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Facial Expression Recognition with sEMG Method

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***Abstract*—Facial expression recognition has broad application prospects in the fields of psychological study, nursing care, Human Computer Interaction as well as affective computing. The method with surface Electromyogram (sEMG), which is one of vital bio-signals, has its superiority in several aspects such as high temporal resolution and data processing efficiency over other methods. Researches regarding EMG signal to study emotional expression have started since the second half of last century. Meanwhile, studies on myoelectrical control systems focusing on the computation of bio-signal processing and data analysis have been blooming in the recent twenty years. To have a comprehensive view of utilizing facial sEMG method, a systematic review is presented in this paper for facial expression recognition from experiment design to measurement systems, and data analysis steps.**

***Keywords*— Facial expression recognition, sEMG, Human Computer Interaction.**

I. Introduction

Emotion recognition has been studied through various approaches utilizing a single or a combination of several biosignals such as Electroencephalogram (EEG), facial Electromyogram (EMG) and physiological signals (e.g. electrodermal activity, respiration rate and blood pressure) [1–4]. Facial expression, as an expressive aspect of emotion, can indicate a person's affective state and also the change of emotion state under stimulation [5]. Several approaches have been employed in facial expression recognition. Except for EMG method, other approaches are based on facial image or video analysis, by manual coding or image processing. Compared with image based method, EMG method has its superiority from multiple aspects, as discussed later.

Among the three mentioned facial action measurement methods, facial EMG has a relatively longer history because the most classical and widely applied Facial Action Coding System (FACS) [6] was developed by using fine-wire EMG to discover how the muscles work to change the appearance. However, the fine-wire EMG or needle EMG is invasive and requires medical training and certification [7]. In contrast, surface EMG (sEMG) method is non-invasive and inherits the high temporal resolution at the same time. The high temporal resolution attribute makes it a suitable method for measuring emotion, which may have rapid onset and short duration [8, 9]. Expressions recognition based on other methods need facial expressions to be overt, however, many emotional reactions are not accompanied by visible facial actions or real emotion is hided or masked by invoked display rules. In these circumstances, it is possible for sEMG to indicate muscle activity in subtle movements even in the absence of visible facial expressions [10–12]. Furthermore, facial sEMG may give a chance for consistent expression interpretation across cultures [13]. Advantages of facial sEMG method in facial expression recognition according to [8, 14–16] and existing devices are summarized as follows:

- High temporal resolution;
- Sensitivity to capture subtle facial muscle activities that are not even visible;
- Efficiency in data processing with significantly less time consumption than manual coding;
- Convenience for testing without head pose or area restriction, compared with difficulties in image or video analysis method;
- Easy to be embedded in wearable devices.

sEMG signal has been widely applied in kinesiological study [17], identifying neuromuscular diseases and myoeletrical control system [18]. Similarly, facial expression recognition with sEMG method has broad prospects in emotion study, nursing care, Human Computer Interaction (HCI) and affective computing. In this paper, we present a concise survey in existing research related to facial expression recognition using sEMG method across psychological, clinical and engineering areas and summarize from experiment design to measurement system and data analysis methods.

The rest of the paper is organized as follows: Section II introduces the attributes of facial sEMG signal and its measurement system; Section III presents involved facial muscles in expressions and methods to arouse some certain expressions; the details of electrode configuration and electrode placement are listed in Section IV; and in Section V, we summarize sEMG data processing and analysis procedures. At last, Section VI concludes the paper.

II. Expressions and facial muscles

According to Darwin and previous studies, six facial expressions of emotion are universal. They are happiness, sadness, anger, fear, surprise and disgust [19]. When studying expressions, a neutral expression is usually added as reference. Researchers in psychology also represent more finesorted emotions in an affective circumplex model with continuous dimensions of arousal and valence [20].

