Emotion Actuator: Embodied Emotional Feedback through Electroencephalography and Electrical Muscle Stimulation

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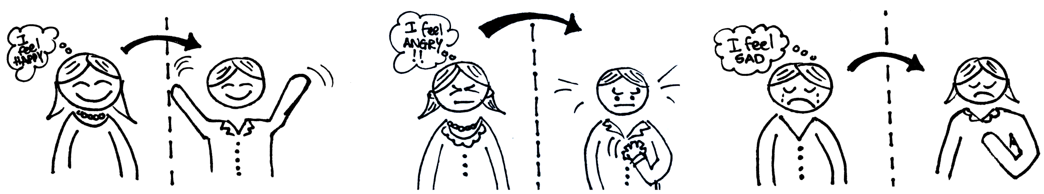

Figure 1. Embodied emotional feedback involves implicitly sensing emotions and displaying them by actuating the recipient's body.

ABSTRACT
The human body reveals emotional and bodily states through measurable signals, such as body language and electroencephalography. However, such manifestations are difficult to communicate to others remotely. We propose *EmotionActuator*, a proof-of-concept system to investigate the transmission of emotional states in which the recipient performs emotional gestures to understand and interpret the state of the sender. We call this kind of communication *embodied emotional feedback*, and present a prototype implementation. To realize our concept we chose four emotional states: amused, sad, angry, and neutral. We designed *EmotionActuator* through a series of studies to assess emotional classification via EEG, and create an EMS gesture set by comparing composed gestures from the literature to sign-language gestures. Through a final study with the end-to-end prototype interviews revealed that participants like implicit sharing of emotions and find the embodied output to be immersive, but want to have control over shared emotions and with whom. This work contributes a proof of concept system and set of design recommendations for designing *embodied emotional feedback* systems.

Author Keywords
Affective computing; affect display; emotion; emotion sharing; EMS; EEG.

ACM Classification Keywords
H.5.2 Information Interfaces and Presentation: User Interfaces – Input devices and strategies; Haptic I/O.

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INTRODUCTION
More and more people are living in long-distance relationships – often because people cannot easily find workplaces in the same city or are sent abroad temporarily [36]. In such situations couples struggle with maintaining social connectedness, typically by relying on text messages, social media, and voice communication [15]. Exchanging intimate information about one's emotions is an important maintenance behavior in long-distance relationships [42]. New ways of sharing and communicating emotions between long-distance partners has been the focus of recent research projects that increase empathy and overcome the drawbacks of traditional and current communication technologies [18, 41, 45].

This work focuses on exchanging information about emotions over a distance. The human body reveals affective states through measurable signals, such as heart rate, blood pressure, skin conductivity, muscle tension, facial expressions, pupil diameter, voice, body movements and posture, and brain activities (e.g., [9, 10, 11, 27, 43, 68]). We propose a system that measures the affective states of one partner and lets the recipient perform an emotional gesture representing the sender's affective state. In this way partners can experience similar sensations of the affective state and get emotionally connected. This may lead to an awareness of the affective state of the other person, which we explore in this work as a proof of concept. We call this kind of setup *embodied emotional feedback*: The recipient's own body is actuated to portray the emotional state of the sender. The recipient interprets his or her own movement and thereby gains knowledge about the emotional state of the sender. If the communication of affective states is set up in a bidirectional way a feedback loop emerges, with mutual effects on both partners.

We present a proof-of-concept implementation realizing *embodied emotional feedback* using electroencephalography (EEG) on the sending side and electrical muscle stimulation

(EMS) on the receiving side. EEG has been used to implicitly detect emotional states with good reliability [7, 37, 44]. EMS is a method adopted from physiotherapy and has been used successfully in HCI to actuate the human body [34, 38, 40, 50, 51, 62]. Combined, these are promising technologies to realize emotional awareness between two persons without needing explicit intervention of verbal or textual communication. In particular, we obtain information about a user's emotional state, for example, whether getting amused, sad, or angry, and use this information to actuate the receiving user such that he or she performs a certain gesture.

To evaluate our concept, we implemented an initial system and evaluated it in three studies. First, we focused on the input side (EEG). We created a classifier capable of differentiating emotional states such as amused, sad, or angry. Second, on the output side (EMS), we developed two gesture sets representing the emotional states and compared them with regard to the best fit to each emotion. We use natural expressions of emotional states which we elicit from the literature and gestures derived from the American sign language (ASL). Third, we combined the findings from the first two studies to assess its ability to create a sense of connectedness between two persons. Therefore, pairs of participants used our system in the context of a scenario taken from the real world.

The results show that participants performed better in distinguishing sign language gestures than natural gestures. These gestures serve as a basis that can be personalized in future implementations so as to reflect individual gestures of the partner. Interviews revealed that participants like implicit sharing of emotions and find the embodied output more immersive than common text notifications. However, they want to stay in control over which emotions to share, e.g., only positive emotions with friends, and both positive and negative emotions with one's partner.

CONTRIBUTION STATEMENT

We contribute the concept of *embodied emotional feedback*, a new way of sharing emotions. Over a distance it implicitly senses emotional states using EEG, communicates them to another person, and actuates the recipient's body using EMS with gestures as a result of these states. We present *emotion actuator*, a prototype to realize this idea, and three initial studies to evaluate the concept.

RELATED WORK

Prior research presents various approaches to achieve emotional communication and connectedness. Lottridge et al. [41] explore what remote couples lack from existing communication technologies and what they want to share and how. They identify *empty moments* (waiting, walking, waking up) as a design opportunity for sharing emotions. Dey and Guzman [17] discuss the design of presence displays for awareness and connectedness. Hassenzahl et al. [28] review design concepts and technologies that aim to create relatedness. They present six strategies for creating a relatedness experience: awareness, expressivity, physicalness, gift giving, joint action, and memories. We focus on awareness and expressiveness to enhance emotion communication between partners.

