Micro Expression Recognition Using the Eulerian Video Magnification Method

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Abstract

In this paper we propose a new approach for facial micro expressions recognition. For this purpose the Eulerian Video Magnification (EVM) method is used to retrieve the subtle motions of the face. The results of this method are obtained as in the magnified images sequence. In this study the numerical tests are performed on two databases: Spontaneous Micro expression (SMIC) and Category and Sourcing Managers Executive (CASME). We evaluate our proposed method in two phases using the eigenface method. In phase 1 we recognize the type of a micro expression, for example emotional versus unemotional in SMIC database. Phase 2 classifies the recognized micro expression as negative versus positive in SMIC database and happiness versus disgust in CASME database. The results show that the eigenface method by the EVM method for the retrieval of subtle motions of the face increases the performance of micro expression recognition. Moreover, the proposed approach is more accurate and promising than the previous works in micro expressions recognition.

Keywords: Micro Expression Recognition, Eulerian Video Magnification Method, Eigenface Method.

1. Introduction

Facial expression recognition usually follows an ordinal structure of processing blocks (Khatri et al., 2015). These blocks include preprocessing, feature extraction, classification, and post processing. In the preprocessing step there are performed actions such as noise removal, normalized relative to the brightness fluctuations or dimensions normalization, and image resolution. Feature extraction is a very important step in facial expression recognition. Feature extraction methods can be divided into two categories: geometric feature-based methods and appearance-based methods (Jain & Li, 2005). Geometric feature-based methods represent the shape and location of the face components (i.e. the eyes, eyebrows and nose). In the appearance-based methods, image filters such as Gabor wavelets are used in all or part of the face to extract the feature vector. Gabor filters remove most of the variability in image caused by changes in lighting conditions (Fasel & Luettin, 2003). The sets of features that are extracted from the face region are used in classification. After the classification is performed, the type of emotional state for the input image is determined, based on the label of a particular class. The output of the classification is one of the six basic emotions that are defined by Ekman, i.e. happiness, sadness, surprise, anger, fear and disgust (Ekman & Friesen, 1978). Most of the studies on facial expression are done based on databases in which participants are pretending to be in an emotional state. The little studies have been done on micro expressions recognition in computer vision (Pfister et al., 2011). For example, Soyel et al. (2010) used a discriminative scale invariant feature transform (D-SIFT) for facial expression recognition. Their proposed method recognized macro expressions in the 3D-BUFE database (Soyel & Demirel, 2010).

The goal of our research is to use the EVM method in micro expression recognition. Then we use the eigenface method to detect the type of emotional states of magnified data. We also analyze the performance for the EVM method in emotional/unemotional detection on the face during micro expression. This paper is organized as follows. In section 2 we review some studies about micro expression recognition. In section 3 we present the concepts of the eigenface method and EVM method. A study on the combination of these two methods is performed in section 4, and then tests results are presented. Finally, a conclusion section is expressed.

2. Related Works

In this section we present a brief history of micro expression and a summary of related psychological works. Gottman & Levenson (2002) and Ekman (2009) have thoroughly studied micro expression on the face. Ekman first discovered the micro expression when reviewing a video of a psychological patient who tried to hide his suicide attempt. He discovered a short-term grief and sadness that was covered with a smile. Ekman showed that it is very difficult to detect micro expressions without words and sound.

Polikovsky et al. (2009) proposed a method for detecting and measuring the temporal characteristics of micro expressions. The core of this method is a combination of preprocessing masks, histograms and their integration into the spatial-temporal gradient vector. Final classification of micro expressions is based on a k-mean classifier and a voting procedure.

Sungsoo and Daijin presented a method for recognition of subtle facial expression using motion magnification. Their method consists of the following steps: 70 feature points in image sequences of the face which are extracted by using active appearance models (AAM). The face image sequence is aligned by the three feature points (two eyes and the nose tip). Then, the motion vector of 27 feature points is estimated using the feature point tracking method. Finally, subtle facial expressions are determined by magnifying the motion vectors. Their experiments were performed on SFED2007 database (Sungsoo & Daijin, 2009).

