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Design of a Wearable Device for Reading Positive Expressions from Facial EMG Signals

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Abstract—In this paper we present the design of a wearable device that reads positive facial expressions using physiological signals. We first analyze facial morphology in 3 dimensions and facial electromyographic signals on different facial locations and show that we can detect electromyographic signals with high amplitude on areas of low facial mobility on the side of the face, which are correlated to ones obtained from electrodes on traditional surface electromyographic capturing positions on top of facial muscles on the front of the face. We use a Multi-attribute Decision-making method to find adequate electrode positions on the side of face to capture these signals. Based on this analysis, we design and implement an ergonomic wearable device with high reliability. Because the signals are recorded distally, the proposed device uses Independent Component Analysis and an Artificial Neural Network to analyze them and achieve a high facial expression recognition rate on the side of the face. The recognized emotional facial expressions through the wearable interface device can be recorded during therapeutic interventions and for long-term facial expression recognition to quantify and infer the user's affective state in order to support medical professionals.

Index Terms—Electromyography, Face and gesture recognition, pattern recognition, wearable interface

1 INTRODUCTION

In recent years, there has been an increased interest in detecting and supporting human physical and psychological wellbeing. This has led to the rise of the field of positive psychology which "focuses on well-being, happiness, flow, personal strengths, wisdom, creativity, imagination and characteristics of positive groups and institutions" [1] and aims to analyze how "individuals and groups thrive and how increasing the wellbeing of one will have a positive effect on the other." [1].

Diener et al. proposed that wellbeing could be defined as high life satisfaction and frequent positive affect [2]. Further, Ryan and Deci describe two distinct theories of psychological wellbeing, hedonism and eudaimonism [3]. Hedonism considers that wellbeing consists of pleasure or happiness while eudaimonism maintains that well-being consists of fulfilling or realizing one's true nature, and more long-term positivity, happiness and wellbeing.

There has been a growing interest in the area of Affective Computing, the study and development of systems and devices that can recognize, interpret, process, and simulate human affective information [4]. This has lead to improvement in affect aware and happiness elicitation Human-Computer Interaction (HCI) technologies [4], [5] and other real-time innovative technologies to assess the benefits of striving for greater happiness [4], [6]. These technologies support users achieving higher levels of wellbeing and it has been proposed that support of wellbeing should be included in the design of technology in order to use data collected via sensors to assist in building tools to help users [7].

Thus, an automatic, objective measure of wellbeing could be used to support therapists, patients, engineers and doctors in order to improve therapeutic activities and devices, but both hedonic and edaimonic wellbeing can be difficult to quantify directly and objectively. However a potential source of information can be the experiences of pleasure expressed though facial expressions, which can be used to infer a person's emotions and give insights into their internal state and happiness.

Facial expressions are an important means of non-verbal communication between humans that play a significant role in social information exchange. Both voluntary and involuntary facial expressions give information about the character of the person, their mood and the emotions they are feeling [8], [9]. The ability to recognize emotions from a facial expression is innate to humans and is present possible as early as from birth [10]. Research in psychology has shown strong evidence for universal characteristic facial expressions for anger, fear, enjoyment, sadness and disgust [11].

In particular, we are investigating the accurate and robust recognition of positive expressions during therapeutic activities, rehabilitation and daily life situations. Smiling can express joy, affection and humor as well as putting others at ease and frowning can convey anger or disapproval. However, it is still difficult to measure facial expressions for long periods

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of time in real environments such as the locations for therapeutic activities.

In the past, several approaches have attempted to recognize emotional facial expressions. Human coders can identify facial expressions by dividing them into their components using tools such as the Facial Action Coding System [12]. However, this approach is very subjective because it depends exclusively on the impression of the human coder and might be influenced by the coder's own emotions, habituation and context leading to the possibility of different coders (or groups of coders) coding differently [13], [14].

A number of approaches to automatic facial expression recognition use video and photographic cameras to capture the face. Several computer vision algorithms are used to identify the facial expression [15]–[20]. These methods have a limitation in the fact that they require a camera directed towards the user's face and little or no occlusion. Also they usually require a fixed view, either the frontal view (usually $<20^\circ$ rotation [15]–[17]) or a side view ([21], [22]). They also require a good resolution and do not perform well under extreme lighting conditions [23]. All this prevents the subject from free movement.

Another possible approach towards automatic facial expression recognition is the wearable approach. Wearable devices allow the subject to have high mobility and broaden the spectrum of environments the facial expression recognition can be performed in. An example of this is the use of displacement sensors attached to the facial skin [24] or a small camera oriented towards the user's face [18]. However, previously developed wearable sensors are placed on the front of the face and can be covering the face, which is undesirable from the point of view of human interaction.

The body's physiological signals have also been used for facial expression recognition using electromyography (EMG) [4]. The EMG signals have been captured by placing electrodes directly over the facial muscles on the front of the face in order to achieve the strongest possible signal and minimize noise [25]–[30]. Electrodes have been placed on the *zygomaticus major* muscle for smiling recognition and on the *corrugator supercilii* muscle, which is activated while frowning [25]. Placing the electrodes on the front of the face has the drawback that the electrodes and the apparatus and tape used obscure the expression giving an unnatural look. Additionally, they have their own weight and stiffness, which disturbs the user's facial movements and could be constantly felt, constantly reminding users of the electrode's presence, which is an undesirable trait in an interface [28]. Further, the front of the face is a highly mobile area and electrodes become easily dislodged or moved.

