: online video viewing, in person observation, and touching the texture. For most of the explored texture patterns, participants consistently perceived them as expressing specific emotions, with similar distributions across all three modes. This indicates that a texture changing skin can be a useful new tool for robot designers. Based on the specific texture-to-emotion mappings, we provide actionable design implications, recommending using the shape of a texture to communicate emotional valence, and the frequency of texture movement to convey emotional arousal. Given that participants were most sensitive to valence when touching the texture, and were also most confident in their ratings using that mode, we conclude that touch is a promising design channel for human-robot communication.**

***Index Terms*—Soft robotics; human-robot interaction; emotion expression; empirical study; texture-change; nonverbal behavior**

I. Introduction

In this paper, we explore the potential of a texture-changing skin as a design modality for robotic emotion expression. In an experimental study we find consistency in how people map skin texture movements to emotions, suggesting that texture-changing skins can be a useful component in the design of social robots.

Internal and emotional state expression is at the core of Human-Robot Interaction (HRI) [1]–[3], and many social robots are designed to convey their states not only with speech but also through nonverbal signals. To date, the vast majority of nonverbal expression in robots is in the form of facial expressions [4]–[6] and body movements [7], [8], including gaze behavior [9]. However, some robots may not necessarily be designed with anthropomorphic features and configurations that allow for such expressive behaviors [10]–[12].

To enable emotion expressions for robots in a manner applicable to different robot configurations, we developed an expressive channel for social robots in the form of texture changes on a soft skin. Our approach is inspired by some biological systems, which alter skin textures to express emotional states. This behavior includes human goosebumps, a cat's back fur raise, a blowfish displaying its spikes, or birds ruffling their feathers [13]. While prevalent in animals, this intuitive and widespread behaviour has not thus far been used to communicate expressions for social robots. Adding such expressive textures to social robots can enrich the design space of a robot's expressive spectrum: it can interact both visually and haptically, and even communicate silently, for example in situations in which they cannot be seen or heard but touched, such as in military or low-visibility scenarios.

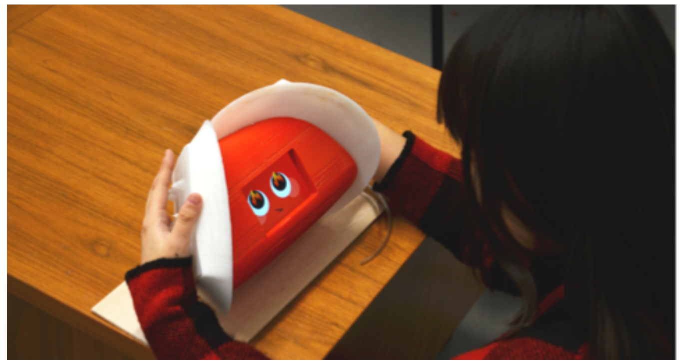

Fig. 1. A social robot prototype combining facial expressions and a texture-changing skin. During the interaction, the user makes eye contact with the screen face and puts their palms on the sides of the robot to touch the actuated textures.

The soft robotic skin generates pneumatically actuated dynamic textures, deforming in response to changes in pressure inside fluidic chambers [14]. In the social robot depicted in Fig. 1, we integrated skins with two textured shapes inspired by nature: goosebumps and spikes. We can then use the shape and volume of the texture, as well as the speed of the texture's movement, to convey a variety of emotional expressions.

Given the novelty of this expressive modality, there are no design guidelines or empirical evidence as to how texture changes map to emotions. To investigate this question, we conducted a controlled study to map emotions to texture gestures, and to assess their expressive capabilities. We developed eight texture gestures using binary values for three parameters: shape, frequency, and amplitude. We then asked study participants to label these gestures with emotion words. Participants did so in three interaction modes: watching online videos of the texture, observing the texture in person, and touching it.

The study results indicate that a robot's skin texture change

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can be a promising channel for communicating specific emotions across different interaction modes. The results also provide insights on how to design texture behaviors to communicate a specific emotion. The choice of texture units and the movement frequency are the two most significant parameters defining the textures' expressive content, with goosebumps conveying a more positive emotion than spikes, and a higher frequencies communicating a more aroused state. Moreover, we found a variance in valence perception between interaction modes, suggesting that touching the robot's texture change is the most promising channel to evoke emotional valence.

II. Related Work

A. Nonverbal Expression in Social Robots

Generating nonverbal behaviors is a central ability for social robots to facilitate communication with humans. To achieve this, the majority of social robots use gestures and facial expressions, *e.g.*, KOBIAN [15], Probo [16], NAO [17], Kismet [18], EMYS [19], and Nexi [20]. On the other hand, the modality of touch that communicates or evokes emotions has received less attention. Yet the sense of touch is important for humans in communicating emotions and for social bonding [21]–[23]. As a result, there are a number of social robots that use affective haptic interfaces for users. These robots include PARO [24], a seal-like robot which has touch sensors embedded under its skin and engages people through sound and movement; the Haptic Creature [25], an animal-like robot that displays its emotions by altering breathing rates and adjusting body stiffness; and Cuddlebits [26], a robot that also displays its emotions through breathing-like behaviors. In all of these cases, the robots express their states either through whole body movements or vibrotactile sensations. None of these robots change their skin textures as an expressive channel.