Michael et al. (2010) presented a study of the automatic deception detection in interrogation interviews using body movements. In this study, the skin blob analysis and an Active Shape Model (ASM) have been used to extract the features that make up the motion profiles. Then, the extracted features are displayed with log-scale histograms.

Shreve et al. proposed an automated method (temporal segmentation) for macro and micro expressions recognition in long videos. In this method, the strain impacted on the facial skin was used for a feature descriptor. The strain magnitude is computed using the central difference method for optical flow in different parts of the face. A detection accuracy of 85% was obtained for macro expressions and 74% of the micro expressions were detected (Shreve et al., 2011; Shreve et al., 2009).

Pfister et al. (2011) have studied micro expression using TIM. They made two tests titled “truthful/deceptive detection” and “emotional/unemotional micro expressions detection". TIM extracts the statistically stable features of the face with the increased number of frames. Their work was performed using the following steps:

1: Detect, normalize, and crop the face using the ASM model.
2: Temporally interpolate images sequence.
3: Extract spatial and temporal local texture descriptors.
4: Classify with SVM, Multiple Kernel Learning (KML) and Random Forest (Pfister et al., 2011).

Wu et al., (2011) proposed an automatic micro expression recognition system. This system locates the face and extracts the features by using Gabor filters. Then GentleSVM is employed to identify micro expressions. They achieved high spotting performance on the METT training database (Ekman, 2002).

Wang et al. (2014) proposed the tensor independent color space (TICS) model for micro expression recognition. In this method, a color video of micro expression treats as a fourth-order tensor, i.e. a four-dimension array. Then, the color information dimension is converted from RGB into TICS. In this approach, Regions of Interest (ROI) are selected based on Facial Action Coding System (FACS) and the dynamic texture histogram is calculated for each ROI. The experiments were performed on two databases: CASME and CASME2.

Yao et al. (2014) presented a new feature tracking approach based on FACS and TLD for micro expression recognition. In this paper, feature points of the first frame are determined based on the Hough forest. In order to improve the accuracy, the local binary pattern (LBP) is used to extract features.

Wang et al., (2014) used Local Spatiotemporal Directional Features (LSDF) together with the sparse part of Robust PCA (RPCA) for Micro expression recognition. Authors achieved an accuracy of 65.4% on CASMEII (Yan et al., 2014).

Liong et al. (2014) proposed a new method for micro expressions recognition. This method utilizes optical strain magnitude feature extraction from the temporal point of view. Authors made their studies on SMIC database. They achieved a recognition accuracy of 53.56%.

Huang et al. (2015) proposed a method based on a spatiotemporal facial representation for micro expressions. In this paper the authors used an integral projection method based on different images for obtaining vertical and horizontal projection. Then they utilized the local binary pattern operators to extract the features of motion and appearance on horizontal and vertical projections.

Liong et al. (2016) proposed a new method for micro expressions recognition by using facial optical strain magnitudes to construct optical strain weighted features and optical strain features. The resultant feature histogram was obtained from concatenating the two sets of features. The authors used CASME II and SMIC databases in this study.

3. Explanation of the eigenface method and the Eulerian video magnification method

3.1 Using eigenface method in facial expression recognition

This method uses eigenface to extract facial features. So the eigenface is applied on the face and unique feature vectors that are extracted for each person’s unknown emotional state. The extracted feature vectors compared with the train set and type of person’s emotional state is determined. The train set is allocated into several classes according to the emotional states. According to the above, at first, the images in the test set are proposed on each class of eigenface, then images of each class are reconstructed. With similarity measure (Euclidean distance) between the input image and the reconstructed image of each class, any of the emotional states can be investigated (Murthy & Jadon, 2007; Bajaj et al., 2013; Chakrabartia & Duttab, 2013).

