# A Survey of Micro-Expression Recognition Methods

##### **Vivek Bindal\*, Navin Kumar Budania\*, Satyanarayan Yadav\***

\* Computer Engineering Department

\*NIT Kurukshetra

**Abstract-** Micro-Expression Recognition is one of the important method for human behavior interpretation. Micro-Expression are brief human expressions that exist on human face for short period of time. Classification of these expression will lead to understand what a person is feeling by analyzing a particular expression. In this paper we first study about human behavior and then generation of micro-Expression then classify those micro-Expression into different types , different databases that stores facial data on extreme conditions and different features for micro-Expression Recognition system.

**Index Terms**- micro expressions; subtle emotions; Feature extractions; classification; Support vector machine; Artificial neural network; challenges; survey

1. **Introduction**

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icro-Expression are brief facial Expression that reveals the feeling of person. A lot of work has been done on these expressions. They exist for short period of time like ½ of second and the intensity of micro expression is very small. Thus, they are negligible by naked human eyes. In 1969, Ekman analyzed a person’s video of psychological treatment who was depressed and tried to commit suicide and found micro-Expressions on his face [1].They can help to find if a person is lying that’s why they have such applications like national security, psychiatric treatment, lie detector, human robotics.

* In Lie detector, when a person is lying some micro-expressions appears on his face due to emotions like fear then this system can be used to recognize whether a person is lying.
* In Human Robotics, as robots begin to interact more and more with humans and start becoming a part of our living spaces and work spaces, they need to become more intelligent in terms of understanding the human’s moods and emotions. Expression recognition systems will help in creating this intelligent visual interface between the man and the machine.
* In National security, these systems can be used for detecting for suspicious activities.
* In Psychological treatment, this system can be used to understand emotions of mental patient so that they can be treated.

There are different facial expression databases but micro-Expression databases are rare. They can be used for designing algorithms for micro-Expression recognition system. these databases are USF-HD, SMIC, CASME & CASME II. the USF-HD, JAFFE and Polikovsky database contain only posed micro expressions and SMIC, CASME, CASME II are contain spontaneous micro expressions. In the ﬁeld of computer vision, Several researchers have come up with systems that are capable of recognizing these concealed emotions using varying combinations of feature extraction and classiﬁcation methods. Features can be extracted either in a static manner or in a dynamic manner. For effective recognition of micro-expressions, dynamic features are more relevant. One of the common methods of extracting features which has been used in the past is local binary pattern (LBP). And some other methods such as LBP-TOP, HOG are exist for feature extraction. many machine learning algorithms are used for micro expression classification. one of the common ML algorithm of classification is SVM(Support vector machine). but there are some other classifier also exist such as ANN (Artificial neural network), Decision Tree, K-NN (k-nearest neighbors). These Expressions are different from normal expressions because these are uncontrollable. These expression occurs on human face when a person is trying to hide his feeling then some facial movements occurs on his face that reveals its true emotions. There are basically 6 type of expressions of person’s face. These expressions also called as 6 P`s-

1) Happiness 2) Sadness 3) Fear 4) Surprise 5) Disgust 6) Repression

This paper is organized as follows: Section 2 provides a detailed review of the related studies including MEs databases, feature extraction and classification. Section 3 discusses some of the challenges that researchers face in this field. A summary and closing remarks conclude this paper.

1. **Micro Expression Recognition**

Micro expression Recognition is very challenging task involving different research fields, including psychology, computer visions, machine learning. there is no doubt that the progress in Micro expression Recognition is continue.

**2.1 The Description of emotions**

**2.2 The difference between Macro and Micro emotions**

1. **THE STATE OF THE ART**

Rather than providing exhaustively coverage of all past efforts in the field of micro expression recognition, In this paper we focus on the efforts recently proposed in the field of micro expression recognition. Due to limitations of our knowledge , we sincerely apologize to those authors whose work is not included in this paper. In micro expression recognition field the readers are referred the following articles:

* Towards reading hidden Emotions: A comparative study of spontaneous micro-expression spotting and recognition methods [6].
* Automatic micro-expression recognition from long video using a single spotted apex [7].
* CASME II An Improved Spontaneous Micro-Expression Database and the Baseline Evaluation [5].
* For micro-expression recognition : Database and suggestions [8].

