An Evaluation of Shape Changes for Conveying Emotions

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ABSTRACT

In this paper, we explore how shape changing interfaces might be used to communicate emotions. We present two studies, one that investigates which shapes users might create with a 2D flexible surface, and one that studies the efficacy of the resulting shapes in conveying a set of basic emotions. Results suggest that shape parameters are correlated to the positive or negative character of an emotion, while parameters related to movement are correlated with arousal level. In several cases, symbolic shape expressions based on clear visual metaphors were used. Results from our second experiment suggest participants were able to recognize emotions given a shape with a good accuracy within 28% of the dimensions of the Circumplex Model. We conclude that shape and shape changes of a 2D flexible surface indeed appear able to convey emotions in a way that is worthy of future exploration.

Author Keywords

Shape-changing Interfaces; Shape Displays; Organic User Interfaces; Actuated Interfaces

ACM Classification Keywords

H.5.2. Information interfaces and presentation (e.g., HCI): User Interfaces—Haptic I/O, Input Devices and strategies, Interaction styles.

INTRODUCTION

In industrial design, the shape of a product has long been associated with the communication of emotion [33]. Psychologists have studied the emotional responses to the perception of shape for decades [19,38]. One consistent finding has been that humans tend to prefer rounded objects over sharp ones [4,29]. The advent of flexible displays has now given rise to computational objects that can be designed to fit such different form factors [24]. E.g., flexible smartphones [15,26] that use displays that can be deformed to alter their shape. Amongst others, this has been shown to be useful for navigating contents through bend gestures [6,26]. Shape changes can also be actuated, for example, to notify users of an incoming message through a screen deformation [15]. Shape changing devices have been studied in terms of their explicit input properties, e.g., by deforming their surface to alter the shape of a 3D model [14]. Shape changing devices have also been designed and studied in terms of their visual and haptic communication properties [3,14,20,35,36]. These explorations range from communication of simple explicit information, such as a notification [15], to more complex and subtle information, such as communicating an emotion [10]. Many studies suggest that textual online communication lacks emotional expressivity because it does not provide nonverbal cues, such as facial expressions, gestures, and intonation [2]. If shape changes are associated with emotional communication, perhaps it could be used as a medium to enhance textual forms of communication with emotional expression. Recent explorations into shape changing interfaces have begun to explore how shapes might be used to output emotions [10,39,42]. However, the understanding of how shape input might be applied for emotional communication is still in its infancy.

Contribution

In this paper, we explore what shapes of a flexible 2D surface users might use to convey messages with emotional content to other users, through two studies. Our main experiment investigates what shape gestures users might use to communicate a set of 12 emotions. A second experiment investigates whether others are able to successfully interpret such shapes back to emotions. We observed the recurrent use of certain shapes to convey specific emotions. While the level of agreement on the use of those shapes varied between emotions, it was high for *Happiness*, *Delight*, *Sadness*, *Love*, *Anger* and *Contentment*. Simple elements of shape, such as curvature parameters and speed of deformation, are significantly correlated with the basic parameters, Arousal and Valence, that underlie emotional states. Users were able to interpret these shape gestures from a 3D animation of a flexible smartphone with reasonable accuracy. With this work, we hope to further demonstrate the utility of shape changes as a communication medium, and provide insights into the design space of shape changing interfaces for such purpose.

BACKGROUND

Emotion and shape changing interfaces are a relatively recent topic of interest in our field [10,39]. First, we discuss models of emotions and embodiment, after which we present a summary of related work on shape changing interfaces.

Valence and Arousal: The Circumplex Model of Emotion

The concept of basic emotions was first introduced by Ortony and Turner [34]. According to them, fundamental emotions, such as Fear or Happiness can be viewed as building blocks that may be combined to produce more complex emotions. However, there are divergent opinions on the exact identity of these basic building blocks [57]. One set of basic emotions was based on facial expressions suggested by Ekman and Friesen [12]. Their set of emotions consisted of Anger, Disgust, Fear, Joy, Sadness and Surprise. These basic emotions were used by Bailenson et al. [3] to study the communication of emotions via a haptic device that conveyed a virtual handshake. The study highlighted the difficulty of conveying emotions implicitly via a technological medium. Only 30% of emotions were correctly identified by participants using their device, as compared to 50% in a face-to-face handshake.

An alternative to the use of discrete categorical emotions was a two-parameter classification introduced by Russell [48]. In his Circumplex Model, Russell mapped emotions to a two-dimensional space: the Arousal or intensity of the emotion, and the Valence of the experience. Typically, the horizontal axis of Russell's spatial metaphor is Valence, otherwise known as the pleasure—displeasure dimension. The vertical axis of the Circumplex Model ranges from highly aroused to sleeping. Emotions are distributed roughly equidistant from the center or neutral point, forming a circular shape. The Circumplex Model was used by Dawson et al. [10] for investigating the design space of a shape-changing phone. Pedersen et al. [39] also applied the Circumplex Model to evaluate the emotional response of users to visualizations of a shape changing phone. While the Circumplex Model proved a useful tool to guide the design of emotive gestures for Dawson et al., Pedersen et al. found little emotional impact of different types of shape changes using the model.

Linking Shape and Emotion

The thought that emotions do not just reside in the brain, but are embodied by and communicated through the body, has a long history. An important proponent of the idea that all aspects of cognition are shaped by aspects of the body is Merleau-Ponty [30]. Merleau-Ponty suggests that we understand emotional states of others through our own experience of bodily expressions [8]. More recent neuroscience studies on mirror-neurons provide support for this perspective [25]. An embodied theory of emotion is also supported by Lakoff & Johnson's image schema

[27]. According to them, dynamic mental imagery of bodily actions forms a basis for understanding and reasoning. E.g., Strack et al. [52] demonstrated that facial expressions not only reflect emotional states, but actively influence our emotional states. Various other studies highlight the important role of body language in our experience of emotions [7,51]. McDonnell et al. [30] studied the attribution of emotions portrayed by virtual renderings of a recorded human. They concluded perception of emotions is robust and independent of representation, as long as form and motion of the human were conveyed. Given this, it is conceivable that humans are also capable of relating the dynamical shape of objects to mirrored embodied image schemas. In this paper, we were interested in studying whether this result would persist through more abstract representations by shape changing devices. Park et al. demonstrated this with Wrigglo [35], a smartphone with appendices used for bilateral shape communication. They found participants used a language akin to body poses to transmit emotional states. According to Pavlova et al. [38], perceived dynamics of shape image schema also influence emotional attribution. They found a strong positive correlation between negative emotions and perceived instability of objects. They suggested that neural circuitry for the production of movement and understanding of others' disposition are linked.