Explicitly sharing emotions has been studied in the context of MobiMood, a mobile system for sharing emotions among friends [12]. Emotishare [67] is a platform for sharing and responding to explicitly reported emotional states among friends. Social media are commonly used to share emotions [6]. People tend to restrict intense and negative emotions to private channels and share positive emotions more widely. This observation is supported by our findings.

Explicitly sharing emotions through emojis, text or speech can impose a burden on the provider. Here we focus on implicitly detecting and sharing emotions. Implicit emotion sharing has been explored by Perttula et al. [48] who present an EEG-based prototype for mood sharing on a public map among visitors of a large-scale event. Various projects aimed at augmenting mobile phones by an emotion channel. Cui et al. [13] use front-camera recordings of emotional reactions to received content to implicitly capture and transmit emotions. The system does not try to recognize the emotion but just captures it and returns it to the sender. The *Poke* system [45] uses an inflatable surface on the phone that receives finger pressure input from the back of another phone. A long-term study found that users developed vocabularies for expressing and understanding emotions.

Looking at emotion input, prior work investigated different ways for detecting emotions. Strohmeier et al. [60] found a relation between deforming an object and the represented emotion. Höök [30] investigated bodily persuasion through *affective loop* experiences, which employ physical, emotional interactions. In particular gestural interactions with a doll (for example, shaking it back and forth) influenced the emotion of a game character (e.g., anger). It was found that the experience of performing the gesture and the game character's feedback also have an effect on the user's emotion, leading to an *affective loop*. In our work, the recipient's body is actuated through implicitly sensed emotions rather than active gestural input.

Fagerberg et al. [22] draw from theories of movement and emotional expression to design a set of affective gestures for emotion input. Sundström et al. [61] propose *eMoto*, a system in which a user can explicitly input emotional states using pressure on a handheld token and the amount of movement of that token. Pressure is mapped to the valence axis while movement is mapped to the arousal axis. In contrast to these works, we use movement as an output modality.

For the emotional output modality beyond the regular displays and mobile phones, previous work looked into various wearables and tangible objects. *United-pulse* [66] are rings worn by a couple that play the heartbeat of the partner. Gooch and Watts [25] present a robotic grasping hand, that supports hand holding over a distance. Tsetserukou and Neviarouskaya [63] reproduce emotions of another person through a haptic device worn on the chest.

Researchers also investigated tangible pairs of objects for input and output. These include lights [1], picture frames [33], beds [18], and teddies [23] for communicating emotions.

EMBODIED EMOTIONAL FEEDBACK

Embodied emotional feedback involves implicitly sensing emotional state changes and displaying them by actuating the recipient's body. The approach involves recognizing emotions from physiological data and transmitting them from the sender to the receiver. Roles of sender and receiver may change depending on the direction of information flow over the bidirectional channel. In the literature there are examples of explicit and implicit forms of emotion input. Implicit emotion sensing has the advantage of not interfering with the emotional experience, yet it lowers control. Another aspect of implicit emotion sensing is that it is not necessary to verbalize the experienced emotion. The recipient becomes the output device of the sender's emotion. We hypothesize that this leads to a stronger sense of immersion, intensity and, possibly, a more intuitive understanding of the received emotion, compared to other output modalities. One reason for this expectation is that it has been shown that gestures are closely linked to emotions. Performing a gesture may increase or even evoke a particular emotion [16, 35]. When a person is more involved in a situation (e.g., in a partnership) empathy and resulting feeling of the other person can increase. In the following we describe the components of embodied emotional feedback.

Measuring Emotions

In a first step the emotions to be shared are measured. Different methods exist and the selection of a recognition method depends on the targeted theory of affect, the emotions of interest, context, as well as the intended goal of the evaluation [24]. These methods can be either subjective or objective.

Subjective methods include structured and non-structured questionnaires and self-assessments. Examples are the Positive and Negative Affect Schedule (PANAS) [65] and the Self-Assessment Manikin (SAM) [8]. These methods cover a large set of possible emotions. However, they depend on affective states that the participants are consciously aware of as well as being biased by language and culture [24].

Objective methods employ physiological and non-physiological sensors. A popular method is using cameras and image analysis to detect facial expressions based on Ekman's theory of emotion [20], which suggests a link between facial expressions and affective states [68]. Additionally, electromyography (EMG) recordings are used to recognize emotions from facial expressions [10]. Other methods measure heart rate [5, 29], skin conductance [58], respiration rate [29], pupil response [46], or electroencephalography signals (EEG) [24, 44] to recognize emotions. Although objective methods overcome some drawbacks of subjective ones, the physiological responses of individuals vary and are sometimes not easy to interpret. Also, the prior emotional state is usually not considered. Rather the emotional change is compared to a baseline or calibration phase. However, Picard argues that a universal solution to this issue is not required if a user-dependent solution is possible [52].

Current research efforts show that classifying emotions from facial expressions can achieve accuracies up to 80–90% under controlled conditions [9]. Psychology explicitly separates physiological arousal, the behavioral expression (affect), and the conscious experience of an emotion (feelings) [7]. Facial expressions and voice are related to the behavioral expression, which can be consciously changed or adapted and its interpretation is not objective [7]. EEG can implicitly and objectively measure the emotional state of the user. Therefore, we focus in this work on EEG for emotion measurement.

Linking Emotions and Movement

Emotions are closely linked to body posture, movement and body language [19, 21, 54]. We conducted a literature review to gain insight into which movement is *naturally* linked to which emotion, focusing on *anger*, *sadness*, and *amusement*. We chose these three emotions since they are basic emotions and well distributed in Russel's model of affect [55]. From the literature review we elicited movements that represent each emotion. Out of this movements we designed a single gesture for expressing each emotion (called *natural gesture*). These gestures are culture and person-depended but we believe that the selected gestures form a valid basis which can be well understood. In addition, we looked into the *American Sign Language*[1] (ASL) and picked the gesture corresponding to each emotion. Even though ASL is an abstract language, the signs representing emotions are chosen so that they are easy to link to the emotion and, thus, are easy to remember.