In this section, we first offer an overview of the existing database of micro expressions. Next we examine available computing methods as feature extraction and feature classification for micro expressions.

**3.1 MEs Database**

There are different facial expression databases but micro-Expression databases are rare. They can be used for designing algorithms for micro-Expression recognition system. In micro expression field, Several database exist such as CASME, CASME2, SMIC, USF-HD and others. These database have enhanced the progress of algorithms for micro expression analysis. However, eliciting spontaneous MEs is difficult. According to Ekman, an ME may occur under 'high-stake' conditions [7], which indicate situations when a person tries to hide true feelings. In [7] Ekman *et al.* created situations to construct a high stack situation such as asking people to lie about what they saw in video; constructing crime scenarios and; asking people to lie about their own opinions. In some earlier studies on automatic MEs analysis, posed ME data were used.

* Shreve el al. [8],[9] collected a database called USF-HD which contains 100 clips of posed MEs. they showed some example videos to the subjects and then asked them to mimic those examples.
* The biggest problem of posed MEs is that they are different from real. SMIC Database contains only 3 classes of expression.

1) Positive 2) Negative 3) Surprise

In this database 16 subjects were there with 164 samples and frame rate of 100 frame per second. The full version of SMIC contains three datasets (all with resolution 640\*480), 1) HS dataset recorded by a high speed camera at 100fps, 2) VIS dataset recorded by a normal color camera at 25 fps and, 3) NIR dataset recorded by a near infrared camera at 25fps. the HS dataset recorded all data while VIS and NIR dataset recorded last eight subjects` data.

For better expressions such type of environment is created like there is punishment threat and highly emotional clips were chosen to create extreme conditions in which participants going under high emotional feeling has to suppress their emotions.

* CASME Database (Chinese Academy of Sciences Micro-expression) contains 195 micro-Expression filmed with 60 frame per second camera. There were 35 participants (22 males and 13 females) with mean age of 22.03 Years. Micro-Expression with the duration less than 500ms were selected for database but some expression that last more than 500ms with their onset less than 250ms were also selected because fast onset facial expression can also be categorized under micro-Expressions. Facial expression for this database were recorded in different environment with two different type of cameras having different resolutions. Frame rate of both the camera were same (60 fps). They can be divided into 2 classes-

1. Class A

The samples in this class were recorded in natural light with BenQ M31 camera with resolution 1280×720 pixels.

1. Class B

The samples were taken in a room with presence of two LED lights with Point Grey GRAS-03K2C camera with resolution of 640×480 pixels.

* A robust automatic micro-expression recognition system would have broad applications in national safety, police interrogation, and clinical diagnosis. Developing such a system requires high quality databases with sufficient training samples which are currently not available. researchers reviewed the previously developed CASME micro-expression databases and built an improved one (CASME II), with higher temporal (200fps) and spatial resolution (about 280x340 pixels on facial area). they elicited participant`s facial expressions in a well-controlled laboratory environment, with proper experimental design and illumination. Among nearly 3000 facial movements, 247 micro-expressions were selected for the database with action units (AUs) labeled. For baseline evaluation, LBP-TOP and SVM were employed respectively for feature extraction and classifier with the leave-one-subject-out cross-validation method. The best performance is 63.41% for 5-class classification.

CASME II Database is one of the preferred database for spontaneous MEs. because of the following characteristics -

1. The samples are spontaneous and dynamic micro-expressions. Baseline (usually neutral) frames are kept before and after each micro-expression, making it possible to evaluate different detection algorithms.
2. The recordings have high temporal resolution (200 fps) and relatively higher face resolution at 280×340 pixels.
3. Micro-expression labeling is based on FACS investigator’s guide and Yan et al [ ] findings that is different from the traditional 6 categories on ordinary facial expression.
4. The recordings have proper illumination without lighting flickers and with reduced highlight regions of the face.
5. Some types of facial expressions are difficult to elicit in laboratory situations, thus the samples in different categories distributed unequally, e.g., there are 60 disgust samples but only 7 sadness samples. In CASME II, they provide 5 classes of micro-expressions.