Outside of the robotics field, designers have explored affective haptics through "shape-changing interfaces" [27]. Recently, Van Oosterhout *et al* studied the effect of shape-change on emotional experience when interacting with an intelligent thermostat [28]. Davis designed an architectural shape changing textile wall panel for emotional expression and nonverbal communication through vision and touch [29].

B. Soft Materials and Mechanisms in Social Robotics

Recently, soft materials and soft mechanisms have been explored in social robot design. The vast majority of such robots conform to a similar design that includes a soft exterior over a rigid or tensile inner mechanism. Examples include Keepon [30], a rigid linkage mechanism covered by a soft snowman-like exterior; Tofu [31], a winch mechanism embedded in a foam structure; and Blossom [32], a compliant tensile mechanism covered with handcrafted exteriors. Although some of these robots deform their soft exteriors for expression, they focus on their full body deformation on a macro scale. Change of skin on a micro scale still remains an unexplored channel for socially interactive robots.

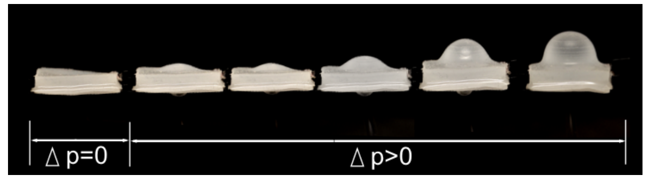

Fig. 2. A goosebump TU transforms from a flat initial surface to a smooth bump under positive pressure. The volume of the bump increases with the increase of internal pressure.

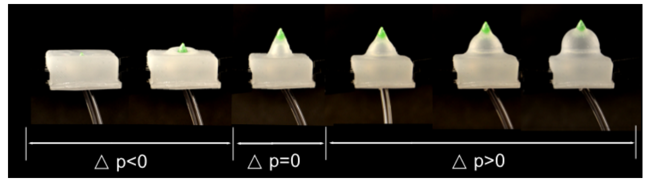

Fig. 3. Spike TU inflation from negative pressure, with the haptic tip hidden inside the elastomer, to positive pressure, with the sharp thorn protruding.

C. Russell's Circumplex Emotion Model

In social and cognitive psychology, a common model for emotional states is Russell's circumplex model of emotions [33]. From Russell's theory, an emotion is composed of two orthogonal dimensions (originally three). One dimension—valence—is scaled from unpleasant (negative) to pleasant (positive), while the other dimension—arousal—ranges from deactivated (low) to activated (high). We use this decomposition in our analysis below.

III. Design of Robotic Skin and Expressions

To implement skin texture changes for social robots, we developed a design using layers of cast elastomer and inextensible films. This design allows us to map pressure to surface deformation of the skin in the form of specifically shaped texture units (TUs). These units can optionally also have rigid components embedded in them for haptic expression. Below the layers of TUs is a network of interleaved fluidic channels connecting the units of the same type for separate control.

We used this design to develop two forms of expressive textures inspired by nature: goosebumps and spikes. A goosebump unit transforms from a flat surface to a smooth bump under pressure, as presented in Fig. 2. A spike unit is structured as a cone with a rigid element embedded on the tip for providing distinct visual and haptic feedback. The spike deforms and retracts the sharp tip under negative pressure (Fig. 3). Fig. 4 shows a skin design with interleaved 2D arrays of goosebumps and spikes under different pressure levels.

Noise is an important consideration for designing the actuation systems for texture units. To address possible distraction due to noise, we designed a power screw actuated linear displacement pump. The core of this design is a re-purposed syringe, which we used as a cylindrical pump with a plunger displaced by a linear stepper motor. This system afforded low noise, high control accuracy and efficiency when compared to the commonly used rotary displacement pump. A full description of the mechanism design is found in [14].

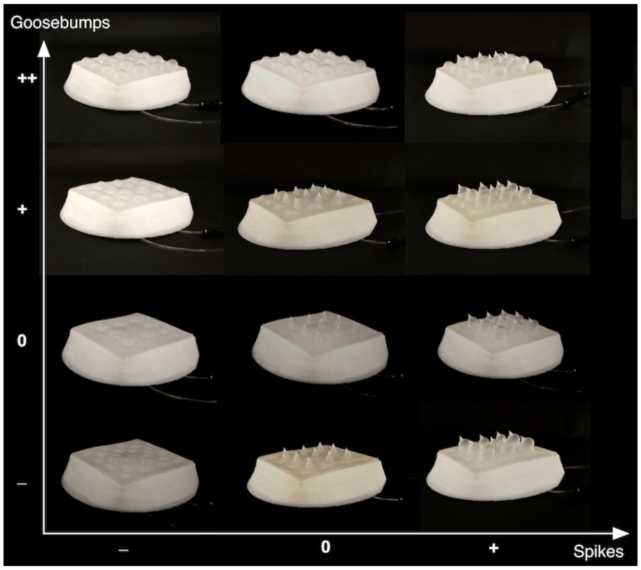

Fig. 4. Deformation of texture module in response to the inner chamber pressure. From left to right, the pressure of the spikes channel changes from negative to positive. From bottom to top, the goosebumps channel inflates from negative pressure to positive pressure.