Although facial expressions are closely linked to emotions [21] we do not actuate the face for emotion output, because attaching EMS pads to the face is socially problematic and may compromise the user's safety. Rather we follow common safety practices to apply EMS to the limbs and the torso [53]. Note that in the future, transcranial magnetic stimulation (TMS) may be used to directly manipulate the motor cortex and thus move arms [3], fingers [32], or lips [59]. However, currently this technology is complex and bulky to use. The TMS coil has to be placed very precisely to actuate specific motor regions and hence cannot be used HCI contexts.

Amusement

The gesture related to amusement is described as an open gesture that extends the body [64]. This emotion is mostly linked to lifting up both arms [19] and keeping the hands high [27]. Thus, we designed the natural gesture so that the user lifts both hands and keeps them up (Table 1, top). In ASL, the gesture consists of making a fist with the right hand and then open and close the index and middle finger while lifting the lower arm up to the face (Table 1, bottom).

Anger

Anger is an emotion that is linked to violence [11] and aggressive forward positioning of the body [14]. In most literature, the core part of the gesture that is related to anger is clenching one's fist [19]. This gesture is sometimes described in combination with shaking the fist [64] or keeping the fist low or at the waist [27]. Based on this we designed the gesture as making a fist with both hands that is slightly lifted (Table 1, top). The related gesture in the ASL is to form a claw with the right hand in front of the face (Table 1, bottom).

[1] ASL: https://www.signingsavvy.com/sign/

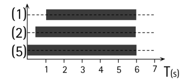
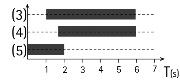
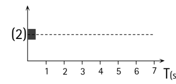
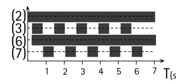
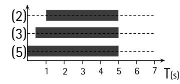
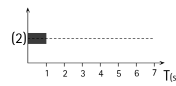
	Emotion	Gesture	Movement	Timing	Muscle
Natural	Amusement		Hand up (5), lower arm up (2), upper arm up (1) (left and right)		Extensor digitorum muscle (5), biceps brachii muscle (2), and deltoid muscle (1)
	Anger		Hand up (5) claw hand (3), hand down (4) (left and right)		Extensor digitorum muscle (5), flexor digitorum superficialis muscle (3), flexor digitorum profundus muscle (4)
	Sadness		Lower arm up (2) (left and right)		Biceps brachii muscle (2)
American Sign Language	Amusement		Lower arm up (2), claw hand (3), tow finger down (6), two finger up (7)		Biceps brachii muscle (2), flexor digitorum superficialis muscle (3), flexor digitorum profundus muscle inside (6), extensor digitorum muscle inside (7)
	Anger		Hand up (5), claw hand (3), lower arm up (2)		biceps brachii muscle (2), flexor digitorum superficialis muscle (3), extensor digitorum muscle (5)
	Sadness		Lower arm up (2)		Biceps brachii muscle (2)

Table 1. Linking emotions to gestures and elementary movements. Different muscles are used to evoke certain movements with a specific timing so that the combination of the different muscle movements results in a gesture. The *movement*, *timing*, and *muscle* columns also depict the numbers of the actuated muscles between brackets which are further illustrated in Figure 4

Sadness

Sadness is characterized as a lack of body tension [19, 64]. It also includes subtle movements of the hands by either folding them in the lap [19] or putting them into the pocket [14]. However, the movements are performed rather slowly and gently [64]. Thus, we designed the gesture such that the user folds both hands on the lap (Table 1, top). In ASL, the gesture consists of moving the right hand up in front of the upper body and slowly sliding it down the chest (Table 1, bottom).

Creating Movements using EMS

From the above-mentioned gestures we isolated elementary muscle movements that can be evoked by EMS (Table 1). EMS delivers an electrical signal to the human body via non-invasive surface electrodes. As soon as the signal stimulates motor nerves, the corresponding muscle contracts and performs the intended movement, for example, lifting the arm. Related work shows examples of supporting interaction by actuating fingers [39], hands [62], arms [26] and legs [50].

Since the muscle position is user-dependent, the electrodes need to be placed at slightly different positions for each user. Even small changes in position can result in a different movement. To achieve a realistic movement, the EMS signal strength needs to be calibrated individually. As the muscle contracts, it changes its form, thereby shifting the relative positions of electrode and muscle. Therefore, the calibration process needs to take the intended movement into account. Furthermore, the timing has to be controlled thoughtfully.

THE EMOTION ACTUATOR

To investigate *embodied emotional feedback*, we created the *emotion actuator* system, which senses emotion changes and creates embodied feedback. The system consists of two main components, namely the *sensing* component, recognizing specific emotions, and the *actuation* component.

Sensing Component

We used the Emotiv EPOC[2] EEG device, which has 14 saline-based felt electrodes and two reference electrodes following the 10–20 electrode positioning system. The EEG signals are transmitted wirelessly to a laptop computer. The EPOC device provides both raw EEG data as well as affective and facial expression information. We used three main affective scores that are provided by the EPOC: *excitement*, *engagement*, and *frustration*. Engagement is the general cortical activation elicited through a stimulus. It is characterized by high EEG beta wave activity and related to heightened cognitive and affective states [43]. Excitement is a feeling of physiological arousal following an external stimulus. Frustration is the cortical activity related to cognitive and affective processes while trying to cope with negative emotional states [43]. The relation between these affective scores and our chosen emotions is not one-to-one. However, following the valence/arousal model of affect [55], amusement is positive valence and high arousal, sadness is negative valence and low arousal, and anger is negative valence and high arousal. We also utilized the EPOC's facial expression information to develop the features for the classifier. We utilized were *smile*, *clench*, and *laugh*. Literature has assessed the feasibility of emotion classification using the EPOC EEG data [2, 37, 47] and facial expression information [4].