Nonverbal Communication

A significant portion of face-to-face communication consists of nonverbal behaviors [11]. The purpose of such nonverbal information is to convey subtleties of expressions that modulate symbolic messages [2]. Often, but not exclusively, such subtleties involve the communication of emotion. In face-to-face interactions, non-verbal cues are often communicated through shape transitions of the face and body, i.e. facial expressions and body language. Other nonverbal cues include paralinguistics—the tone and volume of the voice—as well as touch.

It can be challenging to convey non-verbal cues in technologically mediated communication. While the conveyance of vocal paralinguistics is relatively straightforward over audio, facial expressions require video conferencing tools. However, some body language and touch interactions are still lost, leaving users unable to express certain subtleties that they are accustomed to in face-to-face dialogues [3]. For this purpose, researchers have investigated the use of haptic interfaces such as vibration, force and temperature changes as additional communication channels that can be used to transmit subtle non-verbal cues [5,17,46,47,53]. An example of a product using such non-verbal communication cues is the Apple Watch, which employs touch sensing with vibro-tactile stimulation to convey nonverbal messages, implementing interactions suggested by Paulos [37].

Figure 1. Flexible sensor apparatus used in Experiment 1.

A more commonplace method of compensating for the lack of nonverbals in mediated communication is the use of emoticons [56]. Emoticons have a long history dating back to 19th century Morse code, and were later popularized for use in emails and chat using text-based Internet communications [44]. Emoticons are commonly used for strengthening the verbal part of a message and for expressing humor [11]. A main drawback of traditional emoticons is that they represent a discrete set of symbols that does not involve the kind of movements that are so characteristic of non-verbal expression of emotions in face-to-face scenarios.

Shape-changing and Malleable Interfaces

The emergence of advanced technologies and materials for computer input and display have resulted in a surging interest in Organic User Interfaces favoring shape changes as input [24,50,43]. Grossmann et al. [16] demonstrated an input device capable of sensing deformations as a tool for 3D modeling. Schwesig et al. [49] presented a bendable computer prototype that leveraged flexibility as an affordance for mobile computing. Holman [23] merged the properties of digital media with those of physical paper, allowing for input and output directly on a windowing environment using projected flexible displays. More recently, PaperPhone [26] and PaperTab [54] investigated the effectiveness of shape changes as input modalities deployed on real flexible display prototypes.

While research investigating shape changes as input has been extensive [16,26,49], there is also a body of work exploring shape changes as output. Dynamic Knobs [22] evaluated the concept of a rigid mockup phone capable of changing shape in a small extension on one of its sides. Hemmert et al. [21] also explored the concept of a shape-changing device that uses two-dimensional tapering to display the directionality of off-screen contents. Surflex [9] showcased a programmable surface for the design and visualization of physical forms. Gomes et al. [15] investigated the use of changes in shape as a means to convey notifications in a mobile device encompassing a self-actuated flexible display. Similarly, Pedersen et al. [39] evaluated a conceptual flexible mobile device to

ascertain how users perceive the hedonic qualities of shape changing interfaces.

Shape Transitions as Communication Channels

Changes in shape of an object can be leveraged for communication. inTouch [5] is an early demonstration of a system providing a physical link between people separated by distance. Poupyrev et al.'s [40] Lumen explored the design of an actuated pixelated information display. Similarly to inTouch, Lumen featured a medium for interpersonal communication, offering support for both direct user input and remote output. More recently, Follmer et al. [14] presented inForm, a shape changing rod display providing variable stiffness rendering and real-time user input through direct touch and tangible interaction. Shape transitions can also be used to expressed emotional traits, as proposed by Park et al., who demonstrated the use of shape changes as additional information channels for friends [35] and between lovers in long distance relationships [36].

Shape Resolution

Rasmussen et al. explored different types of shape transitions [32,41]. They distinguish between topologically equivalent shape changes (orientation, form, volume, texture, viscosity, spatiality) and non-topologically equivalent changes (adding/subtracting, permeability). Roudaut et al. introduced the term 'shape resolution' [45] based on the NURBS framework for describing shaped interactions. They defined parameters such as area, granularity, curvature, amplitude, porosity, stretchability, closure, zero crossings, strength and speed to describe shapes and shape changes.

EXPERIMENT 1: USING SHAPES AS INPUT FOR DENOTING EMOTIONS

To investigate whether and how shape changing user interfaces might be used to communicate emotional connotations, we studied how users might deform a 2D flexible substrate to convey emotional cues. Our first experiment studied whether users were able to consistently produce shapes that conveyed specific emotional states. Our second experiment studied whether users can infer the original emotional state when provided with such shapes. When investigating the use of shape in communication, we treated static and dynamic parameters of shape, i.e., shape changes, as a continuum.

Rationale

In our first experiment, we were interested in determining whether participants were able to create a consistent set of shapes that would communicate specific basic emotions from a set. We were also interested in determining which aspects of those shapes, and shape changes, were best suitable for communicating emotions. As such, we analyzed specific shape parameters, as measured by a deformable surface, to determine their correlation with the expression of Valence and Arousal: the coordinates of the basic set of emotions in the Circumplex Model.
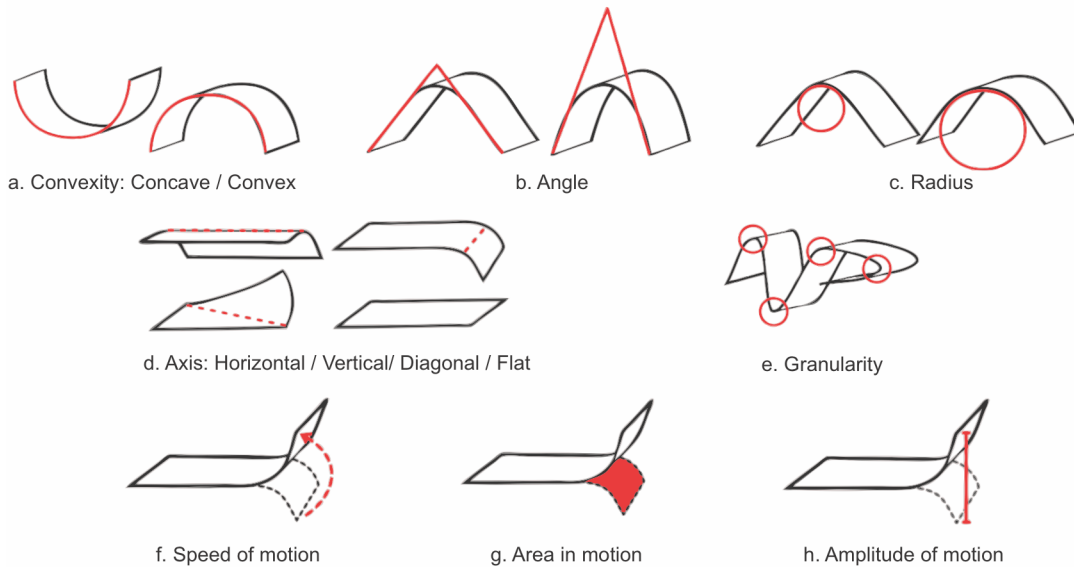
Figure 2. Shape parameters investigated in Experiment 1.