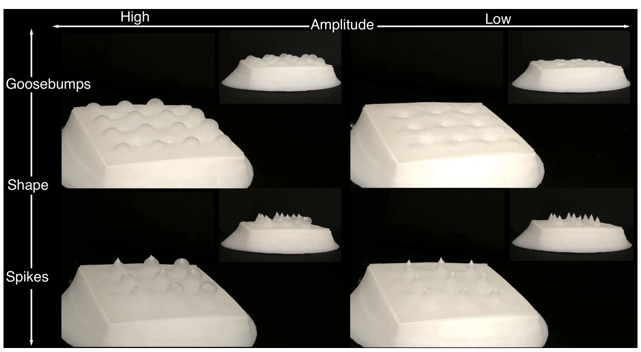

Fig. 5. The eight expressions used in this study vary in a binary fashion along three texture parameters as independent control variables: texture shape, change frequency (not shown) and amplitude.

A. Design of Expressive Behaviors

We created eight expressions, each by selecting from binary values of the three texture parameters (Fig. 5).

1) Texture Unit Type: We varied the two Texture Unit (TU) types described in III: goosebumps and spikes. We hypothesized there would be a mapping between emotion valence and the shape of textures, with negative valence mapping to the spikes TU, and positive to the goosebumps TU. This is inspired by natural responses, where spikes represent an angry, defensive state, and goosebumps are related to pleasure and excitement. Moreover, the spikes with sharp, rigid tips deliver an unpleasant haptic experience when compared to the sensation of smooth soft bumps.

2) Texture Change Frequency: Texture change frequency is defined as the number of texture rises per unit time. The texture change frequency is determined by the inflating and deflating speed of the linear displacement pump. Constrained by the maximum linear speed of power screw ($100mm/s$), available texture change frequencies range from 0 to 60 rises per minute (rpm).

We hypothesized that the frequency of the texture gestures would affect the arousal dimension of emotional states, with higher texture change frequency mapped to a higher arousal level. This is inspired by analogies in human experiences, where humans' physiological "frequency", such as breath and heartbeats falls to a lower rate when in a low arousal state, and increase when being aroused. Through piloting we converged on 20 rpm and 60 rpm as binary frequency values for the expressions used in the experiment.

3) Texture Change Amplitude: Research in human physiology shows that the increased arousal not only results in an increased breathing rate, but also in a larger ventilation volume [34]. Moreover, there exist some natural analogies of various forms of amplitudes, for example, the loudness of voice, and the amplitude of sea waves. In these cases, the lower amplitudes are usually associated with calm and peaceful states. Inspired by these phenomena, we hypothesized that the amplitude of texture change could be used to convey various arousal levels of emotions, with higher amplitude representing a higher arousal level.

In our system, the amplitude of texture movement is determined by the inflating and deflating volume of the pump. Amplitude values range from 0–30ml for spikes channel and 0–40ml for goosebumps. Designing the candidate expressions, we decided to use 15ml and 30ml as two values of amplitudes for spikes channel and 20ml and 40ml for the goosebumps. Note that the amplitude values chosen deliver a qualitatively different texture experience, especially for spike TUs. In low-amplitude spikes the rigid tip detracts fully into the skin, whereas in high-amplitude spikes the rigid tip stays above the surface. This is related to the dynamics of the inflation response to the pressure changes in each TU type.

IV. Research Questions and Hypothesis

In this study, we evaluate the following research questions and hypotheses. First, we wanted to know whether and to what extent robot texture change can be perceived as conveying specific emotions. We had the following hypotheses:

- **H1:** Texture change can be consistently perceived as a certain emotion across different interaction modes.
- **H2:** Consistency of people's perceptions of emotions differs across interaction modes.

Second, we wanted to explore how the three parameters of the texture change correlate with dimensions of valence and arousal. We had the following hypotheses:

- **H3:** Goosebumps textures will be perceived as conveying more positive valence than spikes.
- **H4:** High frequency gestures will be perceived as conveying higher arousal states than low frequency ones.
- **H5:** High amplitude gestures will be perceived as conveying higher arousal states than low amplitude ones.

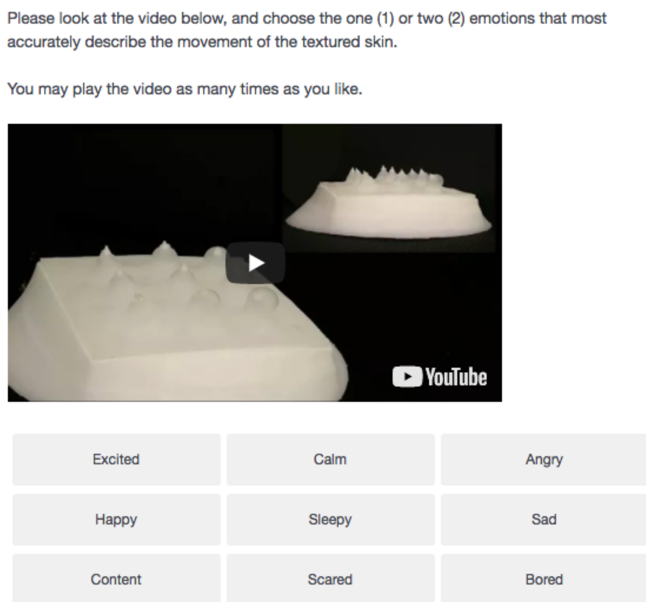

Fig. 6. Screen shot from the online study. Participants watched a video of a texture gesture, then labeled this behavior with emotion words out of a provided list. After this choice, they evaluated their confidence of that choice on a five-point scale from "Very not confident" to "Very confident".

