A More Objective Quantification of Micro-Expression Intensity through Facial Electromyography

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ABSTRACT

Micro-expressions are facial expressions that individuals reveal when trying to hide their genuine emotions. It has potential applications in areas such as lie detection and national security. It is generally believed that micro-expressions have three essential characteristics: short duration, low intensity, and local asymmetry. Most previous studies have investigated micro-expressions based on the characteristic of short duration. To our knowledge, no empirical studies have been conducted on the low-intensity characteristic. In this paper, we use facial EMG for the first time to study the characteristic of low intensity for micro-expression. In our experiment, micro-expressions were elicited from subjects and simultaneously collected their facial EMG through the second-generation micro-expression elicitation paradigm. We collected and annotated 33 macro-expressions and 48 micro-expressions. By comparing the two indicators of EMG :(1) the percentage of apex value in maximum voluntary contraction (MVC%) and (2) the area under EMG signal curve (integrated EMG, iEMG), we found that the MVC% and iEMG of micro-expression were significantly smaller than that of macro-expression. The result demonstrates that the intensity of micro-expression is significantly smaller than that of macro-expression.

CCS CONCEPTS

• **Applied computing → Psychology**.

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KEYWORDS

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1 INTRODUCTION

Emotion is an autonomic response triggered by environmental stimuli involving complex internal autonomic nervous system activity and external bodily responses [1]. External signals generated by emotion, such as facial muscle activity, provide clues to what is happening inside. However, for various reasons, people are often unwilling to express their genuine emotions in social communication and even hide or disguise their emotions. By more accurately perceiving an individual's emotional state, we can better understand others' thoughts and make wiser judgments [2]. Hess and Kleck found that unrestrained or naturally occurring emotional expressions usually last a few seconds or more, while hidden emotions show only very rapid expressions, not even more than 1 s [3]. Later studies considered that micro-expressions are these external emotional signals accidentally "leaked" when individuals try to suppress or manage facial expressions [4].

Facial micro-expressions are generally defined as the brief, subtle and involuntary facial muscle movements that reflect the genuine emotion [5, 6]. Since the generation of micro-expressions is involuntary and uncontrollable, micro-expression analysis can be used in various essential applications, including clinical diagnosis, interrogation, interview, and lie detection [7]. For example, micro-expression can be used in the clinical field to understand patients' genuine emotions and provide better treatment strategies. Meantime, micro-expressions could serve as clues to capture the real feelings of interviewees in interview situations, which is helpful for further investigation. In addition, micro-expressions are often mentioned in the field of lie detection because they are considered an effective cue for lie and risk behavior detection [8].

Due to the potential application of micro-expression being so extensive and essential, the related research is increasing daily. However, micro-expressions have a concise duration and very low movement intensity, so detecting and recognizing micro-expressions has become challenging [9]. In manual labeling, micro-expressions are difficult to detect through the naked eye and the process is time-consuming and laborious. In addition, only partial facial muscle movements of typical facial expressions were found in micro-expressions, making labeling more difficult [10–12]. Therefore, sample size of manually annotated micro-expression database is very small. Currently, there are only eight published spontaneous ME databases, including CASME series [13–16], SMIC [17], 4DME [18], SAMM [19], and MMEW [20].

For the above-mentioned micro-expression databases, the duration is the most commonly used dividing criterion between micro-expression and macro-expressions. Ekman considered 200 ms is the upper limit of micro-expressions, i.e., the boundary between traditional facial expressions and micro-expressions [6]. However, there is no clear evidence of this demarcation. In addition to the classic 200 ms, there are other versions of the upper duration definition, including a quarter of a second [21], a third of a second [22], and half a second [11, 23]. Yan et al. explored the duration distribution of the leaked fast facial expression and gave the duration boundary of micro-expression, i.e., the lower limit and upper limit are about 170 ms and 500 ms, respectively [12]. The initial stage, the period from onset to the apex, is also considered a proper indicator to define micro-expression, with a lower limit of about 65 ms and an upper limit of about 260 ms. All of the above studies classified micro-expressions based on their duration. However, although low intensity is considered to be one of the characteristics for micro-expressions, there is no compelling empirical study to prove a significant difference between the intensity of micro-expression and macro-expression.