Apparatus

Our sensor consisted of a 2D 3.5" x 5.75" 4mm thin flexible surface mounted with an array of 11 flex-sensors by Flexpoint, similar to those used in Lahey et al. [26] (see Figure 1). The dimensionality and 2D form factor of the sensor was chosen such that it could potentially be manufactured as a circuit sandwiched behind a flexible display in a flexible smartphone. The sensor allowed a very high degree of expressiveness when manipulated by the participants. However, based on prototypes currently in development, it is likely that a similar level of malleability will be possible with future FOLED-based smartphones. Since we assumed the device would be held mostly in portrait mode, our apparatus had a higher resolution for bends along a vertical axis (Note that this assumption was confirmed; more than 75% of all shapes were oriented along this axis).

We initially explored the use of an etched flexible circuit, however, this approach was not sufficiently robust to withstand extreme interactions such as crumpling the device. Instead, we created a soft circuit using neoprene as a substrate, with malleable Litz wire as the conductive material. Because the wires and sensors were designed to move independently of one another and of the substrate, there was only negligible stress on the electrical connections in this apparatus. This lead to a stable and precise measurement tool that was able to withstand all deformations created in the experiment. An Arduino Mega was used to record the data from each individual flex sensor, resulting in a shape sensing device with 11 degrees of freedom.

Task and Emotions

We asked participants to create shapes with the apparatus, one for each of a list of emotions. The emotions were chosen based on a model by Ekman and Friesen [12] and included emotions used in similar studies [3,10]: Anger, Boredom, Calm, Confusion, Contentment, Delight, Distress, Excitement, Fear, Happiness, Love and Sadness. As one of the criteria for selection, all emotions are featured in Russell's Circumplex Model, and together cover a broad spectrum of Valence and Arousal levels [48]. Participants were allowed to create static shapes as well as shape gestures that made use of dynamics. To account for potential individual variance in the participants' interpretation of this set of emotions we first asked participants to rate the emotions using the Self-Assessment Mannequin (SAM) method [28]. Participants rated emotions on a five-point Valence scale (very negative, negative, neutral, positive, very positive) as well as a 5 point Arousal scale (very low, low, medium, high, very high).

Participants

Each participant ranked and performed the same subset of emotions. Our 20 participants were between 19 to 30 years old (Mean = 23.3, SD = 2.83). 9 participants were male, 11 female. The majority (18 out of 20) of our participants had no previous experience with malleable electronic devices. Two participants had some exposure through prior laboratory studies. All but one of our participants had experience with the use of multi-touch smartphones. The study took an hour to complete and participants were paid $10 for their efforts.

Software

We used two different custom programs: one for running and one for evaluating the experiment. The experiment software provided the participants with instructions and recorded the shapes created by the participants using our custom apparatus and via a video camera. Sensor data and video data were time-stamped and stored together.
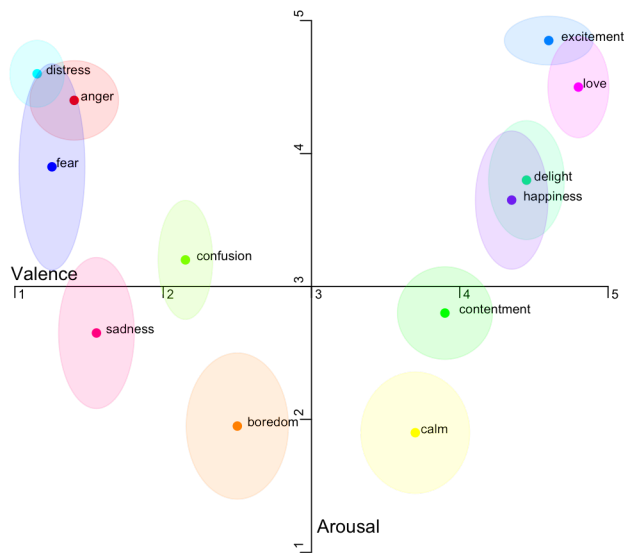
Figure 3. The Circumplex Model used in our experiment. Dots show mean Valence and Arousal scores for discrete emotions, ellipses show the area encompassing 1 std. dev.

Our analysis software visually overlaid video and sensor data, allowing us to match a frame of video to its corresponding sensor readings and vice versa. This allowed the researchers to visually classify the resulting shapes.

Shape Recording and Analysis
Since we were interested in evaluating what aspects of shape and shape change are most effective in communicating emotions, we required a taxonomy of shape parameters for analysis. We adapted our shape parameters from those outlined by Roudaut et al. [45], basing our analysis in those that displayed a significant effect. They are: Convexity (Curvature in [45]), Angle, Radius, Axis, Granularity, Speed, Area in Motion and Amplitude of Motion. These features are illustrated in Figure 2.

a) Convexity
Convexity described the curvature of the shape. A Concave surface curves inward away from the user while a Convex surface curves outward towards the user (see Fig. 2a).

b) Angle
The sensor readings are proportional to the amount of bending, i.e., the angle. We therefore calculated the mean value of the bend sensors per axis.

c) Radius
A bend was described by the size of a circle that inscribes it. As the sensors used in the prototype only provide information of *how much* they are bent but not *where* they

are bent, we measured radius indirectly by counting how many groups of sensors were bent in the same direction along the horizontal axis. Due to the lower vertical measurement resolution of the device, no radius was measured across that axis.

d) Axis
The axis was defined as the orientation of the primary bend with respect to the apparatus (See Fig. 2d). This parameter can take one of four possible values: *horizontal*, *vertical*, *diagonal* (when bending along both axes) and *flat* (no bend). Although this value was derived from the sensors readings, it was verified for correctness by one of the researchers by means of observation of the videos.

e) Granularity
We used a simplified interpretation of Granularity adapted from [45]: the number of bends that constituted the shape. We measured this by counting the number of bends in opposite directions across each axis. Due to the different resolution between horizontal and vertical axis, granularity could take values between 0 and 3 and between 0 and 2, respectively.

f) Speed of motion
The average rate of change of all sensors (see Fig. 2f).

g) Area in Motion
The Area in Motion was defined as the surface area of the apparatus that was dynamic. We measured the percentage of sensors that changed (see Fig. 2g).

h) Amplitude of Motion
We referred to the maximum distance of displacement in a motion as the Amplitude of Motion. We measured the mean difference between the lowest and highest reading of all sensors (see Fig. 2h).