V. Method

Participants experienced the eight different texture gestures under three interaction modes: online video viewing, observing the texture in person, and touching the texture. In all interaction modes, the textures were presented on a 125mm x 125mm Texture Module, as depicted in Fig. 5. In each experiment, we asked participants to label gestures with emotion words representing nine key emotions from Russells circumplex model [33], [35]: *angry, bored, calm, content, excited, happy, sad, scared, and sleepy*. These emotions were chosen to form a set that covers all four quadrants of the emotion.

A. Participants

We recruited 140 participants for this study, 100 for the online video study and 40 participants for a laboratory experiment, which included both in-person observation and touch interaction. Participants were recruited via an internal university participant system and compensated with participation credits. One sample from the online video study was dropped due to missing response data, leaving us with 99 video participants, and 139 overall participants.

B. Procedure

1) Online Video Study: We recorded eight videos, one for each texture expression. Videos showed the Texture Module from a side angle and from a three-quarter top-down angle. Each video clip lasted 10 seconds. Participants were shown the videos in randomized order. Below each video, they were asked to choose one or two emotions that most accurately described the movement of the skin and evaluate their confidence on a 5-point scale. Participants could play the videos as often as they wanted. Fig. 6 shows a screen shot of one page in the online study.

2) Laboratory Experiment: Participants sat in a chair facing a laptop with the Texture Module placed to the right of the laptop. A research assistant sat nearby to activate the robot's textures. They were told to imagine the textured surface as the skin of a creature, and that they would see some changing of textures in the skin during the experiment. They were asked to guess the emotional states of the creature based on the changes in its skin.

The experiment was divided into two sessions: in one, participants were asked to observe the texture expressions without touching it; in the other, they placed one palm on the textured area and experienced its motion only though touch. To avoid sequence effects, the order of two sessions was counterbalanced. Within each session, the order of gestures was randomized across participants. Each gesture lasted for 10 seconds, followed by a pause to let participants select one or two emotion labels, and report their confidence. The questions and responses format were presented on the laptop and were in the same format as in the online study, only without the video element. The textures' motion could be replayed as often as the participants liked by asking the research assistant to replay a texture. After completing the survey, participants would indicate to the research assistant to activate the next gesture. Before each session started, participants were given a practice session, where they observed or touched two examples of texture movements to make sure they fully understood the procedure. We used low-amplitude, low-frequency spikes and high-amplitude high-frequency goosebumps as two examples to illustrate the range of gestures. Participants wore noise-cancelling headphones playing pink noise during the experiment to mask mechanical noises.

VI. Findings

We quantitatively and qualitatively analyze the mapping between texture gestures, texture parameters, emotions, and emotion dimensions to address our research questions and hypothesis. Given the novelty of texture changes as an expressive modality, the analysis is exploratory, viewing the data from a number of lenses to gain better design insights for this technology in social robotics.

In the rest of the paper, texture gestures are denoted by three-letter codes, with the first letter representing the Texture Unit type (G or S for Goosebumps or Spikes), the second letter representing the frequency (H or L for high or low), and the third representing the amplitude (H or L for high or low). For example, SHL is a spikes texture with high-frequency and low-amplitude.

A. Mapping Texture Gestures to Emotions

To assess H1, we first analyze the emotion distribution for each gesture using Pearson's Chi-square test. Table. I lists the results for each of the three interaction modes. All of the gestures were significantly non-uniform, except for GHL in

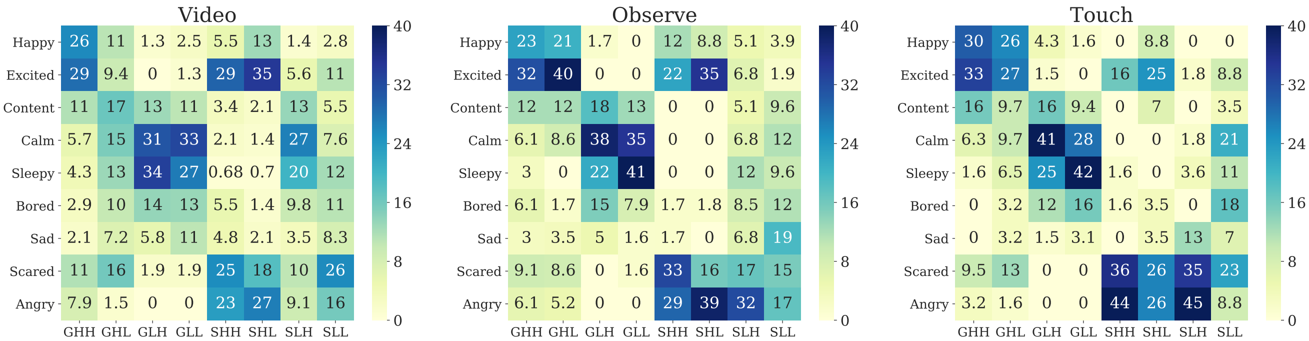

Fig. 7. The emotion selection distributions of texture gestures. Numbers indicate percent of participants choosing this emotion for a specific gesture.