EMG signals are electrical signals that propagate to and from neighboring muscles [25]. Therefore, it can be assumed that EMG signals form the front of the face would propagate to surrounding areas. Thus, we considered placing electrodes away from the front of the face. Previous approaches have used large numbers of electrodes to classify facial expression from the head using EMG and electro encephalogram (EEG) [31], however, accuracy decreases dramatically when using fewer electrodes. For the everyday use by able bodied users as well as by persons with disabilities a large number of electrodes is not desired and a more efficient approach using fewer electrodes is necessary. Work has also been done in the past to find optimal electrode positions on the forehead [32], however this area is in the front of the face and sensors obscure the expression.

Hashimoto et al. [33] has analyzed the facial displacement on top of facial muscles using video and the corresponding EMG signal magnitude, however, an analysis considering the 3-dimensional facial displacement of areas of the front and side of the face is necessary for good distal electrode position selection.

In this paper we present the use of a systematic methodology to find appropriate electrode locations on the side of the face for facial expression recognition and the design of a wearable device that can be used to record emotional facial expressions accurately for long periods of time. This device can be used to quantify the user's facial expressions and infer their affective state and can function in multiple environments, allowing the subject full mobility. The device can be worn during therapeutic interventions as well as during activities of daily life in order to help design therapeutic activities and devices, Human-Computer Interactions, and give feedback to patients.

In Section 2 we first present an analysis of facial morphology using both the facial perpendicular displacement, and the displacement of points on the skin surface using 3-dimensional photography and tracking. Then, the propagation of facial EMG signals, using amplitude and correlation analysis, is examined. Using Multi-attribute Decision-making methods, we find adequate unobtrusive and ergonomic electrode positions on the side of the face that have an adequate signal and can be used to recognize the subject's facial expressions. In Section 3, we show that using independent component analysis (ICA) and an artificial neural network (ANN) a good classification of facial expressions can be achieved from the side of the face. In Section 4, we show how we designed a wearable interface device that uses electrodes placed on the locations selected in Section 2 that can recognize facial expressions from distal EMG signals with high accuracy as well as being ergonomic. In Section 5 we show a discussion of results and possible applications. In section 6 we conclude and present future work.

2 Electrode Position Selection

In order to design of a wearable interface device that uses EMG signals to recognize facial expressions

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from the face, first a good position for electrodes is investigated.

2.1 Multi-attribute Decision-making

The problem of finding adequate electrode positions on the face is a problem with multiple objectives because, for an adequate interface design, two objectives should be taken into account: signal quality and user comfort.

Gemperle et al. [35] proposed dynamic wearability constraints that could be uses as guidelines in the early stages of design. They define dynamic wearability as the interaction between the human body and the wearable object, taking into account the body in motion. They propose that design for dynamic wearability requires unobtrusive placement, where the device contacts with the body in areas that are relatively the same size across adults, have low movement ant flexibility and a relatively large surface area. Devices should also have a comfortable stable fit and the device's edges should be rounded. Further, they specify that to achieve freedom of movement, devices should be designed around more active areas or by creating spaces the body can move into. Gemperle et al. also recommended to minimize thickness as much as possible so the device could stay within the body's intimate space and that weight should be minimal to hinder the body's movement. They also state that aesthetics should be considered to increase user comfort and acceptance of the device. Even though Gemperle et al. investigated devices worn on the body, we apply their general guidelines to a device worn on the head and face.

Taking the guidelines into account, in the electrode position analysis problem there exists no dominant solution because the recommended locations for EMG signal acquisition on the face [25] are also the most mobile areas on the front of the face.

Based on previous work [36], we introduce the use of a systematic methodology for making decisions with multiple objectives proposed by Keenery and Raiffa [37] to find the best electrode positions to use for the interface device. The electrode positions are chosen from a pool of possible electrode positions, while taking into account the conflicting requirements.

First, in order to find an adequate electrode position, attributers that can be used to quantify the objectives are selected. For quantifying the signal quality, the amplitude of the measured signal gives a measure of the signal strength, which we define as our first attribute for analysis. Additionally, by measuring the correlation of the measured signal with the signal captured directly on top of the muscle, we obtain an additional measure of signal quality, which we define as the second attribute of interest.

We try to maximize user comfort taking into account the principles of ergonomics which is the discipline that analyzes the interactions of humans and other elements of a systems in order to optimize human well being and overall system performance [38]. Therefore we consider two attributes of facial morphology by measuring the facial displacement, both volumetric and of the facial surface.

The attributes, their requirements and their calculation method were summarized in Table 1.

In order to evaluate the selected attributes, we use the additive value function shown in equation 1.

$$v(x_1, x_2, x_3, ..., x_n) = \sum_{i=1}^{n} \lambda_i v_i(x_i) \quad (1)$$

where $v(x_1, x_2, x_3, ..., x_n)$ is the score that should be maximized in decision-making, λ_i is a scaling constant so that $\sum_{i=1}^{n} \lambda_i = 1$ and $\lambda_i > 0$ in order to assign weight to attributes according to the perceived subjective importance. x_i is the value of the attribute recorded experimentally and v_i is the component value function that transforms the attribute into a normalized value. Taking into account the requirements in Table 1, the electrode position selection problem is described as follows:

$$\begin{aligned} v(Z_e, L_e, A_e, C_e) &= \lambda_1 v_{Z_e}(Z_e) + \lambda_2 v_{L_e}(L_e) + \\ &\quad \lambda_3 v_{A_e}(A_e) + \lambda_4 v_{C_e}(C_e) \quad (2) \end{aligned}$$

where $v(Z_e, L_e, A_e, C_e)$ is the score of electrode pair e for signal detection in the electrode's effective area, E_e; Z_e represents the total volumetric perpendicular displacement in E_e; L_e is the linear displacement of the marker point in the center of E_e; A_e is the mean amplitude of the EMG signal for sustained expressions and C_e is the correlation of the root mean squares of the EMG signal of e with the electrode pair on the muscle responsible for the expression. The parameters Z_e and L_e quantify facial displacement and A_e and C_e are used to quantify the signal quality.