Statistical Analysis
After the experiment, we correlated the values of these shape parameters for the various shapes created with those of the Arousal and Valence scores of the emotions they were intended to convey. Since Valence and Arousal ratings are ordinal, we performed non-parametric ordinal correlations on the Valence and Arousal scores. We also used a classification algorithm to investigate if it would be possible to recognize emotions from the sensor data.

EXPERIMENT 1: RESULTS
Figure 3 shows the ratings of discrete emotions by participants on a 2D continuum. Each dot indicates the mean value for a given discrete emotion. The ellipses around a dot represent the standard deviation, separately for both the Valence (x) and Arousal (y) dimensions.

	Valence		Arousal	
	Mean	**SD**	**Mean**	**SD**
Anger	1.40	0.60	4.40	0.60
Boredom	2.50	0.69	1.95	1.10
Calm	3.70	0.73	1.90	0.91
Confusion	2.15	0.37	3.20	0.89
Contentment	3.90	0.64	2.80	0.70
Delight	4.45	0.51	3.80	0.89
Distress	1.15	0.37	4.60	0.50
Excitement	4.60	0.60	4.85	0.37
Fear	1.25	0.44	3.90	1.55
Happiness	4.35	0.49	3.65	1.04
Love	4.80	0.41	4.50	0.76
Sadness	1.55	0.51	2.65	1.14

Table 1. Means and standard deviations of Circumplex Model of emotion attributes in Experiment 1.

	τ (Valence)	τ (Arousal)
Concave	**0.26**	**0.14**
Convex	**-0.21**	-0.06
Angle (Horizontal)	**-0.27**	**-0.22**
Angle (Vertical)	0.02	0.01
Radius	**-0.14**	**-0.26**
Axis-Horizontal	**0.23**	0.05
Axis-Vertical	-0.10	**-0.21**
Axis-Diagonal	**-0.17**	**0.23**
Axis-Flat	-0.01	**-0.26**
Granularity	**-0.13**	**0.21**
Speed	0.00	**0.39**
Area in motion	0.05	**0.35**
Amplitude of motion	0.00	**0.36**

Table 2. Correlations between shape parameters and Valence and Arousal. Coefficients in bold are significant at p<0.05

The resulting distribution of emotions was similar to that reported by Russell [48]. However, our participants gave Fear and Anger a more negative rating and Excitement a more positive rating. Actual resulting scores are presented in Table 1.

Frequently used Shapes

Observation of the shapes created by the participants allowed us to identify some commonly occurring shape types across different emotions. Contentment (50%), Delight (75%) and Happiness (80%) were often expressed using concave U shapes. For Sadness, 60% of participants used an "inverted U" shape. Love was expressed with a heart shaped fold by 55% of participants. For Anger, participants often used a crumpled shape (55% of participants). A flat shape was often employed to convey Boredom (30%) and Calm (25%) emotions, with 18% of participants using an animated sine wave to express Calm (10%). We observed that participants did not solely interpret shapes based on the body or face, but on other metaphors as well. These included water (a wave), facial expressions, and body pose (crouching, hiding, jumping, clapping). They also aimed at emulating consequences of actions (e.g., the crumpled shape created by smashing the device in anger).

Agreement

We used Wobbrock et al.'s [58] method to measure the agreement between participants on commonly used shapes for each emotion. The agreement for a certain emotion e is given by:

$$A_e = \sum_{P_i \subseteq P_e} \left(\frac{|P_i|}{|P_e|} \right)^2$$

Where P_e is the set of all shapes used to represent a certain emotion and P_i is the subset of repeatedly used shapes from P_e. The agreement A can therefore take values between $|P_e|^{-1}$ and 1. The level of agreement varied strongly between emotions, with a mean agreement across emotions of 0.24. Agreement rankings for Happiness (0.65), Delight (0.56), Sadness (0.37), Love (0.31), Anger (0.30) and Contentment (0.28) were relatively high. Participants appeared to agree less on how to convey emotions such as Boredom (0.13), Calm (0.11), Excitement (0.09), Fear (0.02), Distress (0.01) and Confusion (0.01).

Correlation of Shape Parameters with Valence and Arousal

We used a non-parametric correlation (Kendall's τ) to establish which parameters of the shape expression, if any, would could be good predictors for Valence and Arousal ratings of the associated emotions. Our reasoning was that such associations would allow a device to classify emotions by measuring deformation. A list of the resulting correlations is presented in Table 2. Correlation values indicate that parameters related to the shape of the surface—*Convex/Concave, Angle (Horizontal), Axis (Horizontal and Diagonal)*—may be good predictors for Valence. While some shape parameters also display association with Arousal, those parameters related to movement (*Speed, Area in motion* and *Amplitude of motion*) were better predictors—with *Axis-Flat* indicating absence of movement. Additionally, complex deformations including both axes (*Axis-Diagonal*) and/or multiple bends (*Granularity*) seem to be more frequently present in emotions with higher Arousal and lower Valence. Only *Angle (Horizontal)* and *Radius* seem to correlate similarly with both Valence and Arousal, while Angle (Vertical) did not present a significant correlation.