Filtering and Feature Extraction

The EPOC comes with built-in notch filters and noise filtering. However, the signal quality varies, in particular for participants with lots of hair and due to some participants fidgeting in their seats during the recording. Thus, we applied an additional filter for further smoothing of the signal [56]. Data was divided into windows of three seconds and features were

[2]Emotiv EPOC: www.emotiv.com

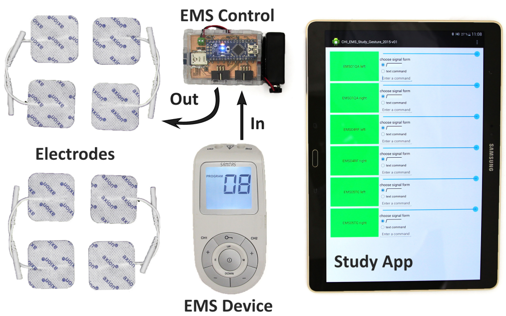


Figure 2. EMS control modules with two galvanically isolated circuits.

extracted per window. Since changes in the affective information evoked by the external stimulus (i.e., movie) are short term (a few seconds), we used windows of three seconds.

For simplicity, we based the features of the classifier on EPOC's affective and facial expression information. A score > 0.3 was counted as a smile/laugh/clench to avoid false positives. By examining the data prior to feature extraction, we found that clench scores were highest in movies with negative valence (sad/angry), whereas smile and laugh scores were highest in amusement movies. Our 18-dimensional feature vector includes the minimum, maximum, mean, median, and standard deviation of the excitement, engagement, and frustration scores as well as smile, laugh, and clench scores > 0.3. A random forest classifier with 100 trees was used to classify the data based on the defined features.

Actuating Component

To realize the actuating component, we use an EMS-based toolkit, which is composed of an off-the-shelf EMS-based massage device, a control board, and an Android app as described in [49]. The toolkit is available open source[3]. In total six EMS/TENS devices (Breuer Sanitas SEM 43) generate the signals for the twelve actuated muscles (Figure 4). As signal EMS parameters we used an electrical current of 10–30 mA, a the pulse width of 100 μs, and a pulse frequency of 100 Hz. These devices are connected to six autonomous modules which are controlled by the Android app via Bluetooth LE (Figure 2). The control module allows turning on/off and adjusting the intensity of the two EMS channels (each of which connects to two electrodes). Each module has two galvanically isolated circuits – one for handling the communication and one for the electrodes attached to the human body.

For composing the different gestures we developed an Android app that connects to multiple control modules. The app can control each muscle individually via a one-to-one mapping of button to muscle. As long as the button is pressed the muscle is being actuated. In addition, the intensity of the EMS signal is controlled through a slider for each muscle. Individual activation and intensity adjustment enable fine-grained calibration. The app allows a precise timing of the gestures. The application is also able to *replay* complete gestures by consecutively actuating muscles using a predefined timing. This is used after calibration to replay gestures.

[3]Let Your Body Move Toolkit https://bitbucket.org/MaxPfeiffer/letyourbodymove/

Emotion	Movie	Scene Description
Amusement	Benny&Joone	Benny plays the fool in a coffee shop
	A Fish Called Wanda	One of the characters is found naked
Anger	Schindler's List	Commander randomly shoots prisoners
	American History X	A neo-Nazi kills a man
Sadness	The Dead Poets Society	A schoolboy commits suicide
	Philadelphia	Andrew describes the pain& passion felt by the opera character

Table 2. The movies used in the study to evoke a certain emotion.

STUDY I: DETECTING EMOTIONS THROUGH EEG

In a first study, we investigated how accurately we could classify emotions using EEG data. Emotions can be evoked using different sensory stimuli such as visual or audio stimuli. In psychology, many different emotion eliciting databases exist [68] where audiovisual stimuli in the form of movies were successfully used to elicit emotions. For our study, we selected movies from the "FilmStim" movie clips database [57]. The database offers 70 movie scenes that were rated by 364 participants on 24 classification criteria. For each of the three emotions (anger, sadness, and amusement) we chose two movie clips that were ranked among the top ten movies on the discrete emotion criteria and on the perceived arousal and valence criteria [57]. The duration of each movie clip is 2–4 minutes. Table 2 provides a short description of each movie clip. Additionally, two neutral videos of 2–3 minutes each were used to elicit a neutral state (i.e., a state in which our system does not trigger feedback regarding the emotion). These movies were not part of the "FilmStim" movie database.

Study Design

Each participant watched each movie clip in Table 2. We collected EEG data and measured how strongly each video evoked the intended emotion through a questionnaire.

Procedure

Ten participants took part in the study (3 female, M=27, SD=4.8 years). As participants arrived at the lab they were briefed about the purpose of the study and asked to sign a consent form and fill out a demographics questionnaire. We equipped them with the EPOC device after applying saline solution to each of the electrodes. Using the EPOC control panel we ensured an optimal fit of the electrodes close to the scalp and in direct contact with the skin.

Participants were seated in a dark room in front of a 30 inch screen on which the chosen movie clips were shown. We first presented a neutral movie clip to establish a baseline for the device and to ensure signal stability. The clip showed a stationary image of a harp and light harp music. After that we showed the movies in randomized order. After each movie the participants provided two subjective ratings of the movie: A 7-point Likert scale rating for each of the three emotions and a 9-point Self-Assessment Manikin (SAM) score [8] for measuring arousal and valence of the emotion they felt during the movie. Both questionnaires were thoroughly explained to the participants before the study and a sample was shown.