3.2 Description of Eulerian video magnification method

The human visual system is sensitive to time and space and low amplitude motions are difficult to see. Therefore, developed and new methods can be used for the retrieval of invisible signals in videos. In this study, the EVM method is used for the retrieval of subtle changes that occur on the face during facial expression. The basic approach in this method is to consider a set of time series of color values at each pixel and amplify them in a temporal frequency band. The temporal filtering approach not only amplifies color variation, but can also reveal low amplitude motions. The EVM process is as follows: a video sequence is divided into different frequency bands that may not be the same signal-to-noise ratio. The Laplacian Pyramid is used on each band and then applies the same temporal filter on all bands. The goal of spatial processing is to increase temporal signal-to-noise ratio using pixels integration. Then the extracted bands signals multiply by amplification factor α which is determined by the user. Magnified signal is added to the original signal and generates the output video. Temporal processing is based on first-order Taylor series using optical flow. Let I(x, t) denotes the image intensity at position x and time t by the motion signal $\delta(t)$. Since the image undergoes translational motion, image intensity is calculated as follows:

$$I(x,t) = f\big(x, \delta(t)\big) \qquad (1)$$

$$I(x,0) = f(x) \qquad (2)$$

The goal of motion magnification is to integrate the signals. The amplification factor α applies to the image according to the following equation (Wu et al., 2012; Rubinstein, 2014).

$$\hat{I}(x,t) = f(x + (1+\alpha)\delta(t)) \qquad (3)$$

Given that the image is estimated by a first order Taylor series expansion and $f(x, \delta(t))$ is in a first order Taylor expansion about at position x and time t, we have.

$$I(x,t) \approx f(x) + \delta(t)\frac{\partial f(x)}{\partial (x)} \qquad (4)$$

Applying a broadband temporal band pass filter to I(x; t) at position x is generated B(x,t):

$$\beta(x,t) = \delta(t)\frac{\partial f(x)}{\partial x} \qquad (5)$$

Then we can write:

$$\hat{I}(x,t) = I(x,t) + \alpha\beta(x,t) \qquad (6)$$

Hence from equations (4), (5) and (6), is obtained the following result.

$$\hat{I}(x,t) \approx f(x) + (1+\alpha)\delta \qquad (7)$$

When the signal is amplified to the size α and added to the image I(x,t), the relationship between the magnification and temporally band signal is:

$$\hat{I}(x,t) \approx f(x + (1+\alpha)\delta(t)) \qquad (8)$$

Equality (8) shows that motion becomes large as $(1 + \alpha)$.

4. Proposed method

In this study we investigate the emotional/unemotional detection on the face and micro expression recognition. As expressed in Murthy & Jadon (2007) and Frank & Nöth (2003) the eigenface method is not able to perform micro expression recognition. So, we use the EVM method for micro expression recognition based on the eigenface method. Using this magnification method, the subtle motions are retrieved from the face during micro expression and those are not visible. In order to do this work, we need a dataset including the spontaneous subtle facial motions. Therefore, in this study we use two databases, SMIC and CASME. According to the obvious features in the EVM method for retrieving and displaying subtle motions, first we test these databases using this method. Then we evaluate the rate of emotional/unemotional detection in the face and micro expression recognition using the eigenface method. An overall structure of our research is shown in Figure 1.