Fig. 1 shows the facial areas that were selected as possible electrode positions for a wearable interface. In order to give as fair assessment of the attributes x_i, the scores for each criteria Z_e, L_e, A_e and C_e, are normalized to values in the range [0, 1]. All values are normalized between the maximum and minimum value of each attribute, and are scaled linearly and proportionally between these two values by their corresponding component value function v_i.

For the attributes Z_e and L_e, the smallest displacement is preferred, for the attributes A_e and C_e, the biggest value is preferred. In the current implementation we use $\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = 1/4$ to give all attributes equal weight in decision-making.

2.2 Facial Morphology

In order to find adequate electrode locations on the face it is necessary to analyze the facial morphology

TABLE 1
Requirements for adequate electrode position selection.

Parameter	Feature Requirements	Evaluation Method
Volumetric displacement (Z_e)	Minimal to avoid obtrusiveness and electrode movement	3D displacement of the points in the electrode's effective area E_e: $Z_e = \sum_{x \epsilon E_e} \lvert \chi_f - \chi_n \rvert$, where $f = \{smile, frown\}$, $n = \{neutral\}$
Surface displacement (L_e)	Minimal to avoid obtrusiveness and electrode movement	Linear displacement of the center of the electrode's effective area E_e: $L_e = \lvert x_f - x_n \rvert$, where x is the center of E_e where $f = \{smile, frown\}$, $n = \{neutral\}$
Main rectified amplitude of EMG (A_e)	High in order to detect a viable signal	$A_e = Mean(\lvert Amplitude_{Se} \rvert)$
Correlation between signals (C_e)	High in order to guaranty expression detection	Correlation of the root mean square of the distal signals with the signals from the top of the muscles: $C_e = Correlation(RMS_{Sm}, RMS_{Sd})$, where $m = \{1, 2\}$, $d = \{1, 2, 3, 4, 5, 6\}$

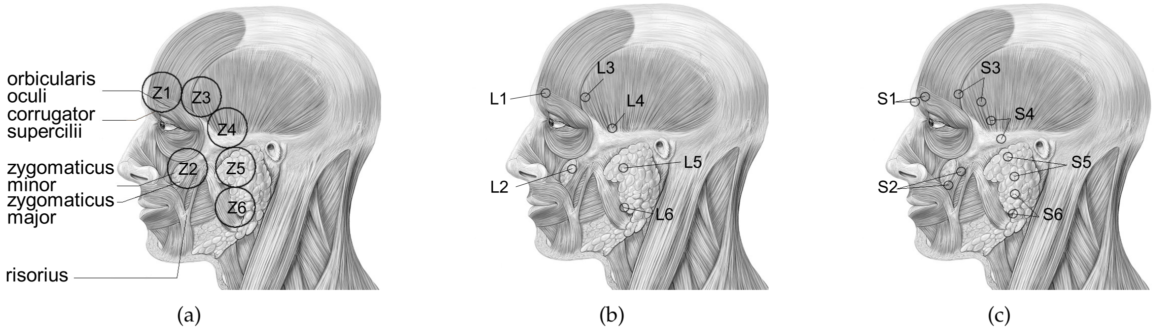

Fig. 1. (a) Selected facial muscles and facial zones for volumetric displacement analysis. (b) Marker locations for surface displacement analysis (c) Electrode pairs' positions (Original image of facial muscles by Lynch and Jaffe [34])

and quantify facial displacement as well as analyze the facial EMG signals. Electrodes for EMG detection should move as little as possible to obtain a stable signal and to avoid movement artifacts. We analyze two kinds modalities of expressions, sustained expressions and dynamic expressions where the subjects alternated facial expressions with neutral faces. The modality depended on the data we intended to analyze in order to design a wearable device that could be used in real world situations. To analyze the amplitude of the signal and the recognition rate of the system, and for the 3-dimensional photography, a posed fixed expression was the most unambiguous choice. In order to evaluate signal amplitude correlation and for the analysis of surface displacement, a dynamic expression was captured by letting subjects make expressions naturally in their own time, to approximate the use of the device in real world situations.

Facial displacement has been measured in the past using vector flows [39] and Active Appearance Models [40]. In this work we use 3D photography and 3D tracking of markers for simplicity to obtain high accuracy in 3 dimensions.

2.2.1 Volumetric Displacement Analysis

First, we analyzed the volumetric displacement of the facial skin in 3 dimensions.

Subjects

12 healthy subjects (mean age 26.08, ranging from 23 to 32 years old; 8 male and 4 female; Japan:5, Usbekistan:1, Brazil:1, Israel:1, China:1, Indonesia:1, France:1, Venezuela:1).

Materials

3-dimensional pictures were taken using an image-capturing device (Danae 100, NEC Engineering, Ltd.).

Task

The subjects were asked to perform the voluntary expressions: *smiling*, *frowning*, and *neutral face* and sustain them for a few seconds while the picture was taken.