Prediction of emotion

Results indicate that several shape parameters have predictive power for the automatic recognition of emotion. To investigate this possibility, we used a Support Vector Machines (SVM) classifier with a Radial Basis Function kernel. A full explanation of SVM is outside the scope of this paper [18]. As predictors for this classifier, we used the shape parameters that presented a significant correlation with Valence and Arousal, as

Figure 4. A frame of one of the videos shown to participants for Experiment 2. This 3D model is representing *happiness*.
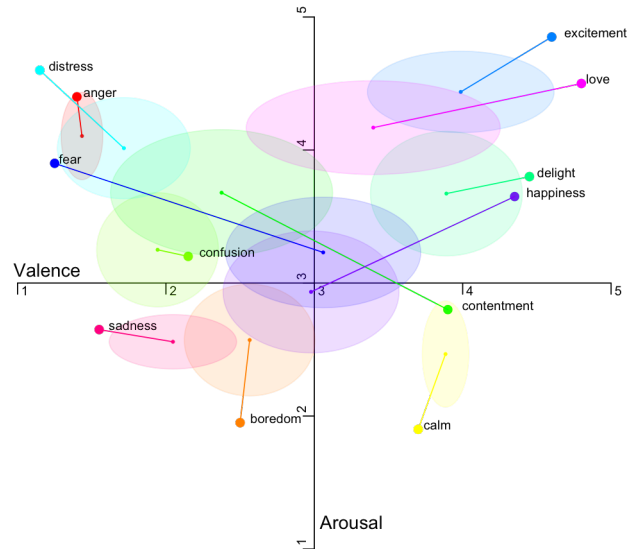

Figure 5. Circumplex Model with mean distance (small dot) and std. dev. (circle) of response emotions from mean locations (large dot) of stimulus emotions.

indicated in Table 2. We trained the classifier and used a 10-fold cross-validation method to find the optimal accuracy rate. That is, we used 90% of all the recorded shapes as training examples. We then tested the resulting model using the remaining 10% of the dataset, obtaining an accuracy rate. We repeated this process 10 times, each time excluding a different 10% the data points. Finally, we chose the model parameters that yielded the best accuracy rate. The resulting model reported an overall Precision of 45.8% (95% CI : (0.34, 0.47)) and Recall of 40.4%. This means that 45.8% of the recognized emotions were true positives, while 40.4% of the input emotions were correctly classified. These values yielded a F-Score of F=0.43[1]. The emotions that were better recognized by our classifier were *Sadness* (F=0.59), *Anger* (F=0.56), *Happiness* (F=0.5), *Confusion* (0.44) and *Calm* (F=0.43).

EXPERIMENT 2: INTERPRETING COMMUNICATING EMOTIONS

The goal of our second experiment was to validate whether different participants would be able to relate shapes from Experiment 1 back to the emotions that participants were trying to convey.

We wanted to capture the shape information of the original prototype from Experiment 1, but avoid biases that would be introduced by the presence of the participants' hands and body. This way, any expression of emotion would be based solely on the shape of the device. We therefore selected a representative video (and its corresponding sensor recordings) of the shape expression with the highest frequency of occurrence for each emotion studied in Experiment 1.

We then built a 3D model using Blender [1], making sure it was as similar as possible to the original prototype in terms of size, proportions and rigidity. We completed the

model by adding a texture map to make it appear as a smartphone (see Figure 4). We used a skeleton with rigid bones located at the position of the sensors in the input device in Experiment 1. Bones were subdivided in segments to allow for softer curvatures; they had parent-child relationships to preserve shape and volume coherence. The model was animated by mapping the sensor values to rotations of the bones using Python. The resulting animated 3D models inherited the shape changes that the participants from Experiment 1 applied to the shape sensing device. The animations were exported as video files.

Procedure

We created a questionnaire in which we embedded these videos, and made it accessible online. For each of the 12 animations, participants were first asked to describe with a single word what they believed the shape of the device shown was trying to communicate. After this, participants were shown the animations a second time, and were asked to select one of 12 emotions that they thought might describe what the shape expressed: *Anger*, *Boredom*, *Calm*, *Confusion*, *Contentment*, *Delight*, *Distress*, *Excitement*, *Fear*, *Happiness*, *Love* and *Sadness* or, if they thought that the shape did not express an emotion, *No Emotion*. Videos were presented in random order.

Participants

Twenty participants were recruited through social networks. None of them participated in the first experiment. There were 6 female and 14 male participants with a mean age of 32.1, (SD: 6.94).

Analysis

In their answers, participants had to choose from a nominal list of emotion labels. Besides calculating the frequency with which they chose the correct emotion

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[1] In information retrieval, the F-score is a standard measure of a test's accuracy, equivalent to the harmonic mean of Precision and Recall.

label, we also used the coordinates of each label in the Circumplex Model in order to obtain a distance measure. We calculated the mean position of the response labels and the stimulus labels. We used the Valence and Arousal ratings obtained from Experiment 1. This gave us an (X,Y) coordinate on the Circumplex Model per emotion. For each response, we then calculated the Euclidian distance between the response emotion and the coordinates of the stimulus emotion. All distances were measured on a scale from 1-5. We also calculated user agreement using the Fleiss' Kappa index (κ). This is a standardized method for measuring agreement, similar to Cohen's Kappa, but extended to include more than two coders [13].

EXPERIMENT 2: RESULTS

On average, participants recognized the correct emotions 33.8% of the time, while 12.3% of the time they considered that the shape was not conveying an emotion. Table 3 shows mean distances and standard deviations between the stimulus emotion and participant responses, ordered by distance. The mean distance across all emotions was 1.42 (SD: 1.60). Overall agreement was low (κ=0.18), but agreement in terms of quadrants on the Circumplex Model was higher (κ=0.31). Figure 5 shows a graphical representation of these distances as lines. The larger dots marking the endpoints of these lines are the locations of the stimulus emotions (as observed in Experiment 1). The small endpoints represent the mean location averaged over response emotions in this experiment. The ellipses show the standard deviation of Valence and Arousal of response emotions, separately (note that we decided not to perform further statistical analysis of these distances as it was unclear what baseline to compare them with: they are provided as qualitative evidence).

DISCUSSION

Symbolic vs. Dynamic Shapes

Participants frequently agreed on the use of symbolic shape expressions based on a clear visual metaphor. It is worth noticing that participants often used a symbolic approach when intending to convey certain emotions by static shapes, while in other cases, dynamic motions were employed.