Currently, the popular labeling method is to label action units (AUs) according to the facial action coding system (FACS) proposed by Ekman et al. [24]. FACS is based on the objective observation of facial muscle movements. However, there is only one subjective classification standard for AU intensity coding. The AU intensity can be divided into five grades, represented by the letters A, B, C, D, and E. Besides, the annotation of facial expression usually requires FACS-certified experts. This subjective and unrepeatable intensity coding method add to the obstacles for AU coders. Objective intensity classification could lead to more reliable and reproducible AU labeling. In addition, relatively little attention has been paid to the measurement of intensity changes in computer science so far [25], with exceptions include [26–29]. Due to the limited number of databases with AU intensity labeling [30], it is difficult to measure AU intensity further.

Addressing the difficulties of the current study, we found that facial electromyography (EMG) may be an appropriate method, using the biomedical signal as an objective indicator for the intensity of micro-expressions. EMG signals with high temporal resolution allow real-time micro-expression detection. With advances in sensor technology, EMG can be recorded wirelessly, with a high signal-to-noise ratio, and thus hold the advantage of being less affected by the environmental factors (such as lighting). For instance, Perusquia-Hernandez et al. detected fast and subtle smiles using a high-precision wearable EMG device [31].

EMG measures the electrical activity generated during muscle contraction and is directly related to the movement produced by the muscle [32]. Specifically, striated muscles consist of groups of muscle fibers. EMG records the potential changes caused by action potential conduction along these muscle fibers. Starting with an article by Cacioppo, Petty, Losch, and Kim [33], who asserted that "EMG activity differentiates the validity and intensity of emotional responses," EMG has become a generally accepted indicator of various visual and emotional responses. Moreover, compared with self-reported measures, EMG is more effective and sensitive, making this approach particularly attractive [34–36]. Therefore, EMG is a very suitable method for studying the intensity of facial movements such as micro-expressions.

In this study, we investigate the intensity characteristic of micro-expression through facial EMG. In particular,

- First, we collected samples with maximum face resolution, allowing for more accurate video-based coding of micro-expressions.
- Second, To the best of our knowledge, we are the first to use an objective physiological indicator, EMG, to measure the intensity of micro-expressions.
- Finally, the experimental results demonstrate significant differences between micro-expressions and macro-expressions in terms of intensity.

2 METHOD

2.1 Participants

Six subjects (4 females; Mean (M) = 25.67 years, Standard Deviation (SD) = 3.3 years) were recruited for the experiment. The visual acuity of the recruited subjects was normal or corrected to normal. None of the subjects had a history of neurological, psychiatric, or other severe medical conditions that could have affected the results. Each subject was informed with detailed experiment instructions. In addition, each subject signed informed consent prior to the experiment and received a monetary reward at the end. Our study followed the Declaration of Helsinki and was approved by the Institutional Review Committee of the Institute of Psychology, Chinese Academy of Sciences.

2.2 Experimental settings

Our collection environment was a quiet and soundproof laboratory. Two LED lights with reflective umbrellas were installed to provide a stable and soft lighting environment. The subjects viewed the stimuli through the monitor with speakers and 2564×1440 pixels resolution in front of them. A Logitech C1000e camera, placed on the monitor, captures moving images of the entire front of the head at a resolution of 3840 × 2160 pixels and a frame rate of 30 FPS. In particular, the resolution of the face region is around 700 × 900 pixels. As listed in Table 1, among the published micro-expression databases, the SAMM database [19] and MMEW [20] have the highest face resolution, around 400 × 400 pixels. The resolution of the face images acquired in our experiments is four times higher than that of the SAMM data, allowing us to code facial expressions more accurately.

Table 1: Approximate value of facial area resolution for commonly-used spontaneous micro-expression databases.

Database	Resolution	Database	Resolution
CASME [13]	150 × 190	SMIC [17]	190 × 230
CASME II [14]	280 × 340	CAS(ME)^2 [15]	200 × 340
SAMM [19]	400 × 400	MMEW [20]	400 × 400
CAS(ME)^3 [16]	250 × 300	4DME [18]	160 × 200

In the process of inducing micro-expressions through emotional video stimuli, facial EMG signals and face videos of the subject were recorded simultaneously. The digital tube display was placed behind the subjects, as shown in Fig. 1, and used as synchronizing EMG and video signals.