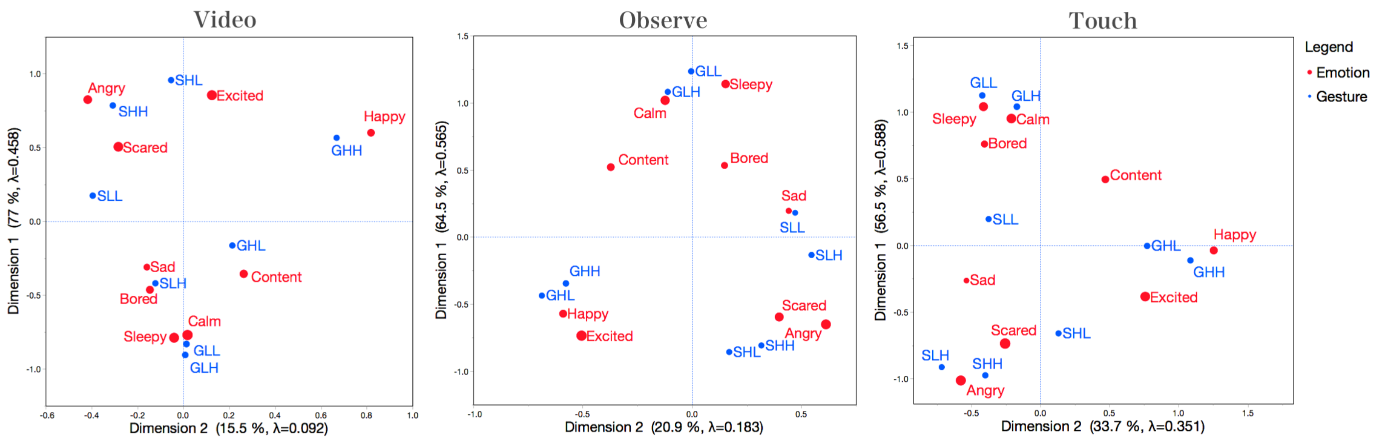

Fig. 8. The result of multiple correspondence analysis in three interaction modes. The two categories: gesture and emotion are plotted onto a plane with two principal dimensions. The plot visualizes the association between the categories: the closer two variables values are, the more often they co-occur in the data.

video mode ($p = 0.031$)[1]. This finding broadly supports H1, namely that **emotions attributed to each of the eight gestures tend to cluster**. Low-frequency, low-amplitude spikes (SLL) was the most uniform, i.e., the least informative, gesture.

Comparing modes, we note that for all gestures except SLL, the video distribution was more uniform than either of the two in-person modes. This indicates that **viewing video textures is less informative than experiencing them in person**. Between the two in-person modes, low-amplitude gestures (••L) were more informative in observation, whereas high-amplitude gestures (••H) were more informative in the touch mode. This suggests that the use of **subtle amplitude differences are more noticeable visually than haptically**.

Fig. 7 illustrates these insights via the mapping between texture gestures and emotions. For example, the GHL column in the video mode, which was not significant based on its Chi-square result, is quite uniformly distributed and thus not informative, whereas in both in-person modes, GHL was mostly seen as being either "happy" or "excited".

Visually inspecting Fig. 7 we can see several trends. Both GL• (low-frequency goosebumps, columns 3–4) and SH• (high frequency spikes, columns 5–6) gestures seem to evoke agreement between in three modes. As a general trend, **emotion mappings seem to determined mostly by the first two parameters: Texture Unit and frequency**.

[1]Following Benjamin *et al.* [36], we consider $p < 0.005$ to be statistically significant, rather than the more common $p < 0.05$.

TABLE I
CHI-SQUARE AND P VALUES OF EMOTION SELECTION DISTRIBUTIONS BY GESTURE AND INTERACTION MODE.

Ges.	*Video*		*Observe*		*Touch*	
	Chi-Sq	*p*	*Chi-Sq*	*p*	*Chi-Sq*	*p*
GHH	*67.81*	*<0.001*	*69.68*	*<0.001*	*117.5*	*<0.001*
GHL	*16.96*	*0.031*	*110.64*	*<0.001*	*65.27*	*<0.001*
GLH	*122.7*	*<0.001*	*127.3*	*<0.001*	*140.38*	*<0.001*
GLL	*99.18*	*<0.001*	*183.73*	*<0.001*	*162.3*	*<0.001*
SHH	*93.5*	*<0.001*	*132.95*	*<0.001*	*218.58*	*<0.001*
SHL	*177.61*	*<0.001*	*174.33*	*<0.001*	*92.55*	*<0.001*
SLH	*46.56*	*<0.001*	*55.18*	*<0.001*	*210.12*	*<0.001*
SLL	*31.72*	*<0.001*	*23.92*	*0.002*	*43.8*	*<0.001*

B. Multiple Correspondence Analysis

To provide an additional view on the data in Fig. 7, we conduct a multiple correspondence analysis (MCA) for each mode (Fig. 8). This method is similar to Principle Component Analysis (PCA), but focuses on the co-occurrence between two categorical variables. The two most significant dimensions account for a cumulative inertia of 92.5%, 85.4% and 90.2% for video, observe, and touch respectively. It is interesting to note that while we have not yet introduced