Facial expressions are mostly categorized into positive and negative in facial expressions recognition systems and research [4, 21–23]. Some research target on some specific facial muscle responses, for example, lateralized facial muscle response [24] and the difference between facial sEMG activity response

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to dynamic and static facial expressions [25]. While some HCI research includes several universal expressions [12, 26], or multiple given facial gestures such as smiling with one side and wrinkling the nose [27, 28]. Moreover, some negative expressions are studied in the context of human well-being and to improve usability in HCI. For example, pain and disgust expressions are studied in [29, 30]. P. Branco *et al.* [31] focus on the expressions when people confront with adverse-event in an HCI context. S. Amershi *et al* [32] aim at building intelligent system which adapt to varying student needs according to emotion patterns so as to improve their learning in educational games.

There are several approaches guiding subjects to make facial expressions. In some research, subjects are instructed to pose facial expressions, like smile, frown or make an angry face. While in some other cases, stimuli is used to cause evoked expressions. Emotion stimuli found across literature is from images, film fragments, sound to environmental changes. Regarding image stimuli, there are some databases available. Two of them are facial stimuli, where the images themselves are emotional expressions, Picture of Facial Affect [33] and the dataset of 3-dimensional facial expressions [34]. Comparatively, pictures from International Affective Picture System [35] are more widely used to elicit a range of emotions in experiments which are representative of daily experiences such as household furniture and extreme encounters such as a mutilated body.

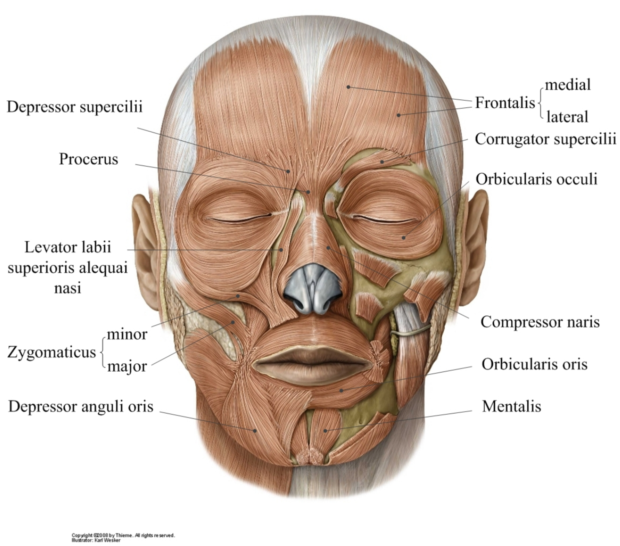

Fig. 1. Facial muscles [36]

The muscles responsible of facial expressions are thin, flat muscles that act either as sphincters of facial orifices, as dilators, or as elevators and depressors of the eyebrows and mouth, presented in Fig. 1. One consistent conclusion through studies is that sEMG activity over the brow (*corrugator supercilii*) and cheek (*zygomaticus major*) can differentiate positive and negative facial expressions. For the six universal emotional expressions, facial muscles involved in each of them can be inferred from corresponding action units from FACS [37], shown in Table I.

TABLE I
UNIVERSAL EMOTIONAL EXPRESSIONS

Expression	Action units	Facial muscles
Anger	4, 5 or 7, 22, 23, 24	Corrugator supercilii, Depressor supercilii, Levator palperbrae superioris, Orbicularis oculi, Orbicularis oris
Disgust	9, 10	Levator labii superioris, Levator labii superioris alaeque nasi
Fear	1, 2, 4, 5, 20	Frontalis, Depressor supercilii, Levator palperbrae superioris, Risorius
Happiness	6, 12	Orbicularis oculi, Zygomaticus major
Sadness	1, 15	Frontalis, Depressor anguli oris
Surprise	1, 2, 5, 25 or 26	Frontalis, Levator palperbrae superioris Depressor labii, Orbicularis oris

III. FACIAL sEMG AND ITS MEASUREMENT SYSTEM

Facial sEMG measures the electrical activity of motor units in the striated muscles of the face. The force and velocity of movement are controlled by the number of motor units and their rate of firing [17]. Fig. 2 shows filtered sEMG signal (with 50Hz notch filter) collected during a posed facial movement from cheek region where *zygomaticus major* is the main functioning muscle. It can be seen from the figure that the muscle activity starts at around 0.7 second and end at approximately 2.4 second. Due to the inherent physiology of an organ, a myoelectrical signal is considered as a non-stationary signal [18].