Table 1

MEs Databases. Elicitation Methods P/S : Posed or Spontaneous

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Database** | | **References** | **MEs** | **Subjects** | **Fps** | **Resolutions** | **Elicitation** | **Emotions** |
| USF- HD | | M. Shreve et al. [21], [22] | 100 | N/A | 30 | 720\*1280 | P | N/A |
| Polikovsky | | Polikovsky et al. [23] | N/A | 10 | 200 | 480\*640 | P | 7 |
| SMIC | HS | Xiaobai Li et al. [18]  T. Pﬁster et al. [25]  Sze-Teng Liong et al. [30]  Yong-Jin Liu et al. [32]  Xiaohua Huang et al. [34] | 164 | 16 | 100 | 640\*480 | S | 3 |
| VIS | 71 | 8 | 25 |
| NIR | 71 | 25 |
| CASME | Class A | Wen-Jing Yan et al. [19]  Yong-Jin Liu et al. [32]  Xiaohua Huang et al. [34] | 100 | 7 | 60 | 1280\*720 | S | 8 |
| Class B | 95 | 12 | 640\*480 |
| CASME II | | Wen-Jing Yan et al. [20]  Yee-Hui Oh et al. [31]  Yong-Jin Liu et al. [32]  Xiaohua Huang et al. [33]  Xiaohua Huang et al. [34]  Yandan Wang et al. [44]  Iyanu Pelumi Adegun et al. [47]  Dae Hoe Kim et al. [48] | 247 | 26 | 200 | 640\*480 | S | 5 |
| MMI | | M. Pantic et al. [24] |  | 90 |  |  | P + S | 6 + AUs |
| JAFFE | | M. Kamachi et al. [26] |  | 10 |  |  | P | 6 + neutral |
| RU-FACS | | M. Bartlett et al. [27] |  | 100 |  |  | S | AUs |
| Oulu-CASIA | | G. Zhao et al. [28] |  | 100 |  |  | P | 6 |
| Multi-PIE | | R. Gross et al. [29] |  | 100 |  |  | P | 6 |

Table 1 lists the key features of existing databases. SMIC, RU-FACS, CASME and CASME II are contain spontaneous MEs and USF-HD, Polikovsky, JAFFE, Oulu-CASIA and Multi-PIE databases contain Posed MEs. MMI database contains both Posed and Spontaneous MEs.

**2.2 MEs Feature Extraction**

Several descriptors are developed to extract the features from persons` face. especially LBP (local binary pattern) and its variants [15], [16], [17]. here, we discussed some features such as LBP, LBP variants, HOG and compare their performance. Details of each descriptor are described below, and their comparison and performance will be discussed in Table 2.

* LBP is a very efficient texture operator which labels the pixels of an image (persons` face) by thresholding the neighborhood of each pixel and consider the result as a binary number. it was first described in 1994. it is a type of visual descriptor used for classification in this field.

due to its computational simplicity, LBP texture has become a popular approach in various applications. The basic methodology for LBP based face description proposed by Ahonen et al [20], is as follows: Divide the examined window into cells (e.g. 16\*16 pixels for each cells); for each pixel in cells, compare the pixel to its 8 neighbors along a circle; where, if the centre pixel value is greater than the neighbors value then write 0, otherwise write 1 and; compute the histogram over the cells, this histogram can be seen in 256-dimensional feature vector; normalize the histogram and concatenate the normalized histograms of all cells, so this gives a feature vector for entire window.

The original LBP operator was defined to only deal with the spatial information. Zhao et al [21] proposed Volume Local Binary Pattern (VLBP) operator. The idea behind VLBP consists of looking at dynamic texture as a set of volumes in the (X,Y,T) space where X and Y denote the spatial coordinates and T denotes the frame index (time). The neighborhood of each pixel is thus defined in three dimensional space. Then, similarly to LBP in spatial domain, volume textons can be defined and extracted into histograms. Therefore, VLBP combines motion and appearance together to describe dynamic textures. To make VLBP computationally simple and easy to extend, an operator based on co-occurrences of local binary patterns on three orthogonal planes (LBP-TOP) was also introduced.