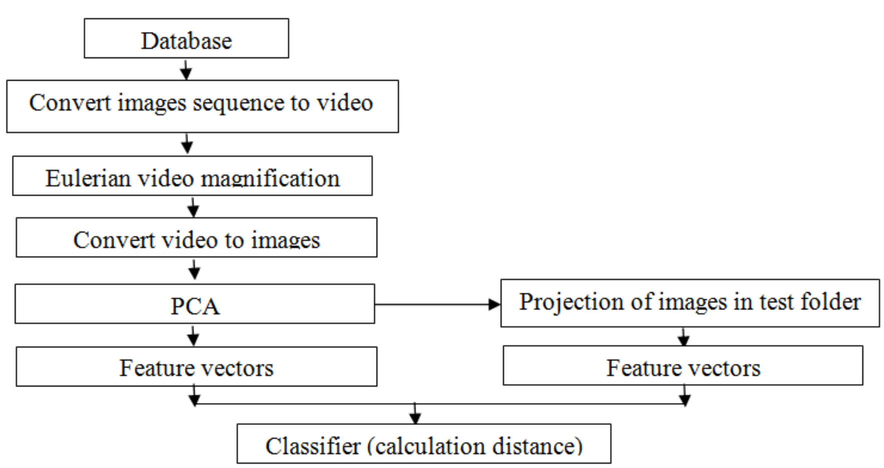


Figure 1. Overall structure of micro expression recognition

In order to use these databases in EVM method, we convert the images sequence of each person to the video. The following values are assigned to input parameters of EVM code.

α: Motion amplification factor

λ_c: Spatial frequency cutoff

$\omega_l(Hz)$ and $\omega_h(Hz)$: Low-order IIR filters can be useful for both the color amplification and the motion magnification

$f_s(Hz)$: Frame rate of the camera

The values of these parameters can be specified by the user or can be calculated to run the EVM method. In this study, the values assigned to the parameters are according to the values in Wu et al. (2012). For the retrieval of subtle motions of the face using the EVM method, two cases can be considered:

1. Select the values of parameters for observation the change of the face color in blood flow.
2. Select the values of parameters for observation head motions and components of the face.

In our research, we focus on the parameter values in the second case. Then we convert the obtained video to the images sequence. The number of images is decreased after the implementation of the EVM method. The reason of this problem is the integration of multiple pixels in the images. The resulting output is a generic extract of all motions created in the face.

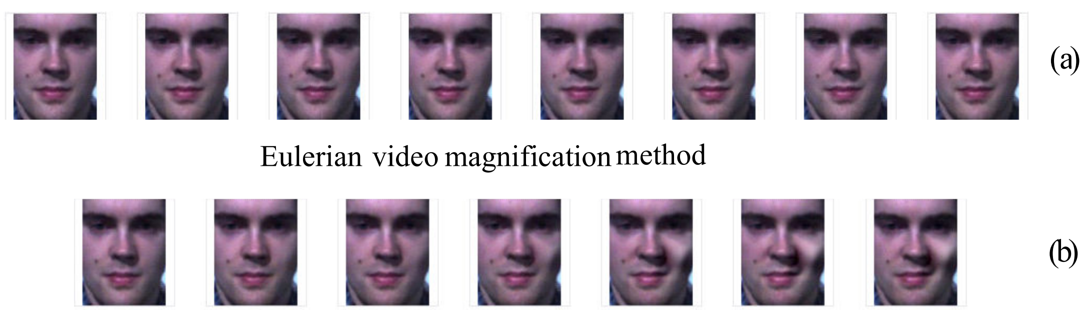


Figure 2. Result of the implementation of EVM method. (a): Regular images sequence (from left to right), (b): magnified images sequence (from left to right) in SMIC database.

In this study, two experiments are performed as follows:

Phase1: investigating the emotional/unemotional detection on face in micro expressions.