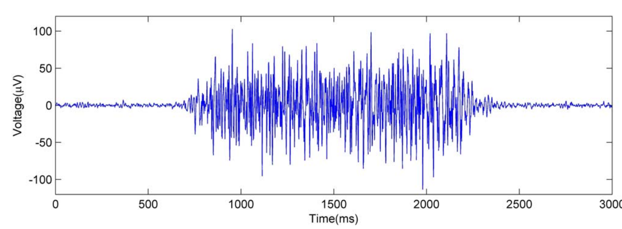

Fig. 2. Raw sEMG signal from cheek region (*zygomaticus major*)

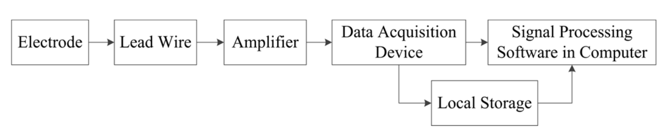

Fig. 3. sEMG measurement system

One sEMG measurement system can be composed of five parts: electrode, lead wire, amplifier, data acquisition device and signal processing software in computer (Fig. 3). When electrode and lead wire are two separate parts, the electrode is often to be disposable. Facial sEMG signal amplitude is in microvolt level and hence it should be amplified before being digitalized in the data acquisition device. In terms of sample rate, it is concluded that a low pass filter frequency between 400 and 500Hz [38] is appropriate for all facial muscles.

Some sEMG measurement devices are designed as small and portable with local data storage in SD card or transmitting data wirelessly after digitization between a transmitter and receiver, for example, [39] and [40]. This flexibility benefits the tested subjects from less posture and movement restrictions during sEMG recording, compared with image or video facial expression recognition system.

IV. Electrode Placement

Test points on face where electrodes are placed are selected in variety of ways through literature. However, there are mainly two trends: one is to put electrodes on dominant facial movement muscles which is applied in most psychological clinical studies and some HCI applications, while the other one is that when wearable HCI devices are designed, distal sEMG signals on the side of the face are captured for facial expression recognition [21, 41].

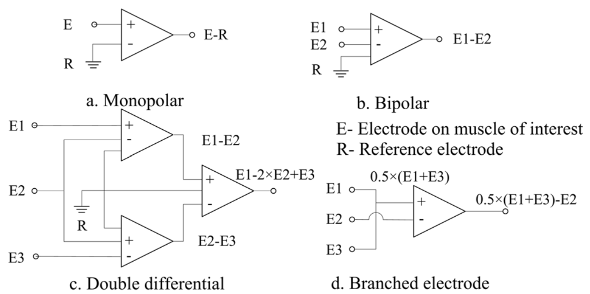

Fig. 4. sEMG electrode configuration

When selecting or designing a sEMG measurement system, several choices in electrode configuration can be found. Typically, there are three types with various names regarding electrode configuration. They are monopolar (i.e. unipolar or single-ended), bipolar (i.e. single differential) and double differential (i.e. spatial filter), illustrated in Fig. 4. Branched electrode in is a simplified approach to equal to double differential. Among all of those types, a pair of Ag/AgCl electrodes for bipolar configuration is the most popular one. Bipolar electrode configuration is believed to have a better selectivity on the muscle of interest because in theory crosstalk from adjacent muscles can be suppressed through differential inputs. Two electrodes are placed parallel to the course of the muscle fibers to reach maximize selectivity. There are two important parameters for bipolar electrodes, one is size and the other one is inter-electrode distance which is defined as center to center distance between two electrodes in one pair. Larger inter-electrode distance can enhance detectability of the reflex response but weaken muscle selectivity [42]. Although electrode size has no significant effects on facial sEMG signal amplitude [43], bulky electrodes can hinder facial movements or alter their behavior [44]. Besides, large inter-electrode distance caused by large electrode size results in decreasing measurement selectivity. Surface electrodes with contact area diameter less than 4-mm are suggested for facial sEMG recording in [2]. Fridlund and Cacioppo (1986) [44] give an instruction on bipolar electrode placement over target muscles covering most of the facial muscles.