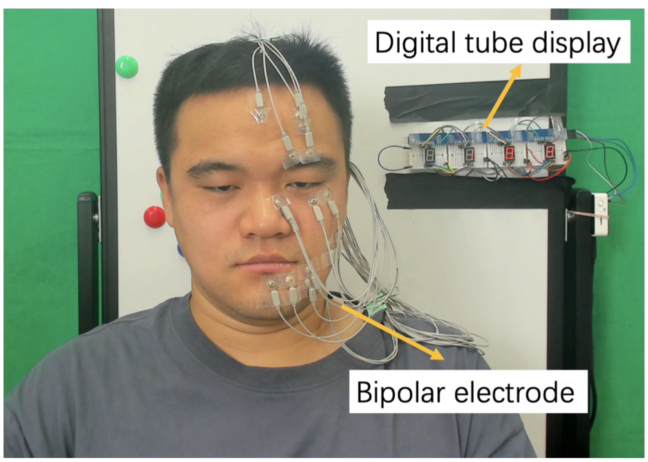

Figure 1: Data acquisition setting. Subjects were recorded on video while watching emotional stimuli. EMG signals were captured through electrodes attached to the subject's face, and a digital tube display on a whiteboard helped the coder synchronize the frames in the recorded video with the EMG signals. This Example image is selected from recorded videos with the subject's consent.

Particularly, as shown in Fig. 2, to avoid the interference of utility power on signal transmission, we utilized a wireless transmission method. Specifically, the collected EMG signals were transmitted to the computer recording the data through a wireless router, with a frequency band near 2.4 GHz, using the TCP/IP protocol. TCP was a connection-oriented, reliable, byte-stream-based communication protocol. Once a connection is established, data can be transmitted multiple times. the EMG signal, on average, the value on the digital tube display increments by one when two EMG signal packets were received. In particular, the sampling frequency of EMG recording equipment was 1 kHz, i.e., 1000 sampling points per second, each packet contains 38 sampling points, so approximately 26 packets were received per second. Therefore, digital tube display counts increased by 13 per second.

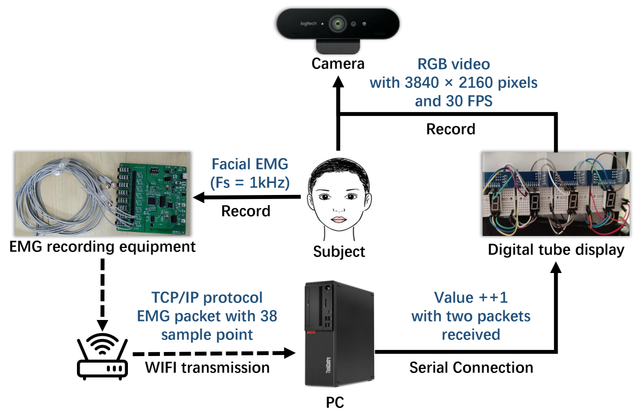

Figure 2: Equipment layout based on data collection and transmission.

Concerning the EMG acquisition equipment, we utilized the bipolar electrode. Specifically, it was set up with two electrodes, one at the forward input and one at the backward input of the differential amplifier, positioned close to the muscle tissue to be measured, as shown in Fig. 3. The bipolar electrode measured the potential difference between the two electrodes. And the electrical signal generated in the distant muscle was attenuated by the difference. Therefore, the bipolar configuration was less sensitive to interference and crosstalk compared with the monopolar electrode. Seven muscles of the face were selected for measurement. As illustrated in Fig. 3, they are frontalis, corrugator supercilii, orbicularis oculi, levator labii superioris alaeque nasi, zygomaticus, orbicularis oris, and depressor anguli oris. Dopson et al. proposed that the left facial region expresses emotions more strongly than the right facial region [37]. Hence, facial EMG was measured only on the left half of the face in our study. Meantime, the right side of the face was not taped with electrodes, allowing the coder to observe the subjects' facial expressions.