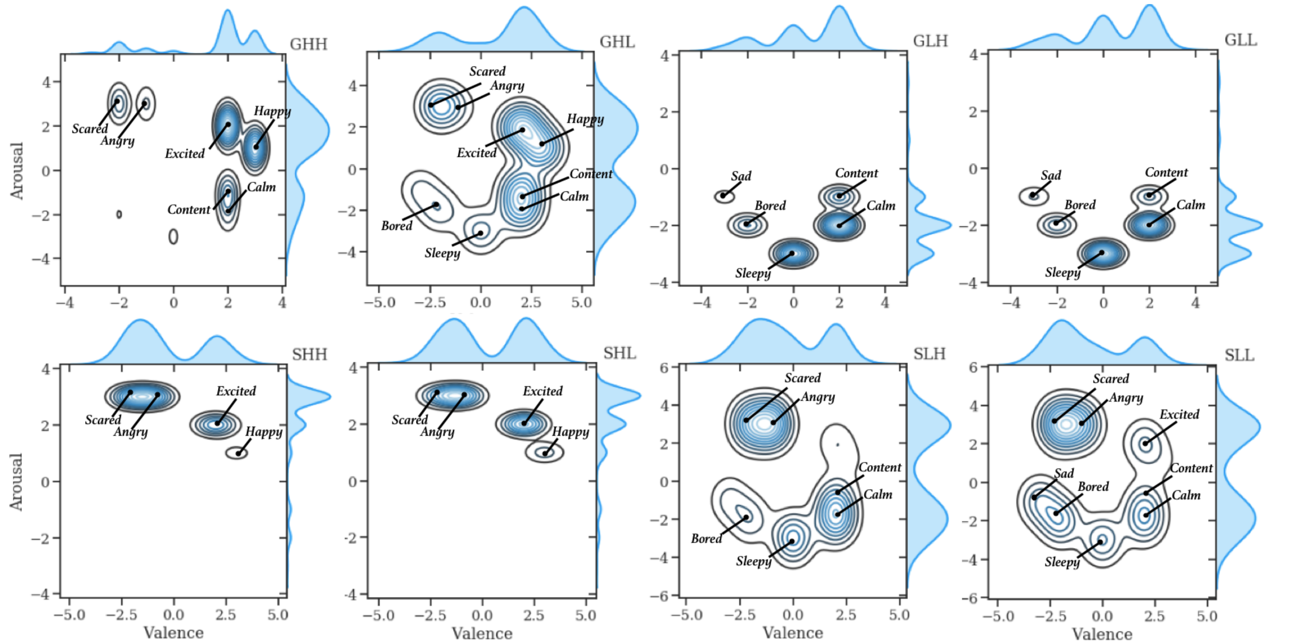

Fig. 9. Kernel Density Estimation (KDE) for each gesture plotted onto an 2D emotion plane. The marginal distributions show the estimations of valence and arousal values for the expressed texture gesture.

the circumplex model, the factored MCA dimensions broadly map onto the commonly used arousal (Dimension 1) and valence (Dimension 2) dimensions. The "valence" dimension (Dimension 2) accounts for the least inertia for video, and the most for touching the texture, suggesting that **valence is most communicative through touch**, and least through video observation.

Some clear relationships emerge from the MCA analysis, which reflect the insights above. In all interaction modes, GL• gestures are strongly associated with sleepy and calm; SH• gestures are associated with angry and scared. In person, GH• are associated with happy and excited, whereas in video, GHH is only associated with happy, and GHL is associated with content. Sad is only associated with gestures in the visual modes (SLH in video, and SLL in person), but not in the touch mode .

C. Mapping Gestures to Valence / Arousal

To further assess the relation between the gestures and the classic valence and arousal decomposition, we mapped the nine emotion labels used in this experiment to the Circumplex Model [33], [35]. There has been much debate about the mapping between emotion labels and these two dimensions, and there is no generally accepted mapping, as it seems to vary between cultures, ages, and other factors. In this exploratory work, we visually map each word to the plane using a 7-point arousal and valence scale ranging from -3 to $+3$, based on the original model published by Russell *et al.*.

Fig. 9 plots the joint probability distributions, pooled for all modes, using a Kernel Density Estimate (KDE) method, with marginal distributions along two axes showing the arousal and valence estimations of the expressed emotion. These, again, show that GL• gestures and SH• gestures are the most informative. **GL• gestures are generally associated with low-arousal emotions and SH• gestures with high arousal emotions.** We can also note that **GHH relates to high-valence emotions**. SL• and GHL gestures are not as informative, but the former tend to low-valence, high arousal (scared and angry), and the latter to positive valence emotions.

D. Texture Parameters and Valence / Arousal

Our exploratory analysis above suggests that the first two parameters (TU and frequency) most reliably relate to emotion expressions. To further dissect this relationship, we analyzed each of the three parameters (Texture Unit, frequency, and amplitude) separately vis-a-vis emotion ratings. Fig. 10 shows the percentage for each emotion by texture parameters.

We can visually note again that TU type and frequency are less uniformly distributed and carry the most emotional information. Video, overall, is less discriminative, and the amplitude parameter is the least informative.