Analysis

The data was analyzed using 3D-Rugle software and the perpendicular 3-dimensional facial displacement using the normal vector between each facial expressions and the neutral face was obtained. 6 areas of

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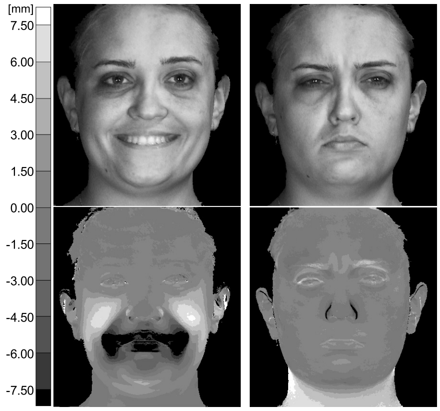
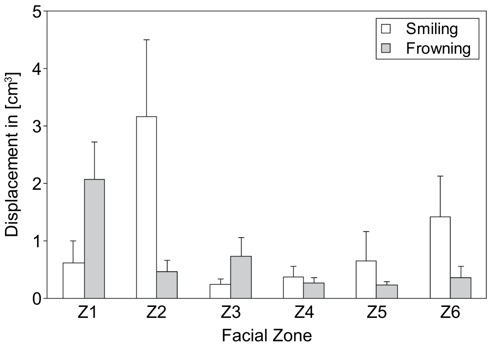
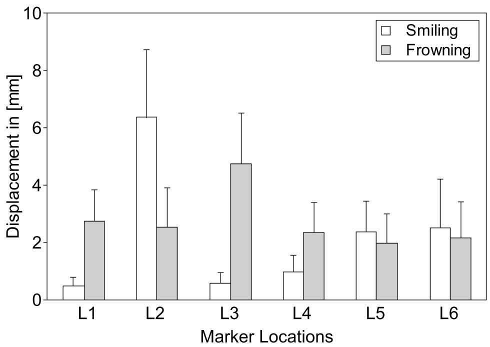


(a) Smiling (b) Frowning

Fig. 2. Perpendicular 3-dimensional facial displacement between emotional facial expressions and the neutral face.



(a) Volume



(b) Surface

Fig. 3. Facial displacement. The error bar represents standard deviation.

interest were selected (circular with a diameter of 3.5 cm) on the 3-dimenional captured image, following the natural features of the face (nose, eyes, eyebrows, ...), 2 on top of the facial muscles *zygomaticus major* and *corrugator supercilii* respectively and 4 on the side of the face, as seen in Fig. 1a. The displaced volume was subsequently calculated.

Results

Figure 2 shows the perpendicular 3-dimensional facial displacement between the emotional facial expressions and the neutral face in one subject.

The average amount of displacement can be seen in Figure 3a. The cheeks are particularly displaced while smiling (Zone Z2, 3.17 cm^3, SD=1.28) while the forehead shows the biggest displacement while frowning (Zone Z1, 2.08 cm^3, SD=0.62). Zones Z3, Z4, Z5 and Z6 show almost no displacement during emotional facial expressions while zones Z1 and Z2 on the muscles show high displacement.

2.2.2 Surface Displacement Tracking

Another method to quantify the facial displacement is to analyze surface displacement by tracking markers attached to the face in 3 dimensions.

Subjects

10 healthy subjects (mean age 26.7, ranging from 23 to 33 years old; 2 female, 8 male; Japan:4, Venezuela:1, France:1, Sri-Lanaka:1, Israel:1, Netherlands:1, China:1).

Materials

A 3-dimensional facial motion capture device (Natural Point Optitrack) with 7 infrared cameras, one of which was used for video recording, was set up and the points recorded using Arena. 6 markers were attached to the face in the pattern shown in Fig. 1b, at the center of the areas used for the volumetric displacement analysis. 4 stationary protruding markers (standard for the Optitrack) were used as reference on the forehead.

Task

The subjects were asked to alternate voluntary facial expressions with the neutral face in a continuous manner. First, they alternated between *smiling* and *neutral face* and then between *frowning* and *neutral face*. The recording time was 30s for each expression.

Analysis

Using the point vectors corresponding to 3 of the forehead markers, a local coordinate system was created and a transformation matrix constructed to transfer the coordinates of markers both in rotation and displacement to the local coordinates in order to exclude head movements from facial expression displacement. Using the synchronized video feed, 3 instances of each expression for each subject were visually selected from the data stream for further analysis. Each selected segment began with the neutral face, continued with the emotional facial expression and ended with the return to the neutral face. For each segment, the maximum 3-dimensional displacement, the difference between the points during the neutral face and the points of maximum displacement during facial expressions at each marker location, was calculated.

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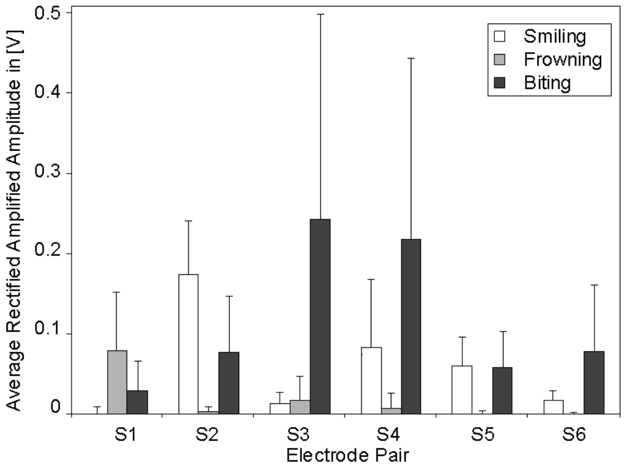

Fig. 4. Rectified mean amplitude on different electrode locations for *smiling*, *frowning* and *biting*. The error bar represents standard deviation.

Results

The average amount of displacement for each expression can be seen in Fig. 3b. During smiling, the maximum displacement was on marker L2 on the cheek area (6.38 mm SD=2.36) and during frowning the maximum displacement was in marker L1 (2.75 mm SD=1.11) and L3 (4.76 mm SD=1.77) in the brow area. Markers L1, L3 and L4 showed little displacement during smiling and markers L2, L4, L5 and L6 showed little displacement during frowning.