2.3 Procedure

The procedure of the experiment is shown in Fig. 4. In the preparation stage, we explained the experiment's specific procedures and the EMG equipment's safety to the subjects. Then, after confirming the subjects' agreement on the experiment operation and the video recording, the subjects were required to sign the informed consent.

In part A, the subjects were required to watch and learn seven different facial muscle movements corresponding to seven EMG acquisition channels. Then, they were asked to perform each movement three times at maximum amplitude. This step was to capture

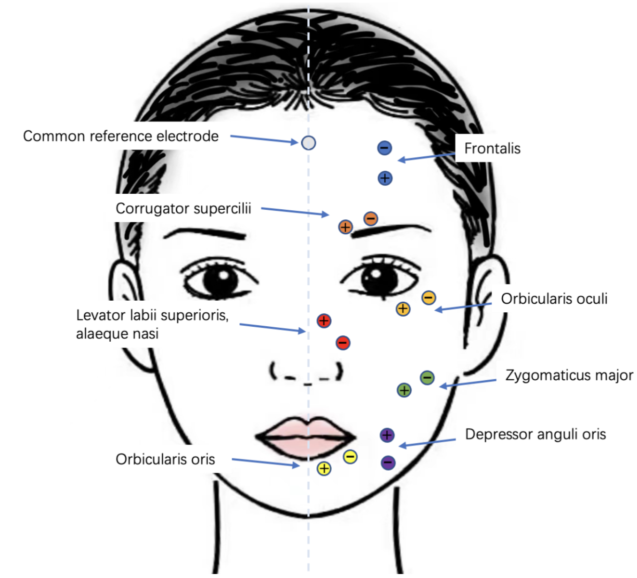

Figure 3: Electrode position distribution for facial EMG signal acquisition based on seven facial muscles.

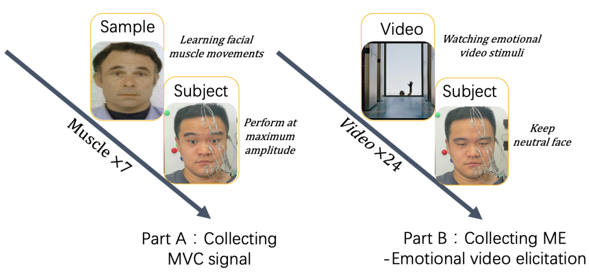

Figure 4: The experimental procedure consists of two parts, A and B. Part A collected the MVC of each muscle, and part B used video stimuli to evoke expressions.

the maximal voluntary contraction (MVC) of each subject across seven muscles as the baseline for further analysis.

In part B, subjects were asked to watch 24 emotional video stimuli. There were six categories of emotions in total, with the same number of video stimuli for each category (i.e., four segments per emotion category), and each video stimuli ranges from 30 seconds to 2 minutes. Video stimuli were presented in a random order but balanced to minimize the sequential presentation of videos with the same emotional category. In the experiment, subjects were expected to keep expressionless while watching the video stimuli. This requirement was to induce the micro-expressions that occur when a person tries to hide his or her genuine expression. The method we used belongs to the second generation of the micro-expression elicitation paradigm [16], which is used in most micro-expression databases. Before the experiment, subjects were told their facial expressions would be recorded on the camera. They would be paid more money if they did an excellent job hiding their facial expressions. This configuration is to increase the subjects' motivation for the experiment.

2.4 EMG signal pre-processing

The raw EMG signal was pre-processed before the meaningful interpretation of the EMG data, because the raw EMG signals usually carry a lot of noise. In our experiment, the EMG signal pre-processing involves removing DC offset, denoise, full-wave rectification, and finally linear envelope, as shown in Fig. 5. All of the processes are implemented on the MATLAB platform.