Results

We labeled each movie with the emotion that received the highest score from the self-assessment. This was done to avoid inconsistencies between the experience of participants and the supposed category of the video. If the first rating was

Figure 3. Snapshots of the different gestures performed in Study II. Each participant performed each of these six gestures.

Participant	Classes	Classification Accuracy(%)
1	AM,REL,SAD,ANG	67.7
2	AM,REL,SAD,ANG	59.4
3	AM,REL,SAD,ANG	67.3
4	AM,REL,SAD,ANG	70.8
5	AM,REL,ANG	89.2
6	AM,REL,SAD,ANG	81.3
7	AM,REL,SAD,ANG	66.9
8	AM,REL,SAD,ANG	70.1
9	AM,REL,SAD,ANG	82.9
10	AM,REL,SAD	77.0

Table 3. Per participant classification using a Random Forest classifier.

ambiguous, the arousal and valence values measured through the SAM were used. One participant rated an *angry* movie as *sad* (P10) and another participant rated a *sad* movies as *angry* (P5). We excluded the particular class from the evaluation for these two participants. Finally, instances in which both scoring systems were ambiguous were removed from the dataset. This happened in one case (P5).

Overall, we achieved an accuracy of 72.6% (*SD*=9.5%). Table 3 depicts the results of our participant-dependent classification which was done using Weka[4]. Results show that classification using features from the EPOC affective suite and facial expressions is possible, with accuracies between 59.4% and 89.2%. For P2, getting a consistent high quality contact between the electrode and the scalp was not always possible due to the participant's hair, which degraded signal quality and could be a reason for the low classification score.

STUDY II: COMPOSING A GESTURE SET

In a second study we explored how well the elicited body movements fit the detected emotions, as judged by participants. We compare the *natural gestures* to *ASL* gestures, ultimately selecting one gesture per emotion for the subsequent concept exploration study. We also collected user feedback in interviews. In particular we were interested whether the played emotions are easy to understand.

[4]Weka: http://www.cs.waikato.ac.nz/ml/weka/

Study Design

We again used a repeated-measures study design in which participants compare two gestures for each emotion. The independent variable was the gesture played via EMS, with these levels (see Table 1, *Gesture* column): natural amusement gesture, ASL amusement gesture, natural anger gesture, ASL anger gesture, natural sadness gesture, and ASL sadness gesture. We used a Latin squared order of gestures to prevent sequence effects. After experiencing a gesture, participants had to rate on a 7-point Likert scale how well they felt each gesture represented the three emotions amusement, anger, and sadness. In addition we collected interview responses.

Procedure

We invited 8 participants (4 female) aged 20–28 years (*M*=22.4, *SD*=2.7) to our lab. We recruited them from our institutional mailing lists.

When a participant arrived we first explained the purpose of the study. Then the participant filled out a consent form and a demographic questionnaire. We introduced the EMS system and tested whether the participant was comfortable with the sensation caused by the EMS actuation by applying EMS output to the extensor digitorum muscle (Figure 4, pad 5). We then equipped them with the electrodes required to actuate the muscles for the intended movements and calibrated each muscle individually. The current was increased step-by-step until we got the expected movement. In case the current got uncomfortable or we got an unintended movement we replaced the electrodes as described in [49]. We avoided to actuate complete gestures so participants would experience each emotion gesture for the first time in the study. We also did not show a depiction of the gestures to the participants. The whole calibration process took about 60 minutes. Then, participants performed the gestures in random order. Each gesture was performed up to 4 times to let the participants focus on the movements and get used to the actuation. When the participants were familiar with a gesture we asked

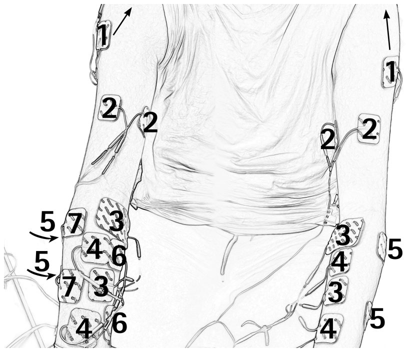


Figure 4. Placement of 12 electrode pairs to actuate muscles via EMS. The numbers refer to the muscles shown in Table 1, right.

them to rank this gesture according to the degree of agreement to the statement "this gesture fits the emotion amusement/anger/sadness" (1=strongly disagree, 7=strongly agree). We also asked participants what they (dis)liked and how they would describe each gesture.

Results

Quantitative Results

In general, the defined gestures conveyed the emotions in the intended way. As can be seen in Figure 5, the intended emotion received the best ranking in all cases except for the natural anger gesture. Looking more closely at this gesture, we found that the natural anger gesture was misinterpreted as representing amusement by participants P7 and P8.

Qualitative Results

We were particularly interested in how the participants experienced the different gestures.

Amusement. Participants described the natural gesture exciting (P1, P6). At the same time, P1 said that he found the gesture somewhat hectic. Some participants mentioned that raising their hands very high made them feel kind of funny, but not very natural. In contrast, the ASL gesture that focused mainly on the actuation of the biceps was also characterized as exciting (P6) but considered to be much more natural (P8).

Anger. Subjective feedback suggests that both the natural as well as the ASL gesture were overall perceived as a good fit. P1 disliked that the natural gesture felt cramped. P5 said that the natural gesture resembled shadow boxing. With regard to the ASL gesture, P1 and P7 said that the gesture created a kind of defensive, almost aggressive attitude, hence well reflecting the emotion. P3 stated that the gesture resembled dancing, since the arm rotates inwards.

Sadness. For the natural gesture, participants felt the gesture was defensive (P6), made them look puzzled (P8), and felt like waving at somebody (P8). P7 said that the ASL gesture made them feel thoughtful, thus nicely reflecting sadness. P8 felt the gesture could be confused with anger.