2.3 Electromyographic Signals

In order to find a suitable electrode location for distal analysis, we analyzed the EMG signal amplitude and correlation during emotional facial expressions away from the front of the face.

Subjects

10 healthy subjects (mean age 24.6 years, ranging from 22 to 29 years old; 5 male, 5 female; Japan:4, China:1, Israel:1, USA:1, Venezuela:1, Indonesia:1, Brazil:1).

Materials

6 differential electrode pairs were attached on the left side of the subject's face in the pattern seen in Fig. 1c, with electrode pairs in the center of the areas used for the Volumetric Displacement Analysis. The signals were recorded at 1kHz using custom-made 5 mm diameter differential electrode pairs, electrode Gel (Spectra 360), amplifiers (HEI EMG-AMP04, Harada Electronics Industry) and a data logger (EMG DDL-2A EMG, Harada Electronics Industry). The ground electrode was placed behind the ear.

2.3.1 Signal Amplitude

We recorded the EMG signals during sustained posed expressions in order to analyze the signal amplitude at different electrode positions, as well as the signal from the *masseter* muscle, used for moving the jaw. *biting* was not taken into account in previous sections and for the overall electrode position selection because the biting action was considered a more internal action with little effect on the skin on the side of the face. However, noise from biting must be addressed if the device intends to record signals from the side of the face.

Task

The subjects were asked to perform voluntary expressions and facial movements and sustain them. The expressions and movements were *neutral face*, *smiling*, *frowning* and *biting*. Four sets were taken of each expression, each set was of length τ=4s.

Analysis

The recorded data was analyzed using Matlab. The mean amplitude of the *neutral face* at each electrode location for each subject was subtracted from the mean amplitude of the emotional facial expressions in order to obtain the difference in amplitude from the baseline.

Results

Figure 4 shows the rectified mean amplitude difference between the facial expressions and the neutral face on different electrode locations. The highest signal amplitude while smiling was recorded at electrode position S2 on top of the *zygomaticus major* muscle, but it was also possible to detect the signal at distal electrode positions S3-S6. The signal could hardly be detected at electrode position S1. The highest signal amplitude while frowning could be detected at electrode position S1 on top of the *corrugator supercilii* muscle, but it also was possible to detect the signal at electrode positions S2-S4. However the signal could hardly be detected at electrode positions S5 and S6. Finally, the signal during biting was present at all electrode locations creating interference. It was especially notable at the distal electrode locations S3-S4 that lie on the side of the face.

2.3.2 Correlation

In accordance with previous works [25], the electrode locations that showed the highest signal amplitude during emotional facial expressions were S1 (*corrugator supercilii*) and S2 (*zygomaticus major*) during frowning and smiling respectively. We analyzed the correlation between these signals captured on top of the facial muscles and the distal signals on the side of the face during continuous expressions, capturing the change in the signal as the face changes from the neutral face to an emotional expression and back to the neutral face.

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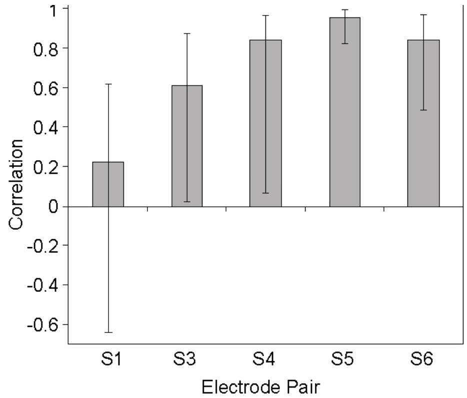
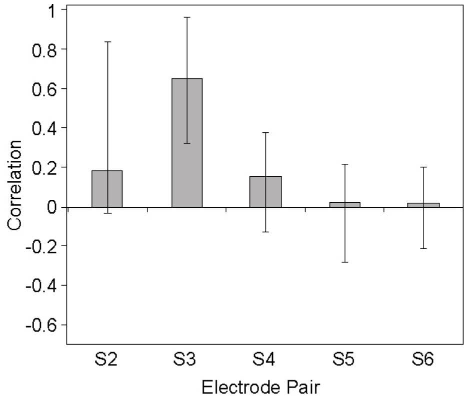


(a) Smiling (Correlation with S2)



(b) Frowning (Correlation with S1)

Fig. 5. Average correlation of signals for all subjects during continuous facial expressions. The error bar represents data range.

Task

The subjects were asked to alternate voluntary emotional expressions with the neutral face in a continuous manner. First, they alternated between *smiling* and *neutral face* and then between *frowning* and *neutral face*. Four sets were taken of each expression, each set was of length τ=20s.

Analysis

The recorded data was analyzed using Matlab. The correlation of the signal was calculated between the signals at different electrode positions and the signal of electrodes directly on top of the muscles, electrode pair 2 during smiling and electrode pair 1 during frowning respectively for each of the 4 recorded sets.

Results

Fig. 5 shows the correlation of the signal on different electrode locations with the signals captured on the electrodes directly on top of the muscles. Electrode pairs 2, 3 and 4 show correlation during frowning and electrode pairs 3-6 show correlation during smiling.

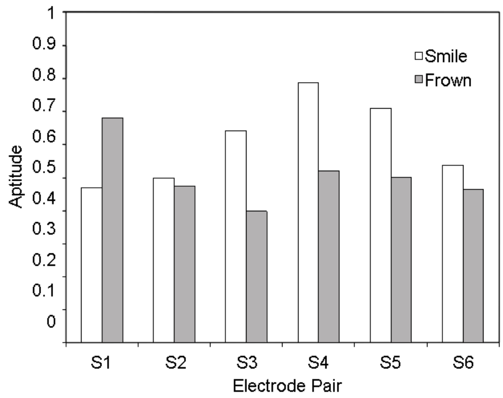


Fig. 6. Score of electrode positions for use in an interface device.

