Recognizing Face Micro Expressions Through Surveys

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ABSTRACT: Recognition of facial expressions is essential in a variety of applications including marketing, commerce, security systems, and psychotherapy. It is rather simple to identify a macro expression, which is a direct representation of an "emotion." Micro-expressions, which are more precise signs of a stream of thought or even subtle, passive, or involuntary thoughts, play an equally important role as macro-expressions. Because micro-expressions have significantly shorter time periods than macro-expressions and can only be classified using a bigger classification scale, detecting them is a far more difficult research question. This article provides a thorough examination of all available micro expression recognition methods. By breaking down the pipeline into its basic elements—namely, face detection, pre-processing, facial feature detection and extraction, datasets, and classification—we are able to assess the overall design of the micro-expression recognition system. In addition to highlighting the models and contemporary trends used in their design, we also analyse the function of these elements. By contrasting their effectiveness, we also present a thorough examination of micro expression recognition systems. We also talk about the new deep learning features that may soon take the role of manually created characteristics for recognizing face micro expressions. This survey was created with an emphasis on the methodology utilized, databases used, performance related accuracy of recognition, and comparison of these to identify efficiency gaps, potential future study areas, and research potentials. Through this survey, we hope to investigate this issue and create a thorough, effective recognition system.

Keywords: Micro-expressions recognition. Feature detection. Feature extraction, Classification

1. Introduction

In daily life, emotions are quite noticeable and have a purpose. A considerable degree of ambiguity exists when attempting to decipher the emotion concealed inside a facial expression that is elicited in low-stakes or ordinary settings. Compared to low and normal stakes circumstances, high stakes events increase the likelihood of properly forecasting the feeling. Micro expressions are the starting point for expressing involuntary feelings and occur in high stakes scenarios. Micro expressions occur in a split second and are challenging to identify in the moment, especially when one has the necessary skills.

Macro-expressions are typically visible lasting between 3/4 and 2 seconds. Despite the wide variety of emotion categories, there are six universal expressions that can be used: anger, disgust, fear, happiness, sorrow, and surprise [14]. Depending on the type of expression, macro-expressions might cover a single or several areas of the face.

Micro expressions are defined as a recognizable pattern of the human face that is too fleeting to adequately portray an emotion. Micro expressions are very brief facial expressions that typically last between 1/25 and 1/5 of a second [22, 66]. In the course of the casual talks, they are readily forgotten.

A Micro-Expression Training Tool (METT) has been created by Ekman [15] to teach a human how to recognize and react to micro-expressions because they are hardly detectable to humans. Micro-expressions, on the other hand, are rarely falsifiable, and the main distinction between macro- and micro-expressions is the length of the expressions rather than their intensity [45]. Although specialists can currently identify and recognize micro expressions, their accuracy is currently only 47% [22]. Therefore, it would be ideal to have a system that enhances micro-expression analyses and aids in accurately and automatically identifying and categorizing a person's feelings.

There is a ton of study already done on automated macro facial expression recognition. For the six commonly used posed macro facial expressions, researchers have created several algorithms that have above 90% recognition accuracy [1, 14, 25]. A recent study in [25] suggests a revolutionary strategy that, when compared to the state-of-the-art methods already in use, yields superior results. Contrarily, due to a number of difficulties, micro-expressions have not yet received considerable research.

Lack of a standardized micro expression database is one of the difficulties most researchers have, making it challenging to collect dynamic facial features for an accurate micro expression identification system to be trained. The dynamics of the micro-expressions have not been the subject of any substantial research. Researchers can train a system based on the current macro facial expression databases by using the appearance information and disregarding the dynamic information because the appearance of the micro-expression closely resembles the six basic macro-expressions. The creation of reliable techniques that can handle the brief duration and low intensity of micro expressions is another difficulty.

The study of micro-expressions has a wide range of practical applications. The fact that micro expressions serve as an essential cue for lie detection is one of the main reasons for the intense interest in them. For instance, while a suspect is being questioned, a short micro expression on the face can indicate to the police that the suspect is being innocent. Additionally, it can help border security personnel see suspicious behaviour in people during routine security checks to look for potential threats. Micro expressions have been found to be particularly useful in the research of psychotherapy for interpreting patients' true emotions. Systems for recognizing micro expressions are occasionally employed in addition to other modules for user authentication [44]. Micro expressions can be utilized as recognition to reflect human reactions and feedback to commercials, products, services, and learning materials in many other industries, including marketing, distance learning, and many more.