This appears to be one of the reasons why Valence is more frequently correlated with shape parameters: Contentment, Delight, Sadness and Happiness were typically represented with a "U" form that was borrowed from facial expressions. Their use was similar to that of emoticons. We observed that different metaphors sometimes lead to the same shape. For example, some participants chose a convex shape for Sadness because it reminded them of a frown, while others chose a convex shape to represent Fear by mimicking cowering body poses. A remarkable example of the symbolic approach is *Love*. Although it was rated as having high arousal, it was

	Distance	SD	κ
Anger	0.29	0.54	0.27
Calm	0.52	1.03	0.28
Sadness	0.55	1.18	0.33
Confusion	0.68	0.79	0.07
Boredom	0.83	0.90	0.02
Distress	0.98	1.81	0.09
Delight	1.08	1.51	0.04
Excitement	1.20	2.21	0.41
Happiness	2.26	1.90	0.04
Love	2.66	3.22	0.40
Contentment	2.99	1.78	0.09
Fear	2.99	2.21	0.03

Table 3. Mean distance scores in the Circumplex Model of emotion attributes in Experiment 2.

frequently represented with a static heart shape, a manifestation of a long visual tradition that is reflected in standard emoticons. Crumpling was used as a physical metaphor for Anger reflecting destructive action. Similar to findings with Wrigglo [35], body shape provided a common metaphor. Finally, *Confusion* appeared to consistently have higher granularity than, for example, *Happiness*. We observed that the dynamic approach was frequently used to establish emotions along the Arousal axis. This ranged from *Calm*, often represented by a slow-moving oscillating motions, to *Excitement*, which most of the time included fast motions. *Calm* and *Boredom* were also frequently represented using flat shapes, so they tended to have low dynamics (as well as high angles and radius). Another trend we noted is that repetitive motions (such as "clapping", frequent in *Excitement*) were more common for positive emotions. For negative emotions the motion was often singular (e.g., one "crunch"). Our findings reflect those of Dawson et al. [10], in that the dynamics of motion in their study were also often based on bodily metaphors, such as rhythmical breathing.

Predictive Value of Shape Parameters

Our models seem to confirm that parameters that convey Valence appear primarily based on the geometry of the shape. Parameters that convey Arousal were primarily based on the dynamics of the shape. The strongest predictor of Valence was the convexity and angle of the curvature across the horizontal axis, while the strongest predictors for Arousal were the speed, amplitude and area of the surface modified by the gesture. In general, we conclude that there does appear to be a significant relationship between basic shape parameters and the location of the emotions they convey in the Circumplex Model.

An SVM classifier trained with our shape data was able to recognize emotions with an acceptable accuracy, although the best results were obtained for emotions such as *Anger*, *Sadness*, *Happiness* and *Boredom*. This is probably a consequence of the agreement in the use of crumples, "inverted U", "U" and flat shapes, respectively, as we previously discussed. This initial effort suggests that it

would be possible to implement an engine for the recognition of bend gestures on a flexible mobile phone. These gestures could then be translated into visual emoticons, or transmitted to actuated shape devices, as a means of tactile-visual emotion communication. Further research is needed to shed more light on how to implement and optimize such device.

Interpreting Shapes as Emotions
Results from Experiment 2 suggest a somewhat lesser agreement between participants on how to interpret shape expressions as emotions. Participants tended towards agreement on scores for *Excitement*, *Love* and *Sadness*. Other emotions fell below the 0.3 level of agreement. Over all emotions, participants correctly identified only 33% of stimuli. This is slightly higher than the 30% of correctly identified emotions reported by Bailenson [3]. Overall agreement in classifying emotions was low, but participants had a higher agreement in terms of positive vs. negative Valence and high vs. low Arousal.

Treating emotions as continuous psychological variables of the Circumplex Model, rather than as nominal categories, provided us with a better method for evaluating interpretations. When results are evaluated in terms of the distance of the response from the location of the stimulus in terms its Arousal and Valence score, participants do appear able to judge shape expressions with good accuracy. Note that we treat this observation as a trend rather than a scientific statement. The average error in terms of model distance was relatively small at 28% (1.42/5). Participants often chose erroneous labels that, however, were close to the stimulus label in terms of the Circumplex coordinates. Some emotions appeared easier to interpret than others: *Anger*, *Calm* and *Sadness* trended the most accurate scores. Participants seemed less able to distinguish emotions with high Arousal levels. In particular, *Fear* often appeared confused with *Happiness*. Otherwise, there appeared to be a reasonable differentiation between distinct emotions. Our results are more clearly differentiated than those by Pedersen et al. who concluded that almost all shape changes are rated with a very low emotional impact around the center of the Circumplex Model [39]. Our findings regarding the speed parameter also contrast those of Pedersen et al., who found little to no effect of speed on user experience. However, Pedersen et al.'s shape changes were computer-generated. By contrast, we played back an actual recording of a human shaping the input device. These recordings were read by participants in Experiment 2 and related back to the original human action, thus interpreting human form and motion in ways similar to McDonnell et al.'s [30] findings. In general, although efficacy varied per emotion, we conclude that it appears that the shape changes in our experiment were able be interpreted as emotions, at least in terms of the Circumplex Model.

LIMITATIONS
Our findings were limited by the form factor of the apparatus used and may only apply to objects and devices with similar dimensions, i.e., that of a large smartphone or small tablet. In Experiment 2, we assessed participant's responses to 12 specific shapes recordings, however, participants might have responded differently had we chosen different shapes. Instead of a physical shape changing device, we used an animated 3D model to render our shape recordings. While haptic qualities of a physical shape changing device would likely affect emotion perception, such prototype is still out of reach. We note, however, that we focused on visual rather than haptic experiences. The realism of the played back 3D animations appears, if anything, to have preserved the perception of the emotional expression due to the conveyance of the original human movement. We strongly encourage further exploration of shape interpretation on future research.

Designing Shape-Changing Interfaces
We hope that our investigations into the parameters of the interpretation of shape for the purpose of communicating emotions gives some insight into the development of actuated shape changing interfaces that allow the communication of such features. Our results suggest that such interfaces would need to be able to create one or more convex and concave curvatures across their surface, be able to modulate their actuation speed, as well as be able to animate curvatures across their surface. We conclude that the communication of emotion through shape changing interfaces still represents a significant design challenge that requires further study and engineering.

CONCLUSION
In this paper, we evaluated how shapes and shape changes of a 2D flexible surface might be used to convey emotions in future shape changing interfaces. We presented two experiments, one that investigated which shapes users might create with such a surface, and one that studied the efficacy of the resulting shapes in conveying a set of basic emotions. Symbolic shape expressions based on clear visual metaphors were frequently used. In terms of shape parameters, we found that the geometry of the shape was often used to indicate the Valence of the underlying emotion, while the dynamics of shape change were often used to convey its Arousal. These results strongly suggest that it is useful to treat emotions as areas in a continuum in terms of the Circumplex Model, rather than as discrete nominal categories. We presented a preliminary approach to machine detection of emotion from shape parameters of a 2D flexible surface. Our classifier was able to correctly recognize 40.4% of the emotions, suggesting that it is a line of research worth to be explored. Results from our second experiment indicate participants were able to recognize emotions given a shape with a good accuracy within the scale range used by the Circumplex Model.