To more specifically address H3–5, we analyze the relationship between texture parameter and emotion dimension. Fig. 11 show this 2×3 relationship split by mode. We use fixed-effects regressions to evaluate these relationships statistically:

1) Texture Types and Valence (H3): A fixed-effects regression for valence with Texture Unit type as a predictor, controlled for participant ID shows that TU type strongly predicts valence rating ($F(1, 2029) = 167.84, p < 0.0001$). Goosebumps communicate high valence and spikes low valence. This supports H3, namely that **TU type relates to emotional valence**. Fig. 11 also indicates that that gestures with goosebumps TU were associated with lower arousal than

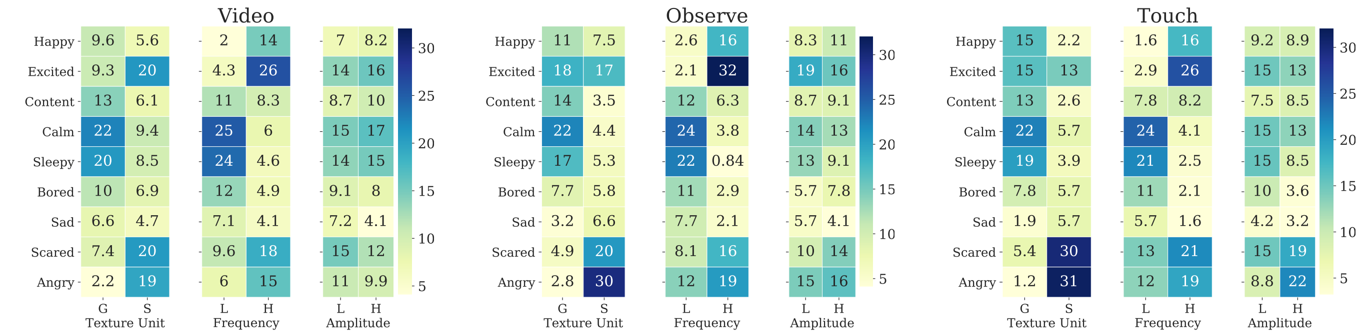

Fig. 10. Emotion selection distributions (in percentage) broken down by texture control parameters: TU type, frequency, and amplitude.

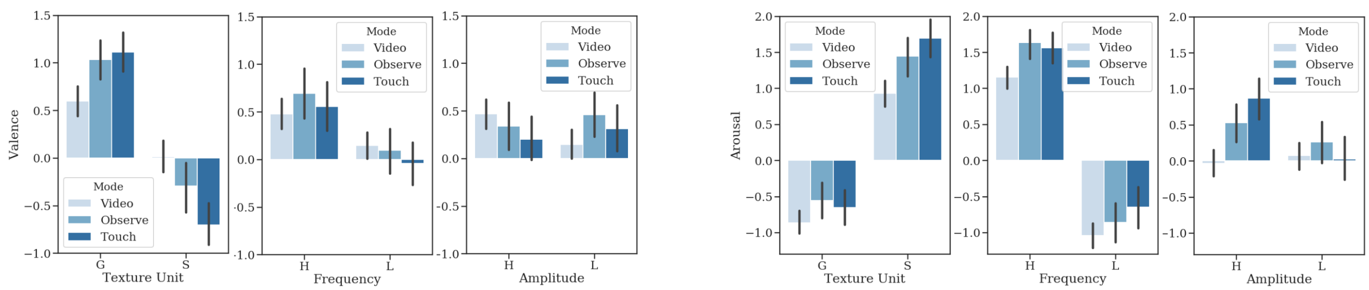

Fig. 11. Comparison of average arousal and valence values between each pair of binary parameter values in three interaction modes.

that those with spikes TU, although this was not one of our original hypotheses.

2) Frequency and Arousal (H4): We ran a fixed-effects regression for arousal with frequency as a predictor, controlled for participant ID. Frequency strongly predicts the arousal rating ($F(1, 2029) = 691.83, p < 0.0001$). This supports H4, namely that **frequency relates to emotional arousal**.

3) Amplitude and Arousal (H5): We ran a fixed-effects regression for arousal with amplitude as a predictor, controlled for participant ID. Amplitude does not significantly predict the arousal rating ($F(1, 2029) = 4.63, p = 0.036$). H5 is thus not supported. **Amplitude does not reliably map onto arousal**.

E. Confidence Between Interaction Modes

Finally, we turn to H2. We already found some support in the lower Chi-square values for the video mode, indicating that watching the texture on video was somewhat less informative than viewing them in person or touching the gestures.

To further evaluate the interaction modes we compare self-reported confidence ratings across modes. A fixed-effect regression with mode, gesture, and the interaction between mode and gesture as predictors, controlled for participant shows that gesture ($F(7, 2007) = 17.92$), mode ($F(2, 2007) = 10.56$), and the interaction between gesture and mode ($F(14, 2007) = 6.58$) significantly predict the confidence level, all at a $p < 0.0001$ level. The mean confidence values of each mode are shown in Fig. 12. This also supports H2.

VII. Design Implications

The results of our study suggest that the proposed new modality of texture changes is capable of conveying specific

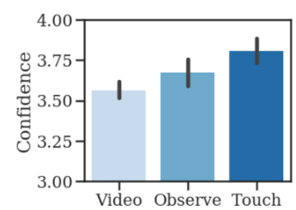

Fig. 12. Mean confidence rating by mode. Error bars show standard errors.

emotional states. For most of the explored texture gestures, participants consistently rated these as expressing the same emotions, making texture a promising choice for a communicative channel in the design of future social robots.