Phase2: investigating facial micro expressions recognition

4.1 A description of the SMIC and CASME databases

A. The SMIC database

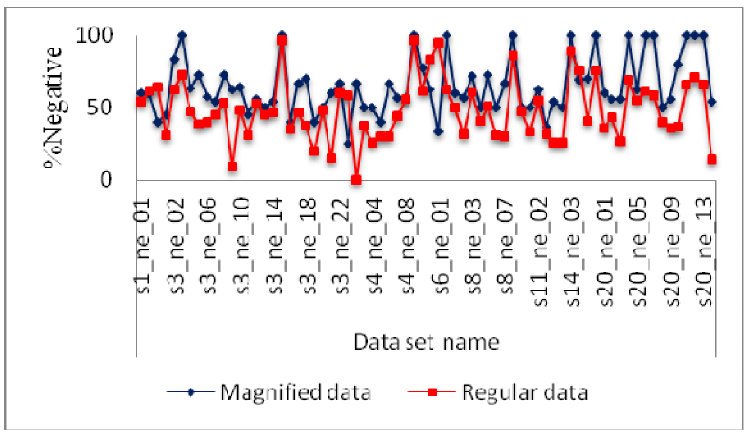
The SMIC database has been collected by Li et al. (2013). This database includes three datasets: HS (high speed camera), VIS (normal visual camera), and NIR (near-infrared camera). The HS dataset has been recorded by acamera of 100 fps and the longest micro expression clips have 50 frames. The VIS and NIR datasets have been recorded by a camera of 25 fps and the longest micro expression clips have 13 frames. The HS dataset includes 164 micro expression image sequences from 16 participants. Micro expression images sequences in the SMIC database are classified into three categories: positive (happiness), negative (sadness, fear and disgust), and surprise. The image sequence starts from a neutral (or relatively neutral) frame, the second frame is as the starting point of the facial expression, and it finally ends when the facial expression goes back to neutral (or relatively neutral).

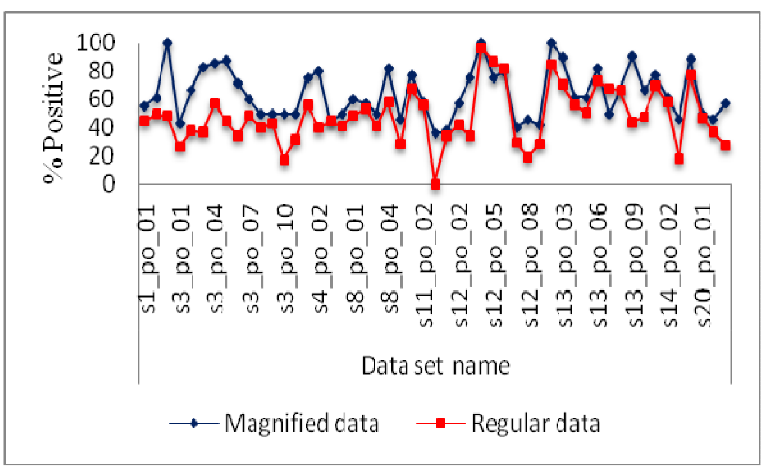
B. CASME database

The CASME database has been collected by Yan et al. (Yan et al., 2013). This dataset includes 195 videos and the longest micro expression clips measure 50 frames. The micro expression image sequences in the CASME database are classified into four categories: positive (happiness), negative (sadness, fear and disgust), surprise and Tense (Tense, Repression). The CASME database consists of two classes: A and B. The samples in Class A were recorded by a BenQ M31camera with 60fps. The samples in Class B were recorded by a Point Grey GRAS-03K2C camera with 60fps. In this study we use the image sequence in class A.

4.2 Phase 1: investigating the emotional/unemotional detection on the face in the SMIC database

To evaluate the emotional/unemotional detection on the face, 328 tests were performed: 164 tests on the magnified data and 164 tests on the regular data. For this purpose, the train set includes the neutral state and only one of the emotional states (negativism, positivism and surprise) according to the test set. So that the train set includes regular data in 328 experiments. The experimental results are shown in Figure 3.