Monopolar configuration has its own advantage being less obtrusiveness with equal number of channels or having a larger channel density with the same amount of electrodes [28]. Moreover, research in [28] and [45] showed that in spite of amplitude difference, signals obtained through monopolar and bipolar configurations have similar or even the same pattern.

Except for separate electrodes, theoretically, all kind of configurations can be implemented in electrode arrays by off-line mathematically substracting signals from monopolar recordings [46]. Electrode arrays have electrodes with small diameter and large density. Within electrode arrays, many complex spatial filters can be implemented to restrain crosstalk which has been verified in anterior tibial and triceps surae muscles [47]. Higher spatial resolution in sEMG, even to detect single motion unit activities can be achieved non-invasively [48]. However, electrode arrays have more potential as a diagnostic tool rather than an expression recognition tool due to its less flexibility and hindering facial movements to some extent [49, 50].

Before sEMG measurements, facial muscles and electrode configuration type need to be selected for a research proposition. Targeted skin area should be prepared such as shaving, cleaning and abrasion for stable electrode attachment and to reduce electrode-skin impedance [51]. Conductive gel and paste or pre-gelled electrodes can also be used for reducing electrode-skin impedance to achieve better sEMG recording. Double-sided tape can help electrode fixation to reduce movement artifact [52]. Electrode lead wires should be dealt properly to keep them from dragging electrodes or hinder the movement of facial muscles.

V. Data Analysis

The complete sEMG signal processing scheme is shown in Fig. 5. Noise due to electromagnetic interference and movement, is mixed with expected sEMG signal unavoidably. This makes it difficult to identity the sEMG signal [53]. The first step of pre-processing is to remove noise from the acquired signal. After that, the muscle activities represented by sEMG signal from each targeted facial muscle can be detected and separated from the muscle relaxed periods. Research on automated onset estimation in sEMG signal has been conducted and the performance of some algorithms are compared in [54]. Besides, the methods that detect muscle activity after a signal transformation are also proposed in [55] and [56]. The raw sEMG signal is not a proper input to a classifier because of low efficiency and thus features from one or several signal domains are extracted. Features are most commonly extracted from time domain, while features from frequency domain and time-frequency domain are also found from literature. In these cases, the transformation from time domain to other domains is also part of pre-processing before feature extraction. The normalization is applied in raw sEMG signal or features when amplitude comparison is needed between muscles, between individuals or between days within an individual [57]. Normalization is also required in developing generic classifiers owing to humans' rich variety [4]. The learning process in facial expression recognition is mostly supervised learning process, that is, certain expressions or categories are assigned for training. In this circumstance, features are reduced and then classified into the targeted categories.