The results indicate that interaction modes have less of an effect on humans' emotional perceptions than we anticipated. That said, the perceived intensity of emotions and people's confidence in their perception are affected by how they experience the texture gestures. Video emotion attribution is less consistent than live modes. Participants were least confident in the video mode, more so in person observation, and most when touching the robot. This finding conforms with the increasing insights in HRI research, that physically present robots have more impact on users and are more informative in contexts than robots depicted in videos [37], [38].

From the results of the MCA analysis, we find that the video mode has the least proportion of inertia for the "valence" dimension, indicating that valence is less likely to be communicated well by a robot that is not physically presented. Some of this effect may be owing to users' physical and psychological "distance" from the robot over video. This is supported by research in Psychology, that the distance from an object has effects on people's "degree of concern", and thus affects the "representational elements' valence" [39], [40].

Valence perception is most strongly discriminated in the touch mode. So, even though we have shown texture changes to effectively communicate both visually and haptically, when a robot designer wants to evoke valence, touching the robot's texture change is the most promising channel. This finding can also shed additional light on using textures skin in robot design. For example, a robot may need to adjust its expressions and emotional expectations by considering the factor of whether it is physically presented, and possibly the viewing distance and the degree of psychological engagement.

In addition to psychological distance, this finding could also be due to the emotional impact brought about by tactile sensations. In our case, spikes are more likely to be interpreted as a negative emotion when sensing a sharp, unfavorable sensation under one's palm. The effectiveness in conveying valence by touching a changing texture skin stands out from most current social robotics research dealing with haptic interactions, when using breathing-like behaviors or through vibrotactile sensations: Most of them were proven to have ambiguity in communicating valence [25], [26]. The tangibility and materiality of TUs, on the contrary, give users direct tactile impressions and can be effective and intuitive in conveying emotional valence.

Of the parameters we chose to vary in our design, the type of TU and its movement frequency had the most significant impact on emotion recognition. We recommend using those parameters in the future design of texture skins for robots. Amplitude was not a good communicative parameter, with the exception that small amplitude changes were readable via in-person observation. The two strongest parameters also map nicely onto the commonly accepted Circumplex Model of emotion plane. As shown through a number of related analyses, the shape of a texture maps roughly to emotional valence, and texture change frequency maps to arousal.

We find that most emotions we tested could be expressed by a specific set of gestures, however, the expressive significance varied across emotions. Emotions with "extreme" (high or low) arousal are more strongly categorized than emotions with medium arousal. This indicates an arousal gap in the expressive content. One possible cause is that in our case, the arousal axis is mainly expressed by frequency parameters, and we only chose two extreme levels. Designers may be able to increase the expressive consistency and enrich the context range by continuously varying the frequency.

Based on our analysis from the findings, we can suggest the mapping between texture gestures and emotion expressions laid out in Table II.

We include the weak mapping between SL• and the sad and bored emotions, but stress that we did not identify any gesture that was selected consistently as sad or bored. Also, Table II shows that several similar emotions are hard to differentiate, e.g., calm and sleepy. We believe that by adding more degrees of freedom of texture parameters, and optional values that they can take, a designer could increase the robot's expressive range. Some other parameters we would like to study in the future include the size of texture units, non-periodic texture movements, and asymmetric texture change patterns.

TABLE II
SALIENT MAPPING BETWEEN TEXTURE GESTURES AND EMOTIONS.

Texture Gesture		Emotions	Notes
Low-frequency Goosebumps (GL•)	→	sleepy / calm	
High-frequency Spikes (SH•)	→	angry / scared	
High-frequency Goosebumps (GH•)	→	happy / excited	In person
High-frequency Goosebumps (GH•)	→	happy / content	Over video
Low-frequency Spikes (SL•)	→	*sad / bored*	*Weak*

There are some limitations on the generality of the results. In the experiment, we surveyed two texture forms: goosebumps and spikes. We do not have empirical data on texture forms beyond these two. Furthermore, emotion perceptions may be affected by form factors of the robot [41]. In this paper, we used a disembodied flat textured skin module. It stands to reason that, when the texture is attached to a robot with a different form factor or when it is combined with other communicative channels such as facial expressions and gaze, the findings may not apply. The interaction between texture expressions and other modalities needs to be further studied.

VIII. CONCLUSION

In this paper, we empirically explored the expressive potential of a new design channel for social robots in the form of skin texture change. We conducted a study with 139 participants labeling eight texture movements with validated emotion words in three interaction modes: watching in video, observing and touching live texture movements. Our results showed that most texture expressions could be perceived as specific emotions, and perceptions were similar across different interaction modes. We also found a strong correlation between texture patterns and Russell's emotional decomposition, with the goosebumps texture perceived as more positive valence than spikes, and high texture change frequency mapped to a higher arousal emotion, leading to clear design implications for the use of texture as expressive modality. Overall our findings identify skin texture change as a promising design tool in social robots design.

Future work will compare the effectiveness of texture expression to other modalities such as facial expressions. We plan to explore more TU shapes and texture change parameters to increase the expressive range of this modality. We further would like to study the expressive capability of texture change in specific applications, such as in autonomous cars, and for developing a communicative channel for robots for visually-impaired people.

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