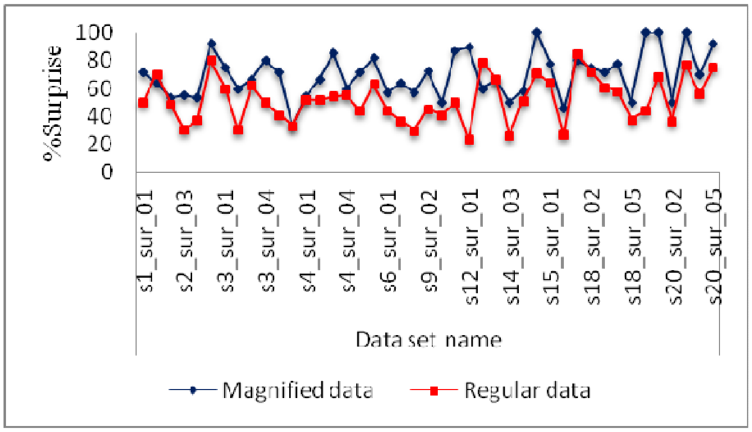


Figure 3.The chart of emotional/unemotional detection on the face in negative, positive and surprise states (Regular and magnified data)

In this chart, two curves are shown with red and blue colors. The red color curve represents the regular data and the blue color curve represents the magnified data. The vertical axis shows the percent of emotional/unemotional detection on the face as two by two in both experimental data sets (magnified data and regular data). As seen, the accuracy rate of detection in magnified data is high. The average percent of emotional/unemotional detection in the three states (positivism, negativism, and surprise) was calculated in the two data sets. Results are shown in Figure 4.

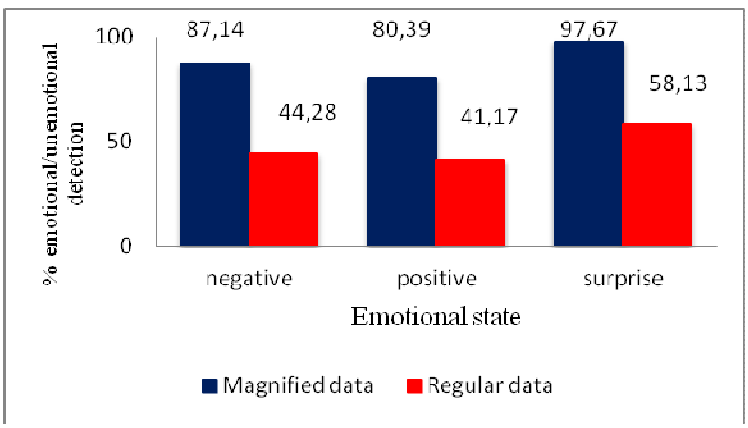


Figure 4. The chart of average percent of emotional/unemotional detection in SMIC

In Figure 4 the blue color curve represents the average percent of emotional/unemotional detection using the EVM method. The red color curve also represents the average percent of emotional/unemotional detection without this method. Table 1 shows the running time and speed in this experiment.

Table 1. Run time and speed in emotional/unemotional detection in SMIC database:

Database	Time(fps) in emotional/unemotional detection		
	Positive	Negative	Surprise
Regular data	53.44002	47.25493	50.26719
Magnified data	14.23065	13.32884	15.02361

The processing time of our proposed method is of 0.420468 fps and in regular data is of 5.27 fps. As the results show, the EVM method has good effect in processing. Of course, the creation time of the magnification image sequence was not considered in the result. In other words, the processing time on a magnified images sequence is less than the non-magnification state. Figure 5 shows the running time in emotional/unemotional detection.