2.4 Electrode Position Evaluation

Using the Multiatribute Decision-making methodology described in Section 2.1, we calculate the score of each electrode position for facial expression recognition taking into account the requirements of both signal quality and ergonomics.

The values for each attribute were normalized to values in the range [0, 1] using the additive value function presented in Section 2.1, Equation 1. The score for each electrode position was calculated using Equation 2.

Fig. 6 shows the score of the different electrode locations for distal signal detection. For smiling, electrodes S4 and S5 show the greatest scores. Electrode position S1 showed the greatest score for frowning, however, electrode positions S4 and S5 also showed high scores for recognizing frowning.

3 Facial Expression Recognition

Using the distal electrode locations on the side of the face obtained from the analysis, we propose the use of distal EMG signals for facial expression recognition. Unlike the conventional way of recognition based on EMG [25], we do not identify the activity of each facial muscle. Instead we propose a pattern-based classification where facial expressions are regarded as a combination of the activity of all facial muscles. Because of the interference from the biting action and the overlapping of the distal signal from different muscle groups, computational methods must be applied to increase accuracy for distal detection.

3.1 Methodology

Independent Component Analysis (ICA) is used to separate statistically independent components from mixed signals by generating a demixing matrix using iterative maximization of negentrophy [41]. ICA has been used in the past to separate the signals that are a mix of sEMG and distal EMG on the arm [42], [43] and

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this leads to the assumption that the different muscle groups on the face could generate statistically independent signals and classification could be improved through ICA.

The signal is initially band-pass and notch filtered (5-350 Hz Bandpass and 50 Hz Notch) in order to reduce motion artifacts and electrical noise. Then, because of the mixed nature of the obtained distal signal, in order to overcome the interference from the biting action and obtain clearer signals for analysis, ICA [44] is used. The ICA in this implementation separates the maximum number of possible independent components possible, which equals the number of recorded signals. After the ICA, the signal is rectified by taking the absolute values of amplitude and then average filtered (100 ms window) [45]. Rectifying avoids values cancelling each other out when the averaging filter is applied. The averaging filter serves to exclude outliers and to increase accuracy because each value then represents a window of measurement.

Because the ICA is an iterative method that does not specify the order the independent components will appear in or their amplitude, an Artificial Neural Network (ANN) is used to recognize the signal pattern and classify the expression. ANNs have been used previously to classify EMG signal patterns [43], [46]. In the current implementation, the ANN is a two-layer feed-forward network, with sigmoid hidden and output neurons trained by back-propagation. 4 neurons were used in the hidden layer. The inputs of the ANN are the rectified, smoothed independent components and output is the classified expression.

3.2 Experiment

Taking into account the scores of different electrode locations, we attempted to identify facial expressions from distal signals from the left side of the face.

Subjects and Materials

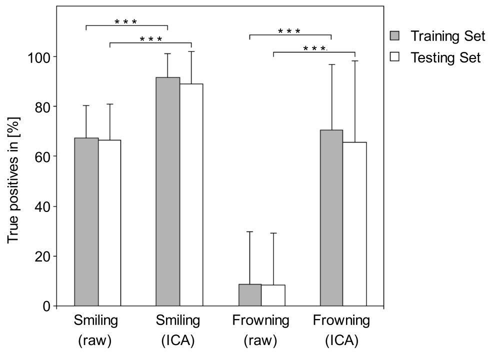
The subjects (5 male, 5 female) had an average age of 24.6 years, ranging from 22 to 29 years old; Japan:4, China:1, Israel:1, USA:1, Vneezuela:1, Indonesia:1, Brazil:1. The signals were recorded on electrode positions S3, S4 and S5 using the equipment and parameters described in Section 2.3.

Task

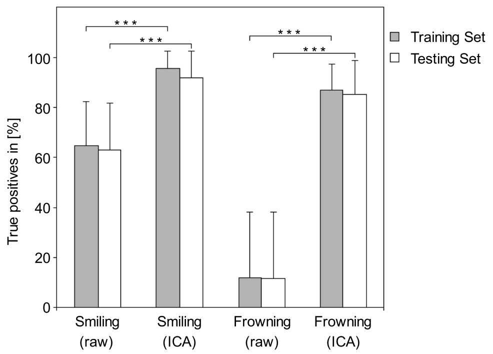
The subjects were asked to perform voluntary expressions and facial movements and sustain them. The expressions and movements were *neutral face*, *smiling*, *frowning*, *biting* and *simultaneous biting and smiling*. Four sets of each expression were recorded, each set was of length τ=4s.

Analysis

The recorded data was analyzed using Matlab. The smoothed and rectified amplitude values of the independent components were used to train an ANN



(a) 2 electrode pairs (S4 and S5)



(b) 3 electrode pairs (S3, S4 and S5)

Fig. 7. Average recognition of positive, negative and neutral affect by the ANN, for raw signals and signals after filtering and ICA from one side of the face. (***P<.001)

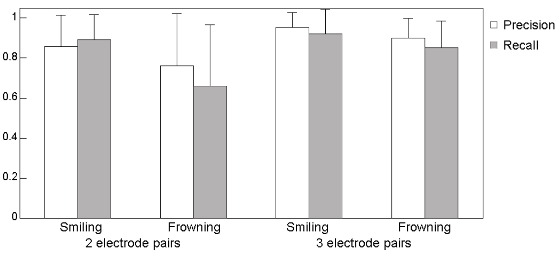


Fig. 8. Error Analysis of the output of the ANN in the testing set.

for each user. The training set consisted of three 4s long sets of each expression. The expressions *neutral*, *smiling*, *biting* , *frowning* and *simultaneous biting and smiling* were used to train the ANN to recognize between *smiling*, *frowning* and *neither*. *Smiling* and *simultaneous biting and smiling* formed the classification class *smiling*; *biting* and *neutral* the class *neither*. The system was calibrated for each subject. The mean true positives were calculated using leave-one-out cross-validation.