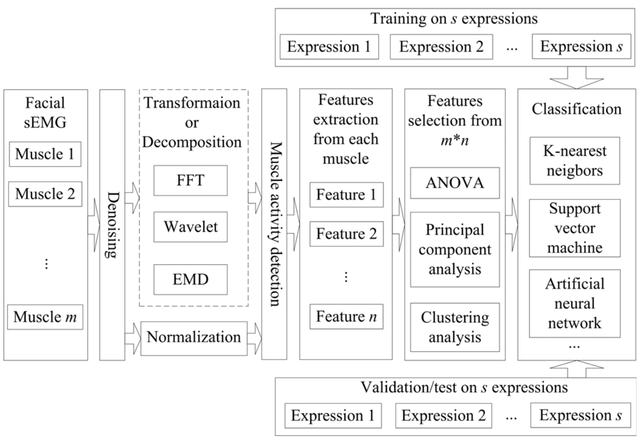

Fig. 5. sEMG signal processing scheme

A. De-noising

De-noising of acquired signal is done to increase the quality of sEMG signal by improving the signal-to-noise ratio while the distortion of sEMG signal must be kept as small as possible [58]. This is especially important for muscle diagnosis applications. Two main noise sources in facial sEMG signals are movement artifact and electromagnetic noise. The former one dominates low frequency part within 20Hz, while the latter one also called power line interference (PLI) is composed of 50Hz or 60Hz noise in frequency and its harmonics.

The power line interference origins from capacitive coupling to patient, electrodes, electrode leads and the amplifier. Solutions are proposed including shielded electrode leads [59] and shielded active electrodes [60], in which noises coupling to the lead wire are weaken significantly by shortening its length. As to differential amplifiers, it is customary to reach a common-mode rejection ratio of 100-110dB and thus this part of noise is slight.

Post-processing methods for de-noising movement artifact and PLI are generally the same. The methods include digital filters, adaptive noise canceler, and wavelet decomposition and reconstruction. Adaptive noise canceler reduce noise influence by subtracting estimated noise from the captured signal. It estimates noise with an adaptive algorithm which adjusts estimated noise through feedback from de-noised output. One level wavelet decomposition with discrete wavelet transform is equivalent to decomposing the signal into low half frequency coefficients and high half frequency coefficients in time domain. When the noise characteristics are known, the coefficients that represent noise separated by several level decomposition can be replaced by zeros before signal reconstruction. The performance comparison in movement artifacts and PLI de-noising among these three methods summarized in Table II [60, 61].

TABLE II
DE-NOSING METHODS COMPARISON

Method	Movement artifacts	Power line interference
Classic filters: FIR and IIR	Easy to set cutoff frequency;	FIR needs to be high order; IIR caused distortion near the cut-off frequencies.
Adaptive noise canceler	Unsuitable	Low order; Attenuate noises with different amplitudes.
Wavelet decomposition	Better performance than classic filters; Manual threshold setting.	Require more computational resources; Filter bandwidth relates to wavelet family, order and decomposition tree.

B. Muscle activity detection

Regarding automatic sEMG onset detection, G. Staude *et al*. [54] conclude that threshold-based methods are very popular due to their intuitive and easy implementation. This approach is well applied in the sEMG signal whose signal to noise ratio (SNR) is larger than 10dB. The test results show that signal conditioning of raw sEMG before detecting onset can substantially reduce the risk of false alarms. Signal conditioning consists of full wave rectified followed by low pass filtering to get the envelope. The threshold to detect muscle activity is usually set by

$$TH = mean + i * std$$

where $mean$ and std are the mean and the standard deviation of the background noise of sEMG, i is a preset value. The smooth incline of the low-passed signal will lead to increased variability of the estimated onset time. Comparatively, an adaptive pre-whitening filter is superior to a low pass filter. While it is found that statistical methods and method based on Teager-Kaiser energy operation always performed better, especially in poor quality signal, such as with a SNR of 8dB or lower [62].

C. Feature extraction and pattern recognition

An sEMG feature is a distinct characteristic of sEMG signal that can be described or observed quantitatively. Features serve as the inputs of a classifier in training and testing. Some common sEMG features are summarized in Table III. Features in are extracted from data points within joint or overlapped time windows. SSI and VAR in time domain can index energy and power information of the signal separately [63]. In sEMG based upper limb motion recognition research, features extracted after Fourier transformation, wavelet decomposition or Empirical Mode Decomposition (EMD) in classification have also been studied to improve the performance of classification (e.g. [64, 65]) while few related studies are found in sEMG based facial expression recognition. Wavelet analysis and EMG, as methods working for non-stationary signals also are applied in sEMG signal de-noising.