This study was created with the goal of giving researchers a quick introduction to the most current advancements in this field by offering a thorough assessment of the available micro-expression detection methods and their results.

Five sections make up the remainder of the essay. The elements that influence the precision of micro expression recognition are highlighted in Section 2. The techniques for recognizing micro expressions are covered in Section 3. In Section 4, we go into further detail about the features and specifications of the current micro expression databases. A comparison of the recent studies carried out using various datasets is provided in Section 5. The obstacles, unresolved problems, and future directions in micro-expression recognition are all highlighted in Section 6.

2. Elements that affect how micro expressions are recognized

When people are attempting to hide their feelings, micro expression is hidden in the flow of expressions. Studies in [45, 66] have shown that some factors influence the ability to recognize micro expressions.

2.1 The Emotional setting

The experiments that have already been conducted used neutral terms both before and after the reaction. According to the research, micro-expressions may be present in both neutral and other facial expressions, including those of grief and happiness. The emotional regulation theory [66] states that longer prime presentations may have a stronger priming effect when used in the priming task. Additionally, emotional information is seen to affect attention [66]. The objectives of this study are to: 1) examine the impact of emotional context on micro expressions; 2) determine whether the impact of context was restricted to a certain material; and 3) examine the cause of the effect. Researchers' predictions on how the emotional context would affect micro-expression recognition will be confirmed by the data.

2.2 Duration of expression

The duration of an expression is a key distinction between a macro expression and a micro expression. The length of a micro expression has been estimated in a wide range of ways. As a result, there is still disagreement on the time frame for the length of a micro-expression. Even though the durational difference might not be particularly evident, it must be considered when using micro expressions.

The researchers ran two studies [45] asking the participants to identify the micro-expressions in the images that were presented to them in order to confirm the influence of time on micro-expressions recognition. In Experiment 1, participants watched expression images for 40, 120, 200, or 300 milliseconds. For Experiment 1, the researchers used the Brief Affect Recognition Test (BART).

The Micro Expression Training Tool (METT) paradigm, which was used in Experiment 2 to teach participants in the recognition of micro expressions, was presented to the participants. The results of the tests showed that without training, participants could identify the micro-expression in the photos in 200 ms and with training, in 160 ms. According to the findings, the key time interval that distinguishes micro expressions was 200 ms or less. In conclusion, the length of the expressions affects how accurately the micro expressions are recognized.

2. Flow of Micro-expression recognition

Systems for recognizing micro expressions are created by taking into account a variety of variables and parameters. Numerous research has been conducted and are constantly being conducted to improve recognition accuracy.

In this paper, we breakdown the face detection, pre-processing, facial feature extraction, classification, and databases of the micro-expression recognition systems into their fundamental parts, as shown in Fig. 1. Below, we go into great depth about each element's function.

3.1 Face detection

The initial step in the recognition process involves the detection of faces. The digital photos or image sequences contain one or more human faces. The regions of interest (ROI) in the photos can be chosen here, or in the case of image sequences, the ROI can be chosen in the first frame and the face tracked in the following frames.

There are now various face detection techniques in use [26, 43, 48-50]. Here is a summary of some face detection techniques. Based on the research of Rowley et al. [43], Mohammad Yeasin et al. [65] employed an automated face detection method to segment the face region. Convolutional neural networks were modified by Matsugu et al. [38] to detect faces, and a rule-based approach was employed for classification.