General feedback by the participants suggested that people did not actively interfere with the actuation but let the system control the movement. P3 mentioned that it was quite uncommon to be externally controlled, but soon got used to it. P7 mentioned that they felt the muscles, rather than the current. Only P2 felt that the actuation was artificial.

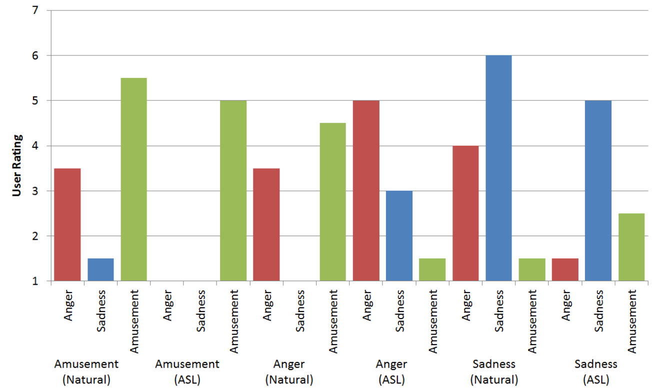


Figure 5. Median rating of how well the gesture fits the emotion for amusement, anger, and sadness on a 7-point Likert scale.

Selection of the Final Emotion Gesture Set

The qualitative feedback indicated that overall the gestures fit the emotions well – in particular the ASL gestures – even though there were some misinterpretations for both types of gestures. We believe that these mainly stem from the fact that people have different ways of expressing emotions. Apart from the qualitative feedback, an important criterion on which we based the decision for the final gesture set was the distinctiveness of a gesture. Thus, we looked at the maximum difference between the top and second rated emotion for the two gestures. In the end, there was a tendency towards the ASL gestures, which not only managed to convey each emotion correctly, but were distinctive and favored by participants.

Deriving Timings for Actuating Gestures

After the study, we derived the timings for each gesture based on the video recordings. We analyzed the individual movements of each participant regarding which timing each muscle needs to perform the gestures in an optimal way.

The automated ASL amusement gesture takes in total 7.2 s. The biceps brachii muscle (Figure 4, pad 2) was actuated from the beginning for the full 7.2 s, followed by the flexor digitorum profundus muscle (6) inwards, and the extensor digitorum muscle (7) inside with a delay of 0.25 s for 7.1 s. The extensor digitorum muscle (7) and flexor digitorum superficialis muscle (3) were alternatingly actuated for 0.4 s in total five times. The biceps lifts the arm up and as soon as the arm starts lifting, the flexor digitorum profundus muscle is actuated inside which closes the hand except for the index finger and middle finger. The extensor digitorum muscle (7) lifts the index and middle finger up and the flexor digitorum superficialis muscle (3) pushes the finger down again.

The automated ASL anger gesture takes 5 s. The biceps brachii muscle (2) is actuated the whole time, then the extensor digitorum muscle (5) is actuated with a delay 0.3 s for 4.7 s, and the flexor digitorum superficialis muscle (3) with a delay of 0.5 s for 4.5 s. First, this lifts the lower arm up, followed by the hand, and finally claws the fingers.

The ASL sad gesture only takes 1 s. The biceps is actuated for 1 s and pushes the lower arm up to the chest where it slides down the chest.

LIMITATIONS

While we used off-the-shelf massage devices and BCIs for creating *EmotionActuator*, we envision a usable and wearable system in the future. Particularly, setting up the actuation component in its current form is time consuming and intrusive due to the placement and calibration of self-adhesive electrodes [49]. The integration of these electrodes in smart garments will increase the usability and wearability of our system (cf. Keller and Kuhn [31]). The user will simply put on clothes with integrated electrodes and the system will be able to actuate the user without extensive prior calibration.

STUDY III: CONCEPT EXPLORATION

A qualitative evaluation of the emotion actuator concept was conducted with groups of two users. We obtained information on the emotional state of one of the participants via EEG and then conveyed it through EMS actuation to the other participant. The purpose of the study was to understand how well our approach helped people to feel connected and in witch situations they would like to use embodied emotional feedback. To create a realistic scenario, both participants were given different tasks. Whereas senders watched the same videos as in Study I, the receivers were asked to play a game on a tablet computer as a distraction task. We chose a non-emotional, non-time critical game called "Find the Difference 38"[5].

Apparatus

We connected the sensing (EEG) and the actuating components (EMS) of the system.The EEG input side involved the Emotiv EPOC connected to a PC. It sends data to the PC which computes features and determines the emotional state. The state is then sent wirelessly to the EMS side. Information on the emotional state of the sender is conveyed either through a standard text notification on the Android tablet[6] on which the participant played the game or through ASL gestures described above. Text notifications served as a baseline, as they are a common way of conveying emotional information. We chose short and easy-to-understand sentences. In particular, the messages stated "I am {angry | sad | amused}." In addition to the visual feedback the tablet computer vibrated twice when a notification was received.

In this study, we used the automated ASL gestures with the timings that were identified in Study II. Table 1, column *Timing*, summarizes the sequence and length of each actuation for the different muscles. For creating the gestures that represent the different emotions we used the same EMS control modules and calibration process as in Study II.

Study Design

The study followed a mixed design in which the sender (EEG) and receiver (EMS) is a between-subjects variable (i.e., a participant was either a sender or a receiver), whereas the feedback channel (EMS vs. textual) is a within-subject variable (i.e., each recipient received both EMS and textual notifications). We focused on qualitative feedback. The goal was to gather a deeper understanding of how people felt connected and involved depending on the kind of feedback.