TABLE III
sEMG FEATURE LIST

Name	Abbr.and Mathematical function
Integrated sEMG	INT $= \sum_{i=1}^{N} \lvert x_i \rvert$
Mean absolute value	MAV $= \frac{1}{N} \sum_{i=1}^{N} \lvert x_i \rvert$
Modified mean absolute value[1]	MMAV $= \frac{1}{N} \sum_{i=1}^{N} w_i \lvert x_i \rvert$
Simple square integral	SSI $= \sum_{i=1}^{N} x_i^2$
Variance	VAR $= \frac{1}{N-1} \sum_{i=1}^{N} x_i^2$
Root mean square	RMS $= \sqrt{\frac{1}{N} \sum_{i=1}^{N} x_i^2}$
Waveform length	WL $= \sum_{i=1}^{N-1} \lvert x_{i+1} - x_i \rvert$
Difference absolute standard deviation value	DASDV $= \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (x_{i+1} - x_i)^2}$
Mean absolute value slope	MAVS$_k = MAV_{k+1} - MAV_k$
Zero crossing[3]	ZC $= \sum_{i=1}^{N-1} \lvert sgn(x_{i+1} \times x_i) \rvert \cap f(\lvert x_{i+1} - x_i \rvert)$
Slope sign change	SSC $= \sum_{i=2}^{N-1} f[(x_{i+1} - x_i) \times (x_i - x_{i-1})]$
Willison amplitude	WAMP $= \sum_{i=1}^{N-1} f(x_{i+1} - x_i)$
Myopulse percentage rate	$\frac{1}{N} \sum_{i=1}^{N} f(x_i)$
Median Frequency	$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j = \frac{1}{2} \sum_{j=1}^{M} P_j$
Standard deviation	SD$(\sigma) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \bar{x})^2}$
Histogram of sEMG	Amplitude statistics
Skewness$(x_1 ... x_N) = \frac{1}{N} \sum_{i=1}^{N} [\frac{x_i - \bar{x}}{\sigma}]^3$	
Kurtosis$(x_1 ... x_N) = \frac{1}{N} \sum_{i=1}^{N} [\frac{x_i - \bar{x}}{\sigma}]^4 - 3$	

Annotation: 1. w_i is weighted function

2. $f(x)=\begin{cases} 1, & \text{if } x \geqslant \text{threshold} \\ 0, & \text{otherwise} \end{cases}$ 3. sgn(x)= $\begin{cases} 1 & \text{if } x \leqslant 0 \\ 0 & \text{otherwise} \end{cases}$

Normalization is applied before or after feature extraction for diminishing the influence of interpersonal inter-day difference in sEMG signals and for boosting the performance of generic classifiers. Feature scaling and standard core are found in sEMG feature normalization [4, 63]. M. Halaki *et al*. [57] summarize that normalization of sEMG signals is usually performed by dividing the sEMG signals during a task by a reference sEMG value obtained from the same muscle. The most common reference is the value during a maximal voluntary isometric contraction (MVIC) from the same muscle. O'Dwyer *et al*. [66] propose a set of MIVC tests to produce maximum activation in several facial muscles need to be identified. The facial muscles in it includes levator labii superiori, zygomaticus major, orbicularis oris and thirteen other muscles. The isometric tests has facial movements such as unilateral snarl, broad laugh and puffout cheeks, mouth closed.

When *m* muscles or test points and *n* features are selected for classification, the total number of variables is $m \times n$, see in Fig. 5. High dimensional variables increase computation complexity, therefore features should be examined before taken as inputs to classifiers. Scatter plot is an intuitional method to reduce feature redundancy when testing several targeted expressions or facial movements. This method restricts to two and three input channels, that is, shown as a two-dimensional or three-dimensional scatter plot. For example, in [67], feature WL showed mussy distribution in three-dimensional feature space which explained the very low classifier recognition accuracy. Another method is statistical test, Analysis of Variance, which is a common method to find relevance between expressions and facial muscle sEMG features in psychophysiology studies. Principal components analysis is a data set dimension reduction method, which is also competent in filtering features.