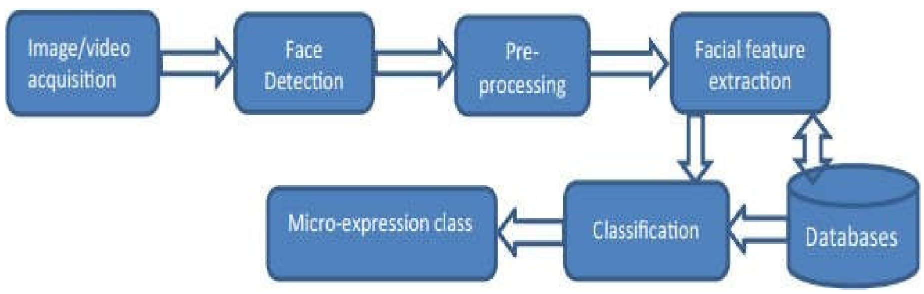

Fig. 1 A framework for micro-expression recognition analysis

3.2 Pre-processing

Pre-processing is the term used to describe actions taken on photographs at the most basic level. The goal is to improve the image data so that undesired distortions are suppressed and certain aspects are enhanced for subsequent processing. Micro expressions occur in very brief bursts during which the intensity of the facial movements is modest. The input data must be normalized using one of several implemented methods in order to obtain enough information about the micro-expression for further processing. Below is a discussion of a few of the unique pre-processing techniques.

To extend the length of brief videos, Temporal Interpolation Model (TIM) is employed [23, 31, 40, 41, 54]. To interpolate images at any location inside micro-expressions, TIM uses graph embedding. This interpolation enables the feature descriptor to be input with an adequate number of frames. After embedding an image sequence, the manifold-based interpolation technique known as TIM inserts a curve in a small-dimensional space. A micro-expression video is shown in Fig. 3 as a collection of images sampled along the curve, which results in a low-dimensional manifold. The micro-expression video is shown as a path of the graph with vertices. To create the temporally normalized image sequence, the interpolated frames are mapped back to a high-dimensional space [34].

3.3 Facial feature extraction

Feature extraction is a crucial challenge for micro expression recognition. Numerous researchers have been paying attention to spontaneous facial micro expression analysis, according to recent studies [30, 41], because these expressions can reveal real feelings that people are trying to hide.

Spatial and spatio-temporal face representations can be classed. While spatio-temporal information treats a sequence of frames inside a temporal window as a single parameter and allows modelling temporal variation to more effectively capture subtle expressions, spatial information contains image sequences frame-by-frame.

Shape and appearance are two more types of information that can be categorized based on how they are encoded in space. Facial expression recognition studies have frequently used geometry-based and appearance-based parameters.

There are two steps in the extraction of facial features: First, feature extraction, then feature detection.

3.3.1 Feature detection

An "interesting" element of an image is what is referred to as a feature. The initial operation on an image is typically feature detection, a low-level image processing technique that examines each pixel to determine whether a feature is present there.

3.3.2 Feature extraction

When extracting features, the quantity of data needed to fully represent a huge set of data is scaled back. The most crucial stage in identifying micro expressions is the extraction of facial characteristics. Numerous scholars have proposed various realistic aspects to describe facial traits. These traits fall under the categories of geometric and appearance-based aspects.

3.4 Classification

Data is categorised using image classification, which examines the statistical characteristics of distinct image features. Training and testing are typically the two steps in the classification process.

4. Differences Between Macro- and Micro Expressions

The movement of facial skin and connective tissue causes facial expressions. Facial nerve nuclei, which are in turn controlled by cortical and subcortical upper motor neuron circuits, trigger the muscles that control these movements in the face. According to one neuropsychological research of facial expression [14], there are two separate neural pathways that mediate facial behaviour and are situated in various brain regions. The cortical circuit, which is found in the cortical motor strip, is primarily in charge of voluntary facial movements such as posed facial expressions. Furthermore, the subcortical circuit, which is housed in the subcortical regions of the brain, is principally in charge of uncontrollable emotion and spontaneous facial expressions. Both systems are likely to be active when people try to hold back or conceal their expressions in a highly emotional scenario, which can lead to the transient leaking of real emotions in the form of micro expressions [15]. We shall emphasize spontaneous micro expressions in this paper.

Localized facial deformations known as micro-expressions are brought on by the involuntary contraction of facial muscles [16]. In contrast, macro-expressions use more muscle across a wider area of the face and have significantly stronger muscular motion. The essential differences between micro-expressions and macro-expressions in terms of neuroanatomical mechanism are that micro-expressions are extremely brief in length, barely vary, and have fewer action areas on the external face features [17], [18]. This distinction can also be drawn from the concealment mechanism [5]: when people try to hide their emotions, their real feelings can easily "leak out" and may appear as micro expressions.