* Zhao et al [21] proposed LBP on Three Orthogonal planes (LBP-TOP), it considers the three orthogonal planes: XY, XT, YT. Excellent facial expression recognition performance has been obtained with this approach. the success of LBP continue, recently, Liu et al. [22] proposed an extensive experimental evaluation of different LBP and deep texture descriptors.
* HOG (Histograms of Oriented Gradients) is a colour invariant feature. it captures the local edge and gradient structures. The basic idea of HOG features is that the local object appearance and shape can often be characterized rather well by the distribution of the local intensity gradients or edge directions, even without precise knowledge of the corresponding gradient or edge positions. The orientation analysis is robust to lighting changes since the histogram gives translational invariance. The HOG feature summarizes the distribution of measurements within the image regions and is particularly useful for recognition of textured objects with deformable shapes. The method is also simple and fast so the histogram can be calculated quickly. To extract HOG descriptors, ﬁrst count the occurrences of edge orientations in a local neighborhood of an image. This means the image is divided into small connected regions, called cells and the histogram of edge orientations is computed for each one. Depending on whether the gradient is unsigned or signed, the histogram channels are spread over 0◦−180◦ or 0◦−360◦. To compensate the illumination, histogram counts are normalized by accumulating a measure of local histogram energy over the connected regions, then use the results obtained to normalize all cells in the block and ﬁnally, the combination of these histograms represents the HOG descriptor.

Table 2

Various Features with applications

|  |  |  |
| --- | --- | --- |
| **Features** | **References** | **Applications** |
| HOOF  (Local Binary Pattern) | Iyanu Pelumi Adegun et al. [47] | Automatic Recognition of Micro-expressions using Local Binary Patterns on Three Orthogonal Planes and Extreme Learning Machine |
|  |  |
|  |  |
|  |  |
| LBP-TOP  (Local Binary Pattern in three orthogonal Planes) | Sze-Teng Liong et al. [43] | Spontaneous Subtle Expression Detection and Recognition based on Facial Strain |
| Yandan Wang et al. [44] | Eﬀective Recognition of Facial Micro-Expressions with Video Motion Magniﬁcation |
| Pavithra M et al. [45] | Capture the dynamic texture. |
| Yee-Hui Oh et al. [46] | Monogenic Riesz Wavelet Representation for Micro-expression Recognition |
| Yong-Jin Liu et al. [32] | A Main Directional Mean Optical Flow Feature for Spontaneous Micro-Expression Recognition |
| Iyanu Pelumi Adegun et al. [47] | Automatic Recognition of Micro-expressions using Local Binary Patterns on Three Orthogonal Planes and Extreme Learning Machine |
| Dae Hoe Kim et al. [48] | Spatial texture feature |
| HOG  (Histogram of Oriented gradients) | Gaurav Mishra et al. [35] | Real-Time Image Resizing Hardware Accelerator for Object Detection Algorithms |
| Soojin Kim et al. [36] | Fast Calculation of Histogram of Oriented Gradient Feature by Removing Redundancy in Overlapping Block |
| Amr Suleiman et al. [37] | Energy-Efﬁcient HOG-based Object Detection at 1080HD 60 fps with Multi-Scale Support |
| SHU Chang et al. [38] | Face Recognition |
| Michael Hahnle et al. [39] | real-time pedestrian detection on Field Programmable Gate Arrays (FPGAs) |
| Kenta Takagi et al. [40] | feature extraction accelerator for real-time multiple object detection |
| Pavithra M et al. [45] | capture the appearance information |
| Vandna Singh et al. [41] | Feature extraction for gender classification from images. |
|  | Mao Hatto et al. [42] | Data Reduction and Parallelization for Human Detection System |
| Maryam Hemmati et al. [53] | Hardware Accelerator for Real-time Pedestrian Detection |

**2.3 MEs Classification**

The images are classified based on the extracted features into predefined categories by using suitable methods that compare the image pattern with images which inside the database. Some Feature Classifications are follows:

* SVM (Support Vector Machine) This method constructs a set of hyper planes in a high dimensional space, which is use for classification or regression. The good separation achieved by the hyper plane. SVM uses non-parametric with binary classifier approach and handles more input data efficiently. Accuracy depends on hyper plane selection. The Structure of the SVM algorithm is more complicated than other methods. This gives the low result transparency. Cheng-Hsuan Li et al. [80] discuss, A Spatial–Contextual Support Vector Machine for Remotely Sensed Image Classification.
* ANN (Artificial Neural Network) is a type of artificial intelligence that emits some functions of the human mind. Monica Bianchini et al. [23] discussed the artificial neural network classification technique. An ANN is having a sequence of layers. Each layer of neural network system consists of a set of neurons. Neurons of all layers are linked by weighted connections to all neurons of the preceding and succeeding layers. The accuracy depends on the number of input and structure of the network. ANN is non-parametric approach. In this method, the classification of the input is very fast, but the training process is slow.