(1) **Removing DC offset**: The DC component is the mean value of the signals. The EMG signal removing DC offset E_d is obtained by subtracting the mean value from the raw EMG signal E_r (Fig. 5. B).

$$E_d = E_r - \text{mean}(E_r) \tag{1}$$

(2) **Denoise**: The predominant frequency range of facial EMG signals E_d is 20-500 Hz [38]. Therefore, we applied a 2nd-order band-pass Butterworth filter (BF_{bp}) from roughly 20 Hz to 450Hz to minimize noise within the EMG signals (Fig. 5. C).

$$E_b = \text{BF}_{bp}(E_d, 2, [Wn_1, Wn_2]) \tag{2}$$

where Wn_1 and Wn_2 represent the lower and the higher cutoff frequencies, respectively. $Wn_1 = 20 \times 2/1000$, $Wn_2 = 450 \times 2/1000$.

(3) **Full-wave rectification**: The true baseline of EMG is zero, and the EMG signal fluctuates around the baseline. Thus, the full-wave rectification of the EMG signal is required before signal analysis [39]. Specifically, The EMG signal E_b was rectified by absolute value to achieve full-wave rectification of the EMG signals (Fig. 5. D).

$$E_f = \text{abs}(E_b) \tag{3}$$

(4) **Linear envelope**: This process on the EMG signals E_f is to obtain a more intuitive data representation, and hence to facilitate researchers to compare and analyze the amplitude and wavelength of the EMG signals. The linear envelope of the EMG signals E_l is implemented through a low-pass filter. In particular, the filter is a 2nd-order Butterworth filter (BF_{lp}) with a low-pass cutoff frequency of 6Hz (Fig. 5. E).

$$E_l = \text{BF}_{\text{lp}}(E_f, 2, Wn) \tag{4}$$

where Wn is the normalized cutoff frequency, $Wn = 6 \times 2/1000$, $[B, A]$ denotes the coefficients of the Butterworth filter.

All the following data analysis is based on the envelop EMG signal E_l.

2.5 Data analysis based on EMG indicators

To correlate facial expressions with facial EMG signals, this study first coded facial expressions on frame-level based on the FACS. Then, we searched for the apparent amplitude of the EMG signal in the time interval corresponding to the onset frame and offset frame of expression.

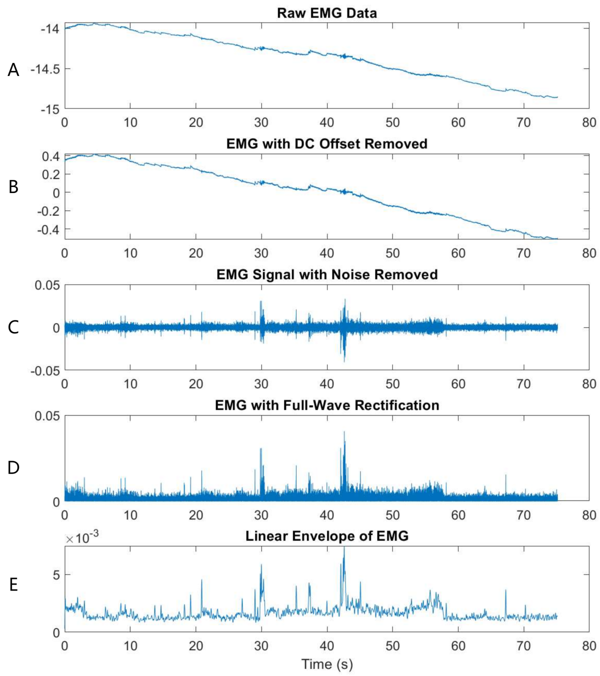

Figure 5: Four steps of EMG signal pre-processing: removing DC offset, denoise, full-wave rectification, and linear envelope.

2.5.1 *Video coding.* In the first step of data analysis, a trained coder coded the facial expressions of the collected videos. During the coding process, the coder need to label all the emotion-meaningful expressions, recording the onset, apex, and offset frame. Then, based on the definition of micro-expression duration [6], we classified facial expressions into micro-expressions and macro-expressions. Therefore, the expressions whose duration was less than 500 ms were classified as micro-expression and the other expressions as macro-expression.

2.5.2 *Detection of expression-related EMG signal intervals.* In the second step of the data analysis, we matched facial expressions to EMG signals through the numbers on the digital tube display. The aim was to find the corresponding EMG signal interval when the subject's expression appeared. In particular, if the time of expression appearance was consistent with the change points of the EMG signal, the EMG signal in this expression period would be considered the facial EMG signal at the time of expression appearance. The example of the correspondence is illustrated in Fig. 6.