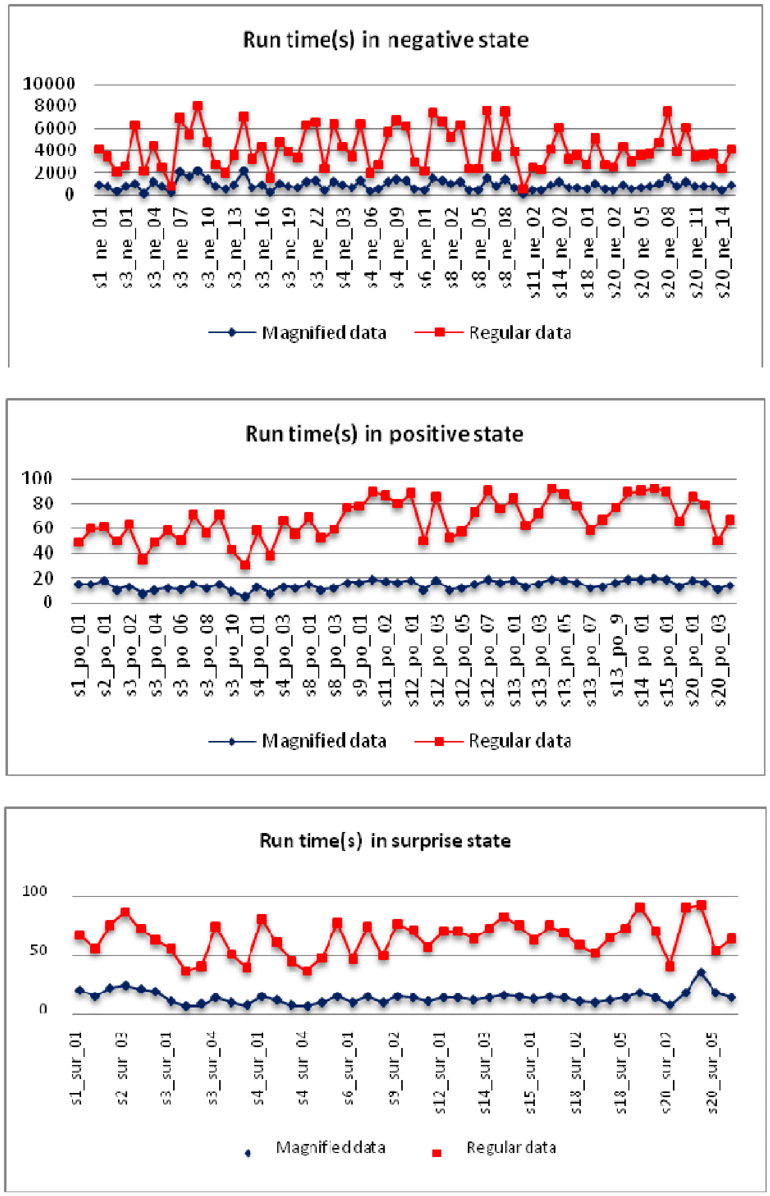


Figure 5.The chart of run time in emotional/unemotional detection in two databases.

As the results show, the eigenface method is not able to perform micro expression recognition without applying the EVM method and this method recognizes data in a neutral state.

4.3 Phase 2: investigating facial micro expressions recognition

A series of 130 tests was performed for micro expressions recognition (only one positive and one negative state of each person) in the SMIC database. A series of 65 tests was done on the magnified data and the series of 65 tests was also performed on the regular data. Thus, the two data sets (magnified images sequence and regular images sequence) are investigated and evaluated with the eigenface method. Considering that in this database every person has several negative or positive states. First, in the both data sets, the test set includes an images sequence of the positive and negative state of each person. In addition, the train set consists of a neutral state, a positive state, and a negative state. The train set includes the magnified data for 130 tests. In this study, the two data sets consist of image sequences and the person's emotion occurs over time in the image sequence. So, if at least 60% of the sequence frames show a single emotional state, it is considered as an emotional state of this images sequence. In these experiments we use four criteria to measure the performance of the EVM method: true positive rate (sensitivity), true negative rate (specificity), precision (positive predictive value), and accuracy. The test results of the two data sets are shown in Table 2 and Table 3.

Table 2. The percent of micro expression recognition (only one positive and one negative state of each person) between the series of 65 tests:

Micro expression recognition	Magnified data	Regular data
Negative state	64.61%	44.61%
Positive state	70.76%	53.84%

Table 3. Result of micro expression recognition (one positive and negative state for each person):

Database	(T_P)	(F_P)	(F_N)	(T_N)	#images
Regular data	35	30	36	29	65
Magnified data	46	19	23	42	65
	Sensitivity	Specificity	Precision	Accuracy rate	Error rate
Regular data	49.29%	49.15%	53.84%	49.23%	50.77%
Magnified data	66.67%	68.85%	70.76%	67.69%	32.31%

Tables 4 show the Confusion matrix in micro expression (positive and negative states) for in the two datasets.