Results

Results can be seen in Fig. 7 and Fig. 8. The use of ICA significantly improved classification when compared

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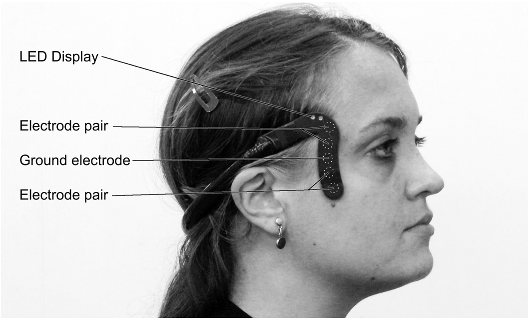

Fig. 9. Wearable device using 2 electrode pairs for facial expression recognition using distal EMG signals.

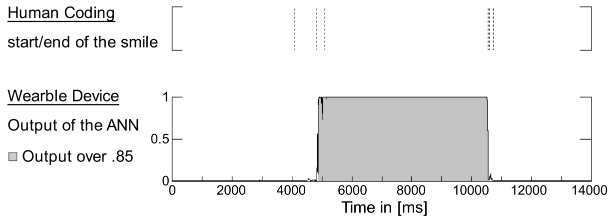

Fig. 10. Coding of a smile from video by human coders and from EMG by the wearable interface device during a spontaneous conversation.

with the raw signal (P<0.001) for both *smiling* and *frowning* in training and test sets. The statistical test used was a Friedman test using blocks of 4 repetitions for each user and 2 treatments: filtered ICA and non-treated raw signal. Further, the use of 3 electrode pairs offered significantly better classification results than using only 2 electrode pairs (P<0.01). Further, the number of false positives in the testing set is small and especially false positives where smiling is misclassified as frowning or vice-versa are less than 1% using ICA analysis and 3 electrode pairs.

4 Wearable Device

We concluded the first part of the design process and found adequate electrode positions on the side of the face using a systematic methodology. We analyzed different numbers of electrodes when attempting automatic facial expression classification, 2 pairs and 3 pairs from the left side of the face and obtained high correct classification rates. We consider that, because the scores for the selected electrode positions were higher for *smiling* than for *frowning*, we obtained a higher recognition rate for *smiling*.

3 electrode pairs on one side of the face offered higher classification rates, however, the size of the interface device would increase because of the added electrode pair to cover the chin. According to the requirements, user comfort could be prioritized and a smaller interface chosen using only 2 electrode pairs, which still offered good classification results. Because we are concentrating especially on smile recognition for quality of life (QoL) evaluation, 2 electrode pairs offer sufficiently good classification.

Taking into account the dynamic wearability guidelines [35], and our electrode position analysis, we built a prototype of the wearable device out of rigid plastic. It is held in place by a head-support that goes around the back of the head made of flexible metal and covered in fabric. The head support has a flexible point above the ear that can be bent in order to account for different head and face shapes, the part of the device against the face has rounded edges. The device uses custom-made 5mm diameter Ag/Cl differential electrode pairs, amplifiers (HEI EMG-AMP, Harada Electronics Industry). It uses electrode gel-tape (Harada Electronics Industry) between electrodes and skin. It weights 67g.

In the proposed device, the facial expression can be transmitted, recorded and displayed in the form of lit LEDs on the side of the face. A prototype of the wearable device can be seen in Fig. 9.

4.1 Comparison with human coders

We verified the use of the proposed interface device by comparing the smile recognition ability of the device with untrained human coders.

Video and bioelectrical signals of one subject(female, Japanese, 33 years old), who was not one of the coders, were recorded during a spontaneous natural conversation. The conversation took place between two women. Video was recorded in HD by a video camera on a tripod 2m in front of them. Signals from the right side of the face (two electrode pairs) were acquired and used for analysis using the proposed methodology. A clear smile with periods of neutral face before and after was selected from the video for further analysis by an untrained coder.

The human coders (one female, two male; mean age 27.33 SD=6.81; France:1, Japan:1, Siria:1) were given the instruction to identify the beginning and end of the smile. They watched the video frame on a 15in computer screen by frame and identified the beginning and end frames.

Results can be seen in Fig. 10. Output of the neural network higher than 0.85 is considered a smile. It can be seen that the interface and human coders recognize the smile in a similar manner.

The Kappa Coefficient is a measure of inter-rater agreement for categorical items that takes into account chance agreement [47]. We consider two categories, *smile* (output of the ANN is higher than the predetermined threshold 0.85) and *other expressions*. The Kappa Coefficient among human coders was in average 0.89. The Kappa coefficient between human coders and the recognition by the classifier was in average 0.95.