We used two indicators, MVC%, and iEMG, for statistical analysis of EMG corresponding to facial expressions.

- **MVC%**: For each muscle EMG signal of each subject, the apex amplitude of the facial expression EMG signal was divided by the maximum voluntary contraction (MVC) of the corresponding muscle to obtain the amplitude ratio of that expression action to the muscle MVC. This ratio is denoted as MVC%.

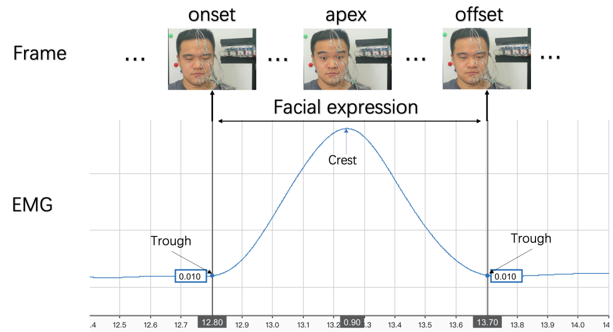

Figure 6: EMG signal extraction based on the frame-based annotation of facial expression.

- **iEMG**: The integrated electromyographic (iEMG) is the mathematical integration of the absolute value of the EMG signal during the facial expression. In other words, iEMG is the area under the curve of the EMG signal, which can be understood as the sum of the absolute values of the EMG amplitude.

3 RESULT

We labeled 98 facial expressions, 17 of which were deleted due to the lack of corresponding EMG signals. This may be because the electrodes cover only seven muscles on the left side of the face and there are uncaptured facial movements in the remaining facial regions. In sum, 48 micro-expressions and 33 macro-expressions were used for statistical analysis. Specifically, as shown in Fig. 6, the EMG signal of each expression is extracted between the trough before the EMG crest and the trough after the EMG crest. The statistical analysis is conducted on two indicators of the EMG signal for each expression: MVC% and iEMG, as listed in Table. 2.

Table 2: The numerical distribution of the two indexes of micro-expression and macro-expression. N represents the number of facial expressions, Mean represents average value, and SD represents standard deviation.

	Expression type	N	Mean	SD
MVC%	Macro-expression	33	27.14	23.83
	Micro-expression	48	10.87	12.82
iEMG	Macro-expression	33	20.73	25.44
	Micro-expression	48	2.54	2.24

The data showed that the average maximum amplitude of micro-expression EMG signals was only about 10% of MVC. Because the amplitude of the EMG signal represents the intensity of movement of micro-expressions, that is, the muscle movement at peak for micro-expressions was only about 10% of the MVC of muscles. Thus, we can conclude that the EMG amplitude of micro-expressions is tiny. In other words, the intensity of micro-expressions is low.

The MVC% and iEMG between micro-expressions and macro-expressions were compared respectively, as shown in Fig. 7. The independent sample T-test results at a 95% confidence level showed that the MVC% of micro-expressions (M = 10.87, SD = 12.82) was

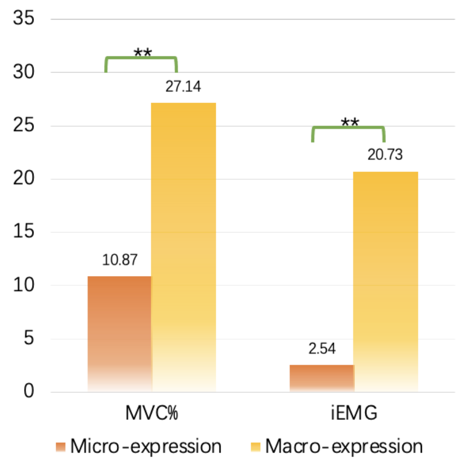

Figure 7: Statistical analysis on MVC% and iEMG between micro-expressions and macro-expressions. The EMG data of micro-expressions and macro-expressions were significantly different by independent sample T-test with a 95% confidence interval. ** in the figure represents p<0.01.

significantly smaller than the MVC% of macro-expressions ($M = 27.14$, $SD = 23.83$), $t(79) = 3.581$, $p < 0.01$, $d = 0.81$. Meantime, the iEMG of micro-expressions ($M = 2.54$, $SD = 2.24$) was also significantly smaller than the iEMG of macro-expressions ($M = 20.73$, $SD = 25.44$), $t(79) = 4.095$, $p < 0.01$, $d = 0.97$. This result indicates that the EMG amplitude of micro-expression is significantly smaller than that of macro-expression.