Rather than mislabeling responses as categorical errors, by using this Circumplex model, we were able to demonstrate that responses were actually within 28% of the distance of the actual emotion locations in terms of Valence and Arousal, on average. This is a methodological improvement over prior work. Although efficacy varied per emotion, we conclude that shape and shape changes of a 2D flexible surface indeed appear able to convey emotions in terms of their underlying parameters of Valence and Arousal. This suggests that shape changing interfaces may provide a medium for conveying emotional communications that is worthy of further exploration.

REFERENCES
1. Blender: https://www.blender.org/

2. Michael Argyle. 1988. Bodily Communication. New York: Methuen & Co. (1988).

3. Jeremy N. Bailenson, Nick Yee, Scott Brave, Dan Merget, and David Koslow. 2007. Virtual interpersonal touch: expressing and recognizing emotions through haptic devices. *Human-Computer Interaction* 22, 3, 325–353.

4. Moshe Bar and Maital Neta. 2007. Visual elements of subjective preference modulate amygdala activation. *Neuropsychologia* 45, 10 (2007), 2191–2200.

5. Scott Brave and Andrew Dahley. 1997. inTouch: a medium for haptic interpersonal communication. In *CHI'97 Extended Abstracts on Human Factors in Computing Systems*. ACM, 363–364.

6. Jesse Burstyn, Amartya Banerjee, and Roel Vertegaal. 2013. FlexView: An evaluation of depth navigation on deformable mobile devices. In *Proceedings of the 7th International Conference on Tangible, Embedded and Embodied Interaction*. ACM, 193–200.

7. John T. Cacioppo, Joseph R. Priester, and Gary G. Berntson. 1993. Rudimentary determinants of attitudes: II. Arm flexion and extension have differential effects on attitudes. *Journal of Personality and Social Psychology* 65, 1, 5.

8. Taylor Carman. 1999. The body in Husserl and Merleau-Ponty. *Philosophical Topics* 27, 2, 205–226.

9. Marcelo Coelho, Hiroshi Ishii, and Pattie Maes. 2008. Surflex: A programmable surface for the design of tangible interfaces. In *CHI'08 Extended Abstracts on Human Factors in Computing Systems*. ACM, 3429–3434.

10. Jessica Q. Dawson, Oliver S. Schneider, Joel Ferstay, Dereck Toker, Juliette Link, Shathel Haddad, and Karon MacLean. 2013. It's alive!: Exploring the design space of a gesturing phone. In *Proceedings of Graphics Interface*. Canadian Information Processing Society, 205–212.

11. Daantje Derks, Arjan E.R. Bos, and Jasper Von Grumbkow. 2008. Emoticons in computer-mediated communication: Social motives and social context. *CyberPsychology & Behavior* 11, 1, 99–101.

12. Paul Ekman and Wallace V. Friesen. 1975. Unmasking the face: A guide to recognizing emotions from facial cues.

13. Joseph L. Fleiss. 1971. Measuring nominal scale agreement among many raters. *Psychological Bulletin* 76, 5, 378.

14. Sean Follmer, Daniel Leithinger, Alex Olwal, Akimitsu Hogge, and Hiroshi Ishii. 2013. inFORM: Dynamic physical affordances and constraints through shape and object actuation. In *Proceedings of the ACM Symposium on User Interface Software and Technology*. ACM, 417–426.

15. Antonio Gomes, Andrea Nesbitt, and Roel Vertegaal. 2013. MorePhone: A study of actuated shape deformations for flexible thin-film smartphone notifications. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 583–592.

16. Tovi Grossman, Ravin Balakrishnan, and Karan Singh. 2003. An interface for creating and manipulating curves using a high degree-of-freedom curve input device. In *Proceedings of the SIGCHI conference on Human Factors in Computing Systems*. ACM, 185–192.

17. Antal Haans, Christiaan de Nood, and Wijnand A. IJsselsteijn. 2007. Investigating response similarities between real and mediated social touch: A first test. In *CHI'07 Extended Abstracts on Human Factors in Computing Systems*. ACM, 2405–2410.

18. Marti A. Hearst, Susan T. Dumais, Edgar Osman, John Platt, and Bernhard Scholkopf. 1998. Support vector machines. *Intelligent Systems and their Applications*, IEEE 13, 4, 18–28.

19. Fritz Heider and Marianne Simmel. 1944. An experimental study of apparent behavior. *The American Journal of Psychology* 57, 2, 243–259.

20. Fabian Hemmert, Susann Hamann, Matthias Löwe, Anne Wohlauf, and Gesche Joost. 2010. Shape-changing mobiles: Tapering in one-dimensional deformational displays in mobile phones. In *Proceedings of the 4th International Conference on Tangible, Embedded, and Embodied Interaction*. ACM, 249–252.

21. Fabian Hemmert, Susann Hamann, Matthias Löwe, Josefine Zeipelt, and Gesche Joost. 2010. Shape-

changing mobiles: Tapering in two-dimensional deformational displays in mobile phones. In *CHI'10 Extended Abstracts on Human Factors in Computing Systems*. ACM, 3075–3080.

22. Fabian Hemmert, Gesche Joost, André Knörig, and Reto Wettach. 2008. Dynamic knobs: Shape change as a means of interaction on a mobile phone. In *CHI'08 Extended Abstracts on Human Factors in Computing Systems*. ACM, 2309–2314.

23. David Holman and Roel Vertegaal. 2008. Organic user interfaces: Designing computers in any way, shape, or form. In *Communications of the ACM*. ACM 51, 6, 48–55.

24. David Holman, Roel Vertegaal, Mark Altosaar, Nikolaus Troje, and Derek Johns. 2005. PaperWindows: Interaction techniques for digital paper. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 591–599.

25. Marco Iacoboni, Istvan Molnar-Szakacs, Vittorio Gallese, Giovanni Buccino, John C. Mazziotta, Giacomo Rizzolatti, and others. 2005. Grasping the intentions of others with one's own mirror neuron system. *PLoS Biol* 3, 3, e79.