Table 4.Confusion matrix in micro expression (positive and negative states) on Magnified data and Regular data:

Data set	Emotional/unemotional detection	Negative	Positive	Neutral
Magnified data	Negative	68.7489%	17.76187%	13.48923%
	Positive	19.57735%	68.71983%	11.70283%
	Neutral	11.67375%	13.5183%	74.80794%
Regular data	Negative	43.92745%	25.82071%	30.25184%
	Positive	27.17581%	56.83178%	15.99241%
	Neutral	28.89674%	17.34751%	53.75575%

A confusion matrix represents the conflict percent in the classification of emotional states. As the Table 4 shows, the percent of correct recognition in three emotional states is more than the false recognition percent in magnified data. For example, the correct recognition percent of negative states is of 68.74%. Confusion in magnified images is less than in regular images.

4.3.2 Investigating the micro expressions recognition (several positive and several negative states of each person) in SMIC database

Next, magnified and regular image sequences are tested and evaluated by the eigenface method for detecting several positive and negative states of each person. In this study, a series of 8 tests is performed and it consists of 30 magnified data sets and 30 regular data sets. The test set includes several image sequences of the positive and negative states. The train set consists of a neutral state and several positive and negative states. The train set includes the magnified data for 8 tests. The tests results in two data sets which are shown in Table 5 and Table 6.

Table 5. The percent of micro expression recognition (several positive and several negative states of each person) between the series 8 test:

Micro expression recognition	Magnified data	Regular data
Negative state	60.00%	40.00%
Positive state	73.33%	66.66%

Table 6. Results of micro expression recognition (several positive and several negative states of each person):

Database	(T_P)	(F_P)	(F_N)	(T_N)	#images
Regular data	9	6	9	6	15
Magnified data	11	4	6	9	15
	Sensitivity	Specificity	Precision	Accuracy rate	Error rate
Regular data	50.00%	60.00%	50.00%	50.00%	50.00%
Magnified data	73.33%	69.23%	73.33%	66.67%	33.33%

The test was performed on the CASME database for detecting the states of happiness and disgust. The tests results and the comparison of our proposed method with the TLD and TIM methods in the CASME and SMIC databases are shown in Table 7.

Table 7. The comparison experimental results:

	database	Method	Accuracy rate
Emotional/unemotional micro expressions detection	SMIC	MKL+TIM	73.60%
		HF+TLD	78.40%
		EVM+ eigenface	88.40%
happiness	CASME	HF+TLD	84.00%
		EVM+ eigenface	100.00%
disgust		HF+TLD	74.50%
		EVM+ eigenface	100.00%

As the results show, our proposed method is more accurate in detecting micro expressions than the TLD and TIM methods.

5. Conclusion

The very small motions that occur on a person's face during micro expression are not visible. Thus the facial expression recognition methods will not be able to detect those emotional states. Regarding the performance of the EVM method in the retrieval and display of small motions, we used this magnification method for retrieving subtle emotions. Then we investigated the output of a facial expression recognition system based on the eigenface method. The EVM method improved the rate of emotional/unemotional micro expressions recognition on the face. The eigenface method can also detect the type of micro emotional states. The results of the experiments show that the eigenface method using the EVM method recognizes negative state with a rate of 60.00% and a positive state with a rate of 73.33% in the SMIC database. While, without using the EVM method, the eigenface method recognizes negative states with a rate of 40.00% and positive states with a rate of 66.66%. According to the experimental results, the EVM method improves the performance of micro expression recognition and emotional/unemotional detection based on the eigenface method up to 16.00% in the SMIC database. We also investigated the detection of two states of happiness and disgust in the CASME database. As the results show, the proposed method recognizes these emotional states with a rate of 100.00%.

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