TABLE 2
Long-term continuous facial expression recognition precision and recall in [%]

Tested data	Smile		Frown		Other	
	Precision	Recall	Precision	Recall	Precision	Recall
Training set (0 min)	98.77	99.28	98.11	97.52	99.37	99.15
1st test set (60min)	98.77	90.01	98.05	97.76	90.94	99.14
2nd test set (120min)	98.73	97.47	95.20	97.50	97.47	97.54
3rd test set (180min)	98.69	88.64	92.22	97.64	89.41	95.88
4th test set (240min)	97.83	93.95	97.78	97.72	94.18	97.95

4.2 Long-term verification

In order to verify the long-term continuous facial expression recognition using the wearable device described in section 4.1, one adult subject, female, 31 years old, Venezuelan, wore the wearable device for an extended period of time. The subject was seated comfortably and watched a movie on a 13in screen, 50cm from the person. The accuracy of expression recognition was verified by recording the posed expressions *smiling*, *biting*, *biting and smiling*, *frowning* and *neutral face* every 60min. *biting* and *neutral face* were considered *other expressions* and *smiling* and *biting and smiling*, *smiling expressions*. A training set was created first at the beginning of the recording period. Then the testing sets were recorded at 60min, 120min, 160min and 210min while the movie was paused. Signals were transmitted wirelessly to a PC for recording using an EMG Telemeter (Harada Electronics Industry). Training and test segments were each 25s long (5s for each expression), each class was recorded once for each time segment.

The accuracy of the classification using the training set recorded at $t = 0$min can be seen in Table 2. The results show that the facial expression recognition is good even after prolonged recording.

5 Discussion

5.1 Wearable Device

A concern when using EMG signals is the possibility of artifacts. Because of the design of the wearable device, electrodes are held in place on the side of the face and are not affected by head or environmental movement. Additionally, bandpass filtering removes strong movement artifacts and those that come from other biosignals. Because we use a moving average filter, outliers are also smoothed out, removing potential sources of artifacts. The trained device is robust against mouth and jaw movement and smiling can be detected while talking, likewise talking does not usually cause false positives. The use of ICA allows for the separation of pertinent signals and robust classification through the ANN. Additionally it is of importance to note that the device performs poorly when trained on one person and testing the classifier on data from another [45], which might be due to differences in muscles size and location as well as shape and type of surrounding tissue and bone. This makes a person-independent training phase not feasible, however, the training phase has been shortened as much as possible, only 4s for each expression.

5.2 Application

The proposed device can be used in multiple situations to help recognize and improve the wellbeing of users and recognize their affective state. The advantages of using facial EMG lie in the fact that it is a continuous and quantitative measure of the facial expression with a high temporal resolution.

The developed device can be used to record facial expressions of subjects as they experience therapeutic interventions that require the subject have full mobility. For example, the device was used to record the positive facial expressions of children with autism spectrum disorders (ASD) as they experienced animal assisted activities [48]. Because children with ASD suffer difficulty expressing thoughts and emotions and interacting in social situations [49], therapy for them focuses on helping them improve their social and interpersonal behaviors [50]. An objective measure of their facial expressions using a wearable device in addition to the observations of medical examiners can be of benefit for the evaluation of the subject's wellbeing at the time of the therapy and the long-term evaluation of the intervention. It is important to note that the proposed wearable device does not aim to replace the medical observer, but rather to offer an additional objective measure of affect, as human coders can be influenced by their own emotions and expectations and different examiners can code the same intervention differently [13], [14]. The proposed device can be used to recognize the facial expressions of persons with ASD in multiple environments and therapeutic interventions.

Likewise, the device could be used to aid persons suffering from major depressive disorders and their physicians, as their affect-related shifts in expression in response to robust positive stimuli have been reported to differ according to whether they have current depressive symptomatology [51]. By using the proposed device, subjects could easily quantify their reactions. Further, medical examiners treating persons with depression often use self-reports of their affective state [52], [53], long-term continuous facial expression recognition using a wearable device could potentially be used to and obtain an additional measure of their affective state that can be helpful to medical examiners to quantify the subject's wellbeing and progress towards recovery.

Additionally, the device can be used to directly control devices, for example, a facial prosthesis for people with hemi-facial paralysis to support the rehabilitation by pulling on the facial skin [54]. The wearable device can be used to recognize smiling expressions from the healthy side of the face and use them as a voluntary control signal to the facial prosthesis. This type of prosthesis can be used to aid in rehabilitation interventions by medical professionals.

6 Conclusion and Future Work

Facial morphology is a fundamental factor when recognizing facial expressions from EMG signals. In this work, we systematically identified areas of low facial displacement that contained viable signals for classification that had both a high amplitude and good correlation with the signals detected on top of the facial muscles responsible for the emotional facial expressions using Mutliattribute Decision-making.

By manipulating the weight parameters $\lambda_{1,..,n}$, the attributes can be modified to prioritize signal strength, correlation, or displacement in the decision making. This can be useful for the design of interface devices for diverse groups, such as adults or children or for electrodes of different sizes.

By using ICA and ANN, we were able to read facial expressions from these distal EMG signals and classify *smiling*, *frowning* and *neither* with high accuracy. We use person-specific calibration of the proposed device to achieve the highest possible accuracy and to make the system robust against slight changes in electrode position from session to session, in order to inconvenience users as little as possible, training sets are only 4s for each expression.

The proposed device design was verified by evaluating continuous spontaneous expressions using the device and comparing the results to the facial expressions identified by human coders. Further, to verify that the device could be used for long-term facial expression recording, it was shown that over a 4 hour time frame there is little difference in the classification accuracy. For future work the device can be further compared with human perceptions of facial expressions for both trained and untrained coders in variable circumstances and the design of the device can be improved using qualitative user feedback.

The wearable device we developed can be used in various environments to objectively record facial expressions for long periods of time. It is less obtrusive to the user because it is away from the front of the face and uses a small number of electrodes. The wearable device can be used in rehabilitation and in smile training and long-term smile monitoring where the subject has full mobility. We believe that QoL and wellbeing can be quantified based on the facial expressions during activities of daily life over long periods of time without disturbing the user with the proposed interface.

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