TABLE 1: Main differences between macro- and micro expressions

Difference	Micro-expression	Macro-expression
Noticeability	Easy to ignore	Easily noticed
Time interval	Short duration (0.065-0.5 seconds)	Long duration (0.5-4 seconds)
Motion intensity	Slight variation	Large variation
Subjectivity	Involuntary (uncontrollable)	Voluntary (Under control)
Action areas	Fewer	Almost all areas

5. Existing micro-expression databases

Ample facial expression databases, such as the widely used CK+, MUG, MMI, JAFFE, Multi-PIE, and various 3-D facial expression databases, are essential for the success of macro-facial expression identification. In contrast, there aren't many robust micro-expression datasets, which has hampered the advancement of research into micro-expression recognition. Some databases are created by having individuals quickly exhibit various facial expressions. These "micro-expressions" are posed, as opposed to being natural. For academic study and real-world use, databases of impromptu facial micro expressions are required. Recently, participants were instructed to watch several videos while their facial expressions were being recorded in order to capture involuntary micro expressions. The participants later validated the recorded expressions.

The datasets used to assess micro-expression recognition systems are briefly described in Table 2. The accessible datasets statistics and characteristics are listed in the table. The six emotion categories of sadness, fear, happiness, disgust, rage, and surprise are included in posed and non-posed datasets for micro expression recognition, as are the three emotion categories of positive, negative, and surprise. The datasets with impulsive micro expressions may be helpful for evaluating how well the systems perform at spotting subtle expressions.

TABLE 2: Micro-expression datasets.

Characteristics	Datasets								
	MEVIEW	SMIC			CASME	CASME II	CAS(ME)^2	SAMM	MMEW
		HS	VIS	NIR					
Num of samples*	40	164	71	71	195	247	57	159	300
Participants*	16	16	8	8	35	35	22	32	36
Frame rate	25	100	25	25	60	200	30	200	90
Mean age	N/A	N/A			22.03	22.03	22.59	33.24	22.35
Ethnicities	N/A	3			1	1	1	13	1
Resolution	1280×720	640×480			640×480 & 1280×720	640×480	640×480	2040×1088	1920×1080
Facial resolution	N/A	190×230			150×190	280×340	N/A	400×400	400×400
Emotion classes	7 categories: Happiness (6) Anger (2) Disgust (1) Surprise (9) Contempt (6) Fear (3) Unclear (13)	3 categories: Positive (107) Negative (116) Surprise (83)			8 categories: Amusement (5) Disgust (88) Sadness (6) Contempt (3) Fear (2) Tense (28) Surprise (20) Repression (40)	5 categories: Happiness (33) Repression (27) Surprise (25) Disgust (60) Others (102)	4 categories: Positive (8) Negative (21) Surprise (9) Others (19)	7 categories: Happiness (24) Surprise (13) Anger (20) Disgust (8) Sadness (3) Fear (7) Others (84)	7 categories: Happiness (36) Anger (8) Surprise (89) Disgust (72) Fear (16) Sadness (13) Others (102)
Available labels	Emotion/FACS	Emotion			Emotion/FACS	Emotion/FACS	Emotion/FACS/ Video type	Emotion/FACS	Emotion/FACS
Download URL	http://cmp.felk.cvut.cz/cechj/ME/	http://www.cse.oulu.fi/SMICDatabase			http://fu.psych.ac.cn/CASME/casme-en.php	http://fu.psych.ac.cn/CASME/casme2-en.php	http://fu.psych.ac.cn/CASME/cas(me)2-en.php	http://www2.docm.mmu.ac.uk/STAFF/M.Yap/dataset.php	http://www.dpailab.com/database.html

Fig. 2: Snapshots of six micro-expression datasets. From left to right and from top to bottom, these are as follows: MEVIEW [28], SAMM [29], SMIC [30], CASME [31], CASME II [32], and CAS(ME)2 [33].

6 Challenges, open issues, and future directions

This part will go over the difficulties encountered, the problems that need to be fixed right now, and the future direction of the study.