Fuliang Wang et al. [24] explains, Artificial Neural Network is efficiently handling the noisy data and this method capable of representing AND, OR and NOT

* Lizhen Lu et al. [25], Decision Tree classifier calculate the class membership by partitioning the input into categories. Decision tree is a tree-like graph of decisions. Each branch represents the decisions to be made graphically. It is a non-parametric supervised approach. It partition input into uniform classes. This method permits the acceptation and rejection of class label at each intermediate stage. This method gives the set of rules after classification that should be understood.
* In Fuzzy classification, various stochastic associations are determined to describe characteristics of an image. The various types of stochastic are combined in which the members of this set of properties are fuzzy in nature. It provides the opportunity to describe different categories of stochastic characteristics in the similar form. Performance and accuracy depends upon the threshold selection and fuzzy integral.

Table 3

Advantages and Disadvantages of different Classification Techniques

|  |  |  |  |
| --- | --- | --- | --- |
| **Classification**  **Method** | **References** | **Advantages** | **Disadvantages** |
| SVM  (Support Vector Machine) | Shereen Afifi et al. [49]  Pooja Kamavisdar et al. [50]  Chaitali Dhaware et al. [51]  M. D. Borrás et al. [52]  Maryam Hemmati et al. [53]  Iyanu Pelumi Adegun et al. [47]  Yandan Wang et al. [44]  Yee-Hui Oh et al. [46]  Cheng-Hsuan Li et al. [80]  Pavithra M et al. [45]  Osiris Villacampa et al. [54] | * Deliver Unique Solution * Very efficient than other methods * Avoid over-fitting * It gains flexibility in the choice of the form of the threshold | * High Algorithm Complexity * Run Slowly * Determination of optimal parameters is not easy when there is nonlinearly separable training data. |
| ANN  (Artificial Neural Network) | Pooja Kamavisdar et al. [50]  Chaitali Dhaware et al. [51]  Monica Bianchini et al. [23]  Fuliang Wang et al. [24] | * Robust to noisy training dataset * Very efficient for large dataset * capable to present functions such as OR, AND, NOT * It is a data driven self adaptive technique | * High computational cost * Lazy learner * It is semantically poor * Problem of over fitting |
| K-NN  (k-Nearest Neighbor Classifier) | Osiris Villacampa et al. [54] |  |  |
| Decision Tree | Lizhen Lu et al. [25]  Pooja Kamavisdar et al. [50]  Chaitali Dhaware et al. [51]  Osiris Villacampa et al. [54] | * Require little efforts from users * Easy to interpret and explain | * Splits are very sensitive to training dataset * High classification error rate |
| Fuzzy Measure | Pooja Kamavisdar et al. [50] | * Efficiently handles uncertainty * Properties are describe by identifying various stochastic relationship | * Without prior knowledge output is not good * Precise solutions depends upon direction of decision |

**4 CHALLENGES**

**4.1 Database**

**4.2 Feature Extraction**

**4.3 Feature Classification**

**5 CONCLUSION**

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HOG Feature Extractor Hardware Accelerator for Real-time Pedestrian Detection

Maryam Hemmati, Morteza Biglari-Abhari, Stevan Berber Department of Electrical and Computer Engineering University of Auckland Auckland, New Zealand mhem941@aucklanduni.ac.nz, m.abhari@auckland.ac.nz, s.berber@auckland.ac.nz

Smail Niar Institut des Sciences et Techniques de Valenciennes University of Valenciennes and Hainaut-Cambresis Valenciennes, France smail.niar@univ-valenciennes.fr

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Osiris Villacampa

**Authors**



Navin Kumar Budania received undergraduate degree in Computer Engineering from NIT Kurukshetra, India in 2017. He is currently a Researcher in TRIO in India. His main research interests include image processing, computer vision, machine learning, and cloud computing.