26. Byron Lahey, Audrey Girouard, Winslow Burleson, and Roel Vertegaal. 2011. PaperPhone: Understanding the use of bend gestures in mobile devices with flexible electronic paper displays. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 1303–1312.

27. George Lakoff and Mark Johnson. 2008. *Metaphors we live by*. University of Chicago Press.

28. Peter J. Lang, Margaret M. Bradley, and Bruce N. Cuthbert. 2008. International affective picture system (IAPS): Affective ratings of pictures and instruction manual. *Technical Report* A-8.

29. Helmut Leder, Pablo P.L. Tinio, and Moshe Bar. 2011. Emotional valence modulates the preference for curved objects. *Perception-London* 40, 6, 649.

30. Rachel McDonnell, Sophie Jörg, Joanna McHugh, Fiona N. Newell, and Carol O'Sullivan. 2009. Investigating the role of body shape on the perception of emotion. *ACM Transactions on Applied Perception* 6, 3, 14.

31. Maurice Merleau-Ponty and Colin Smith. 1996. *Phenomenology of perception*. Routledge Publishers.

32. Mie Nørgaard, Tim Merritt, Majken Kirkegaard Rasmussen, and Marianne Graves Petersen. 2013. Exploring the design space of shape-changing objects: imagined physics. In *Proceedings of the 6th International Conference on Designing Pleasurable Products and Interfaces*. ACM, 251–260.

33. Donald A. Norman. 2004. *Emotion design: Why we love (or hate) everyday things*. Basic Books.

34. Andrew Ortony and Terence J. Turner. 1990. What's basic about basic emotions? *Psychological Review* 97, 3, 315.

35. Joohee Park, Young-Woo Park, and Tek-Jin Nam. 2014. Wrigglo: Shape-changing peripheral for interpersonal mobile communication. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 3973–3976.

36. Young-Woo Park, Kyoung-Min Baek, and Tek-Jin Nam. 2013. The roles of touch during phone conversations: long-distance couples' use of POKE in their homes. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 1679–1688.

37. Eric Paulos. 2003. Connexus: A communal interface. In *Proceedings of the 2003 Conference on Designing for User Experiences*. ACM, 1–4.

38. Marina Pavlova, Arseny A. Sokolov, and Alexander Sokolov. 2005. Perceived dynamics of static images enables emotional attribution. *Perception,* 34, 9, 1107–116.

39. Esben W. Pedersen, Sriram Subramanian, and Kasper Hornbæk. 2014. Is my phone alive?: A large-scale study of shape change in handheld devices using videos. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.* ACM, 2579–2588.

40. Ivan Poupyrev, Tatsushi Nashida, Shigeaki Maruyama, Jun Rekimoto, and Yasufumi Yamaji. 2004. Lumen: Interactive visual and shape display for calm computing. In *ACM SIGGRAPH'04 Emerging Technologies*. ACM, 17.

41. Majken Kirkegaard Rasmussen, Erik Grönvall, Sofie Kinch, and Marianne G. Petersen. 2013. It's alive, it's magic, it's in love with you: Opportunities, challenges and open questions for actuated interfaces. In *Proceedings of OzCHI '13: Augmentation, Application, Innovation, Collaboration*. ACM, 63–72.

42. Majken K Rasmussen, Esben W. Pedersen, Marianne G. Petersen, and Kasper Hornbæk. 2012. Shape-changing interfaces: A review of the design space and open research questions. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 735–744.

43. Christian Rendl, David Kim, Sean Fanello, Patrick Parzer, Christoph Rhemann, Jonathan Taylor, Martin Zirkl, Gregor Scheipl, Thomas Rothländer, Michael Haller, and others. 2014. FlexSense: A transparent self-sensing deformable surface. In *Proceedings of*

the *ACM Symposium on User Interface Software and Technology*. ACM, 129–138.

44. Stefan Rosenträger. 2008. Emoticons as a new means of communication in Italy and Germany. University of Bologna.

45. Anne Roudaut, Abhijit Karnik, Markus Löchtefeld, and Sriram Subramanian. 2013. Morphees: Toward high shape resolution in self-actuated flexible mobile devices. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 593–602.

46. Loy Rovers and Harm A. van Essen. 2004. HIM: a framework for haptic instant messaging. In *CHI'04 Extended Abstracts on Human Factors in Computing Systems*. ACM, 1313–1316.

47. Loy Rovers and Harm A. van Essen. 2004. Design and evaluation of hapticons for enriched instant messaging. *Virtual Reality* 9, 177–191.

48. James A. Russell. 1980. A circumplex model of affect. *Journal of Personality and Social Psychology* 39, 6, 1161.

49. Carsten Schwesig, Ivan Poupyrev, and Eijiro Mori. 2004. Gummi: A bendable computer. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 263–270.

50. Jürgen Steimle, Andreas Jordt, and Pattie Maes. 2013. Flexpad: Highly flexible bending interactions for projected handheld displays. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 237–246.

51. Sabine Stepper and Fritz Strack. 1993. Proprioceptive determinants of emotional and non-emotional feelings. *Journal of Personality and Social Psychology* 64, 2, 211.

52. Fritz Strack, Leonard L. Martin, and Sabine Stepper. 1988. Inhibiting and facilitating conditions of the human smile: a non-obtrusive test of the facial feedback hypothesis. *Journal of Personality and Social Psychology* 54, 5, 768.

53. Paul Strohmeier and Ike Kamphof. 2014. Mediated Touch: Exploring embodied design for remote presence. In *Proceedings of the International Society for Presence Research*, 131–140.

54. Aneesh Tarun, Peng Wang, Paul Strohmeier, Audrey Girouard, Derek Reilly, and Roel Vertegaal. 2013. PaperTab: Tablets as thin and flexible as paper. In *CHI'13 Extended Abstracts on Human Factors in Computing Systems*. ACM, 2881–2882.

55. Frank Thomas and Ollie Johnston. 1995. *The illusion of life: Disney animation*. Hyperion, New York.

56. Chad C. Tossell, Philip Kortum, Clayton Shepard, Laura H. Barg-Walkow, Ahmad Rahmati and Lin Zhong. 2012. A longitudinal study of emoticon use in text messaging from smartphones. *Computers in Human Behavior* 28, 2, 659–663.

57. Terence J Turner and Andrew Ortony. 1992. Basic emotions: can conflicting criteria converge? *Psychological Review* 99, 3, 566–571.

58. Jacob O. Wobbrock, Meredith Ringel Morris, and Andrew D. Wilson. 2009. User-defined gestures for surface computing. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 1083–1092.