6.1 Challenges

Because of their brief duration and spontaneous nature, micro expressions pose significant recognition issues. The authors' top concerns for automatic micro-expression recognition are covered in the section below. This includes, among other things, the limited datasets that are now available, problems with getting ground truth, and creating effective recognition algorithms.

1) Temporal information

- There are numerous ways for normalizing spatial data, but very few for normalizing temporal data. It is required to normalize the temporal dimension for micro expressions due to the variability in micro expression duration. Temporal Interpolation Model (TIM), a normalization technique based on the Laplacian graph, is one illustration.
- The algorithm may classify little expressions as neutral faces due to low-intensity facial movements in the database. Even the human eye has difficulty identifying and detecting little facial emotions in the absence of time information. Therefore, researchers should consider temporal information in order to more accurately detect and discriminate micro-expressions.

2) Dimensionality reduction

When high-speed (200fps) and high-resolution (800×600) cameras are utilized to record micro-expression video sequences, very high dimensional data are produced. Simple dimensionality reduction techniques, such as PCA, may not be adequate for such high dimensional data since they may not preserve the necessary feature information. Therefore, it is essential to create an algorithm that is more effective.

3) Micro-expression detection

It's crucial to identify the onset, peak, and offset frames of a micro expression in order to increase recognition accuracy. Instead of determining the beginning, peak, and offset frames, current research focuses on discovering and detecting micro expressions. For the purpose of creating databases of spontaneous micro expressions, the program is in high demand for helping to collect onset, peak, and offset frames.

6.2 Open issues

As a result of the numerous difficulties the researchers are encountering in this new and emerging field of study, they have highlighted a number of issues that require attention. Some of these unresolved problems indicate that more research should go into developing micro-expression recognition techniques and databases.

1) Databases

- People may react differently to the same film due to varying cultural upbringings and life experiences. This makes it challenging to label spontaneous micro expressions. The act of chewing a worm, for instance, is not necessarily described as "Disgusting". It was also described as "Funny" or "Interesting" by several individuals. Since action units are frequently used to define facial expression, a suitable database might contain data on action units in relation to various expression categories. The micro-expressions need to be categorized, which calls for more in-depth research.
- Micro-expression databases may not include the micro-expressions in various contexts because they are often developed in a controlled setting, such as laboratories. To examine and investigate variations of micro expressions in various contexts, more research should be done.

- To make micro-expression recognition more useful, it would be better if the databases could contain the expressions of individuals from various age groups and cultural backgrounds.

2) Micro-expression recognition methods

- Current micro expression systems are unable to distinguish between micro expressions and impersonal, quick motions like eye blinks.
- Even cutting-edge techniques can fail to correctly identify micro-expressions. To boost system effectiveness, the false positive rate must be decreased.

6.3 Future directions

Although workable methods in the area of micro-expression recognition have been suggested, we may yet be able to recommend a few potential study avenues. The obstacles and open topics covered in earlier parts served as the inspiration for the suggestions listed below.

- Real-time improvement of the micro-expression recognition effectiveness can be achieved by estimating the pixel-level movement.
- A larger participant pool in the databases will improve the training data for the recognition algorithms. To make the database more current, participants from all age groups and cultural backgrounds could be incorporated.
- A micro expression recognition system ought to be effective under less restricted and uncontrolled circumstances. videos of micro expressions.
- To enhance the results of the micro-expression recognition, more investigation into deep learning features, such as CNN features, is necessary.

7. Conclusion

Numerous potential real-world uses for micro expression analysis exist, such as making it easier for individuals to recognize micro expressions in everyday situations and to understand their meaning. We need to create dependable algorithms with accurate and trustworthy samples in order to make the detection and recognition of micro-expressions applicable to real-world circumstances and make micro-expression analysis effective in practice. In light of this, we evaluate the relevant literature on the study of spontaneous facial micro-expressions (including datasets, features, and algorithms) in this survey and suggest a brand-new dataset, MMEW, for micro-expression recognition. We also contrast the efficacy of current state-of-the-art techniques, assess the potential, and identify the unresolved problems for micro-expression analysis research in the future. Since micro-expression analysis is currently a hot topic for research, we believe that this survey will serve as a good starting point for scholars looking to review recent advances in the field and discover potential lines of inquiry.

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