Table IV shows some cases which vary from the selection of expressions, targeted muscles, features and classifiers.

VI. Discussion and Conclusions

For facial expression recognition, accuracy is one of the main concerns regarding expression classification. An accurate sEMG classification relies on both proper electrode placement and signal processing. Based on the existing research, placing electrodes on specific expression related facial muscles, has better resolution when differentiating multiple emotional expressions. Electrodes in smaller size and larger density can lead to a better selectivity in detecting activities of target muscles. However, obtrusiveness can be caused by electrodes in large amounts or densities, a balance needs to be found in between.

In addition to the study of emotional expressions, the arousal degree of each emotion is also worth of exploring, especially for negative emotions. It is not only necessary for further clinical diagnosis, but also because of having potentials in improving humanization in Human Computer Interaction. The calibration of emotional levels and the corresponding emotion stimuli are needed in this case. Well-designed questionnaire and manual coding method from recorded video may help with better understanding in emotional changes and comparing results in early research stages. In some other cases, when the categorization of expressions in a task is not clear, unsupervised learning needs to be implemented to find potential patterns.

The scope of sEMG features needs to be narrowed aiming at facial muscles and expressions. Some comparisons and studies have been carried out in facial expressions classification

TABLE IV
SOME EXAMPLES OF FACIAL EXPRESSION RECOGNITION WITH sEMG METHOD

Authors	Expressions	Facial muscles	Features and feature reduction	Classification method and results
E. Broek *et al* [4]	Neutral, mixed, positive, negative;	Frontalis, corrugator supercilii, zygomaticus major;	Mean, AD, SD, VAR, skewness and kurtosis; Reduction: repeated measures ANOVA	k-NN (k=8): netural 71.43%, positive 57.14%, mixed 64.29%, negative 52.38%; SVM:60.71%; ANN: 56.19%.
G. Gibert *et al* [12]	Anger, disgust, fear, happiness, sadness, surprise;	Frontalis, corrugator supercilii, orbicularis oculi, levator labii, zygomaticus major, masseter, depressor anguli oris;	Envelope of absolute values	Gaussian model classifier: 92.19%.
L. Ang *et al* [26]	Happy, angry, sad;	Corrugator supercilii, levator labii, masseter	Mean, SD, RMS, power density spectrum; Reduction: feature differentiation.	Minimum-distance classifier: 92.78.%
P. Branco *et al* [31]	Expressions when a person is facing different level of difficulties;	Frontalis, corrugator, zygomatic	Mean and SD of RMS (time window:30ms)	Paired t-test: in general, the proportion of tasks with muscle activity increases with the increase on the task difficulty.
M. Hamedi *et al* [41]	Neutral, smile, smile with right/left side, anger, rage, gesturing ”no” with mouth, open the mouth like saying ”a”;	Frontalis, right and left temporalis	RMS (time window:256ms)	FCM: 91.8%; SVM: 80.4%.
M. Hamedi *et al* [67]	Smile, smile with right/left side, saying ”a”, clenching the molar teeth, gesturing ”notch” by rasing eyebrows, frown, close both eyes, close right/left eye;	Frontalis, right and left temporalis	INT, MAV, MAVS, RMS, VAR and WL, respectively	Fuzzy C-Means: INT 87.5%, MAV 84.6%, MAVS 87.9%, VAR 35.7%, RMS 90.8%, WL 21.5%.

and hand gestures classification, but inconsistency is found from their conclusions. Further and comprehensive evaluation among features as well as classifiers in terms of effectiveness and computation efficiency are needed in facial expression recognition. The computation efficiency is especially crucial in wearable and wireless sEMG devices where computation and energy resources are both restrained.

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