[5]Find Difference 38 https://play.google.com/store/apps/details?id=free.find.difference38

[6]Android Notification http://developer.android.com/guide/topics/ui/notifiers/notifications.html

Procedure

For the study we recruited 8 participants (6 male, mean age 25.6, *SD* = 4.4 years) from a student mailing list and from our lab. Two of them were a married couple (P1, P2), two had been friends since childhood (P3, P4), two were colleagues (P5, P6), two did not know each other (P7, P8).

As participants arrived at the lab, they received an introduction on the purpose of the study. They were then divided randomly and assigned to one of the two groups – either the EEG group or the EMS group. Both were then led to separate rooms and were not informed about the task of their partner. People in the EEG group were quipped with the Emotiv EPOC and after that shown the neutral movie for calibration, before showing them the same set of movies (two per emotion) as in the first study (Table 2). During each movie, information on the respective emotional state was measured by the EEG device and directly sent to the other participant. Note that we checked each detected emotion before it was passed on to the receiver, because we could not guarantee that people responded to the movies in the intended way or the emotion was correctly recognized. An unexpected emotion happened twice, when participants responded with *anger* to a *sad* video. Our approach ensured that the intended emotion was transmitted to the receiver. The videos were played in a counterbalanced order and took 2–3 minutes each. The introduction and calibration took about 45 minutes. The participants watched approximately 20 minutes of video or played the game. Six emotion responses were sent during that time.

Participants assigned to the EMS group were first introduced to EMS. As in Study II, one muscle was actuated so that they could get used to the sensation and the strength be adjusted. After that, electrodes were attached to the muscles required to perform the gestures and the system was calibrated (Table 1). We let the participants experience each gesture and told them about their meaning. We then handed the tablet to the participants and asked them to play the game. Furthermore, we explained them that they would receive either a text notification on the tablet or would be actuated via EMS while playing the game. Participants were asked to name the received emotions.

After the study, one researcher removed the BCI and EEG equipment. Both participants were brought to the same room and a semi-structured interview was conducted.

Results

We clustered the statements and comments participants made during the interview according to different themes that were discovered during the analysis process.

Emotion Reception: Intensity and Immersion

First we were interested in how intensive and immersing the gestures were, compared to the text notifications. P4 stated that he found "emotions conveyed through motion much stronger than the textual emotions". P4 added, though, that he was not sure whether this increased strength stems from the gestures or his surprise that the approach indeed works. P6 pointed out that "electrical feedback is much more haptic" and added that it is "much more emotional if the body reacted compared to when you just look." He also felt that more brain activity was involved. P2 stated that "[the feedback] happens within the body and it somehow feels as that the emotion is inside the body." P8 said that with "EMS you feel the emotion [...], the text message you can just neglect." P4 explained that in the case of the text message he was more involved in the game than connected to the other person. P4 pointed out that he could feel the anger and amusement for the EMS feedback, but not sadness. Asked about what they (dis)liked, P4 responded that "it [EMS] is more expressive, that is an advantage." "It [EMS] is much more immersive than text." (P6)

Gesture Set

Participants said that it would have helped to know ASL. P4, P6, and P8 would have liked the gestures to more strongly differ from each other and that they could be more natural. "Apart from the fact that the gestures did not differ too much, they were quite nice" (P4). We asked P8 whether she expects facial gestures to work better than the proposed gestures. P4 felt that they might not be diverse enough and added "smiling and opening my mouth could work." When asked about how they liked the movement caused by EMS, P6 answered that it was "just normal – neither negative or positive." Furthermore he said that it "was quite funny to see the arm alone go up without this being caused by the brain."P4 was happy and surprised that it works so well. Furthermore, P4 said that despite being able to feel it without looking, he would have liked a notification to be "aware of that something is going to happen." P4 also suggested to repeat the gesture.

Sharing Emotions

We were interested with whom people would like to share emotions through the presented system. There was agreement among participants, that they would mostly share this information with close friends, family, or partners. P3 stated that this would be appropriate for "friends and people I am close to." P5 felt that his girlfriend "would be happy about that" and that his parents would be very interested in receiving this kind of information ("Parents! Oh parents are interested in that"). However, he also pointed out that it depends on the emotions themselves as well as on the granularity of the emotions.

We found a tendency that participants would share negative emotions with close friends only, whereas it would be okay with them to share positive emotions with a wider audience. P5 stated that "the last scene was very dark [...] happy information would have been nicer." He added that he would prefer sharing only nice or positive emotions like "how well I was feeling" to a broad audience and even social media. "Bad emotions are more for people that are close."

Some participants explicitly mentioned that they would like to stay in control of what is shared with whom by being allowed to select specific emotions to share as well as by constraining specific emotions to a specific audience. P6 said "I would like to select which information would be transmitted." P7 mentioned that "it depends on the context." He would not share emotion in that way "if you feel that you will be judged by people, knowing about that specific emotion that are you feeling" for instance "if you enjoy a particular scene that others might think is [bad]" or "misinterpret the emotion."

Emotion Provisioning: Implicit vs. Explicit

A lot of the feedback focused on whether people would favor providing emotional feedback implicitly or explicitly. Participants had mixed views. On one hand, participants clearly liked to stay in control of what would be conveyed (P3: "I would like to stay in control of what I give away"), on the other hand, participants also stated that they think they would probably not share emotions unless this happened in an automated way. P5: "Feedback should be given implicitly." He mentioned that he is lazy and finds it hard to talk about his feelings. He also added "I would never write, 'Oh, hey sweetheart, I feel ...' [...] But when I can engage my girlfriend with it, wonderful." Similarly, P3 emphasized that he also would not share such information in case he would need to do this explicitly. He said that "[it] would have been really great if somebody else was made aware of that I saw something bad". He mentioned that he would have had a hard time to formulate his emotions. He added that "when the system does it, it would be much easier." When asking P7 in which cases he would like to share his emotion implicitly he answered "[...] if I am busy [...] or if I am focused on something."