4 DISCUSSION

This experiment aims to study one of the characteristics of micro-expressions by an objective physiological indicators (EMG): low intensity.

MVC% is the ratio between apex value of the facial EMG signal and the corresponding muscle's MVC. It represents a comparable relative proportion. This relative ratio allows cross-muscle and cross-subject comparisons while avoiding individual differences between EMG signals and enabling direct comparison of the seven muscle activities. Experimental results showed that the intensity for micro-expressions was only up to 10% of the MVC. Hence, it can be intuitively proved that the movement intensity of micro-expressions is subtle.

Besides, we could conduct some explanations and reasoning for the muscle movement at peak for macro-expression in this experiment, only reaching the MVC of 27%. One possibility is that the macro-expression passively induced by the emotional video stimuli is tiny. The intensity of macro-expression movements that are actively generated during socialization may be greater than those that are passively induced. Another explanation is that our experiment requires subjects to suppress their emotions and keep their faces expressionless. Although the intensity of macro-expressions in our experiments was smaller than common, the comparison between MVC% of micro-expression and macro-expression showed significant differences. As a result, by comparing the relative values of EMG amplitude of micro-expressions and macro-expressions, we can conclude that the intensity of micro-expressions is lower than that of macro-expressions.

In addition, the iEMG indicator involves an additional temporal dimension compared with MVC% and measures the sum of time and space of the electrical activity of muscle fibers (sarcoid depolarization) in the recording electrode region. Our results show that the iEMG of micro-expressions is significantly smaller than that of macro-expressions. Due to the addition of the time dimension, micro-expression characteristics, i.e., short duration and low intensity, can be preliminarily verified. However, because of the small sample size, we could not provide the continuous-time distribution of micro-expressions. The demonstration that the duration of micro-expressions is in a specific time range from 0 to 500 ms could be expected by increasing the sample size.

However, it is relatively difficult to give the specific intensity boundary between micro-expression and macro-expression through EMG signals for the following three reasons. The first two are individual differences in muscle movement among subjects and the differences in EMG signals between muscle channels. These two problems can be primarily overcome by the relative value indicators selected in our study. Nevertheless, the third and most crucial point is that the EMG signals collected by different researchers are also different in many aspects, such as recording and preprocessing methods. Furthermore, unlike the time scale for the duration, there is no uniform metric or unit for intensity. In the subsequent research, we will continue exploring the specific intensity range of micro-expressions reflected by MVC% by increasing the expressions' sample size. In this way, other researchers could use the MVC% interval as one of the partitioning criteria to classify micro-expressions in the future. Specifically, by determining whether the ratio of the EMG peak to each expression' MVC is in the MVC% interval of macro-expression or micro-expression, the expression type could be classified in terms of the EMG signal.

5 CONCLUSION

In response to the absence of empirical studies on the intensity of micro-expressions, our study proves the low intensity of micro-expressions through facial EMG. In particular, we utilized EMG signals to describe the essential characteristics of micro-expressions. Significant differences were found by comparing the EMG amplitudes of micro-expressions and macro-expressions. Thus, EMG signal can be used as one of the distinguishing criteria between micro-expressions and macro-expressions. Meanwhile, the amplitude of the EMG signal of micro-expression is minor, indicating that the electrical activity of muscle movement during the generation of micro-expression is smaller than that of macro-expression. Furthermore, the generation process of micro-expressions can be further explored through the facial muscle activities. Our study is a preliminary attempt to explore the physiological mechanism of micro-expressions. Future research could also combine EMG and electroencephalogram signals to determine how micro-expressions are transmitted from the cortex to the facial nerve.

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