Application Areas

Participants had a number of ideas on further applications of emotion sharing with our approach. P6 would like to apply the concept to *video calls* to enhance the experience. P5 said that he would like to share emotions he had during *sports* activities. Participants suggested to use an emotional connection at *work* or in *lectures* to communicate cases in which they were overloaded or not being challenged enough (P5, P6, P7, P8). P5 and P6 could imagine emotions as a *complementary communication channel* between friends to implicitly share when they were bored. P7 mentioned that emotions could not only be transmitted to a remote person, but it could also used for *self-reflecting* his own emotion. He said "one might benefit from knowing more about oneself." In line with this comment, P8 added that she would find it helpful to get to reflect: "I often tend to be unfocused and am not aware of that. But the system could help me to get my focus back."

Finally, participants saw potential of the approach in cases where two people do not speak the same language or one person is disabled (deaf and mute) (P4). P6 mentioned he could imagine a number of places where this would be annoying: "it needs to be context aware. [...] I would not use it in a car."

DESIGN RECOMMENDATIONS

We focused on testing a prototype and understanding how people would share and perceive emotions in an immersive way through embodied emotional feedback. We discuss the implications of our findings on creating embodied emotional feedback systems and provide design recommendations.

Implicit and explicit sharing

Sensed emotions could be implicitly or explicitly shared. Explicit sharing allows senders to control when and what she/he shares. This induces effort and interrupts the sender. Several participants stated that they would only share if the process was automated with low effort (P3) and that they otherwise find it hard to talk about emotions explicitly (P5). Implicit sharing does not involve the sender and is seamless.

Design Recommendation: Depending on the situation, senders should have the possibility to decide between implicit and explicit sharing of the emotional state.

Providing Senders Control over What to Share

We found that there are situations in which the sender would like to stay in control as to when to share and which affective state should be shared (P3, P5 and P7). As mentioned before, senders would like to share positive emotions more then negative ones with certain recipients.

Design Recommendation: Senders should be provided the opportunity to specify which emotion to share with whom. For example by preselecting groups of emotions that are sent to a specific group of receivers. The time and context should be selectable, as mentioned by P5, emotions during a sport event would be shared more than emotions of a private moment.

Emotion Granularity and Information Overload

Some emotions are felt momentarily whereas others persist longer. For example excitement in a roller-coaster is a short experience compared to the bad mood after a separation in a relationship. Additionally, emotions are not categorical, they can be strong or weak on the arousal/valence scale [55]. In an everyday life system for affective communication, the frequency, timing, and granularity of transmitted information is relevant. It is probably annoying to continuously be made aware of a person's affective state, as mentioned by P6. Thus, embodied feedback could be constrained to strong affective states or changes, or be guarded by contextual factors.

Design Recommendation: Embodied emotional feedback systems need to consider the granularity of emotional changes. The thresholds of emotional responses triggering embodied feedback need to be defined to transmit *important* emotions. Users should have ultimate control of the amount and intensity of emotions transferred and received so as to balance immersion, consider context, and avoid information overload. For example, the output can vary between visual or tactile feedback to a full actuated posture or gesture.

Considering the Context of the Recipient

Affective information is privacy sensitive. There may be situations where the receiver is not alone and hence information on the affective state of the sender should not be disclosed. At the same time, in certain situations sharing emotions might be inappropriate or even dangerous (e.g., while driving).

Design Recommendation: Before providing embodied feedback, the receiver's context should be considered. As personal and environmental sensors allow information on a user's location, activity and people in the vicinity to be obtained, feedback should not be provided in situations where people maybe put at risk as well as in situations where private information may not be disclosed.

Future work could look at how to cope with such situations. Strategies include not delivering the information at all or postponing it. Yet, mechanisms are required that notify the sender about this, in particular in cases where an immediate response is expected. In addition, senders could be provided the opportunity to'force' the emotion to be transmitted in certain situations, for example, as others are present.

FUTURE WORK

The presented studies investigated unidirectional communication of affective information. In a real application, bidirectional exchange of emotions would be necessary. This would close the feedback loop. An important question for future work is how this feedback loop influences the emotional state of the connected persons: Will received sadness result in sadness in the recipient, which when played back will lead to a downwards spiral? Will received amusement cheer a sad person up? Another question is how and when the affective channel should be escalated to other forms of communication such as text or voice communication. Will the exchanged affective information be a "ticket to talk" – a reason to start a conversation around the causes of the other person's emotion? These questions require long-term studies with couples and more practical sensing and output technologies.

We presented an interpreted embodied emotional output through ASL gestures. The question is whether the sensory input necessarily needs to be classified into affective states. It is also conceivable to just replay the sender's bodily state with the recipient: For example, if an EMG sensor detects muscle tension, that muscle tension could be played back on the recipient using EMS without the need for interpretation on the system's side. Interpretation could be completely left to the recipient. Participants of Study I remarked that the body's expression of emotion and the recipient's interpretation differ among individuals. The gestures that partners usually perform given a certain emotion could be transmitted.

CONCLUSION

This work focuses on fundamental aspects of communicating emotions between two people remotely. Emotions are sensed with an EEG system, classified as amused, angry, sad, or neutral, sent and played back using EMS to actuate the recipient's body. The presented studies showed that EMS actuation may lead to an embodiment of emotional states, contributing to an intuitive understanding, immersion, and empathy.

Two different sets of playback movements have been investigated. The output is based on natural movements related to emotions and emotion-related sign language gestures (ASL). The ASL gesture set was shown to be more intuitive than gestures selected from the literature. One reason could be that we only considered gestures and body posture, but not facial expressions. Facial expressions play a crucial role in the judgment of emotion [21]. Open questions include how to determine opportune moments of sending embodied emotional feedback, how bidirectional feedback influences the states of the partners, and how and when the emotional feedback channel should be escalated to other forms of communication.

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