Revised version

Facial Micro-Expressions Recognition using High Speed Camera and 3D-Gradient Descriptor

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Abstract

Facial micro-expressions were proven to be an important behaviour source for hostile intent and danger demeanour detection [1]. In this paper, we present a novel approach for facial micro-expressions recognition in video sequences.
First, 200 frame per second (fps) high speed camera is used to capture the face. Second, the face is divided to specific regions, then the motion in each region is recognized based on 3D-Gradients orientation histogram descriptor.
For testing this approach, we create a new dataset of facial micro-expressions, that was manually tagged as a ground truth, using a high speed camera. In this work, we present recognition results of 13 different micro-expressions.

1 Introduction

The increase of violence and extreme actions around the world encourage us to look for new technological solutions that can be helpful in detection and prevention of those actions. The combination of computer vision and psychology research fields has large potential for developing such technology.

Two independent research groups , first included Ekman, Frank and O'Sullivan [1] and second was led by Porter [2] found that facial micro-expressions are the most important behavioural source for lie indication and can be used for danger demeanour detection as well [1]. Therefore, the method for micro-expressions detection and analysis is demanded.

Facial micro-expression is a brief, involuntary expression shown on the face of humans when they are trying to conceal or repress an emotion. They usually occur in high stakes situations, where people have something to lose or gain [3]. They consist of and completely resemble the seven universal emotions: disgust, anger, fear, sadness, happiness, surprise, and contempt.

However, there are technical problems to recognize micro-expression. First, is the duration of micro-expression is from 1/3 to 1/25 seconds and appears with low intensity. The necessity of analyzing such brief expressions calls for the use of a high speed camera. Second, detection of the such subtle changes in facial skin areas applying traditional computer vision approaches is difficult task. Therefore new 3D gradient descriptor is used on predefined face regions. Face regions was defined following facial action coding system (FACS) [4] introduced by Ekman.

In this work we present a novel approach for facial micro-expressions recognition by using 200fps high speed camera. Usage of 200fps assure approximately 10 frames for the fasters facial motion, that is the sufficient time resolution for detecting of the micro-expression.

The face is first divided to specific regions, then the motion in each region is recognized based on 3D-Gradient orientation histogram descriptor.

The structure of the paper is as follows. In Section 2 we discuss related work. Suggested algorithm is described in Section 3. Section 4 present a new dataset of facial micro-expressions. Experimental results and new dataset are discussed in Section 5. We conclude the paper in Section 6.

2 Related work

The general approach to automatic facial expressions analysis system (micro-expressions as well) consists of three steps: (1) face acquisition, (2) facial data extraction and representation, and (3) facial expression recognition.

Face acquisition (1) includes an automatic detection and tracking of the face in the input video. Extraction of the face direction could be added to this step.

In facial data extraction and representation for expression analysis, two main approaches exist: geometric feature-based methods and appearance-based methods.

The geometric facial features is presented by the shape and location of facial components (such as mouth, eyes, eyebrows, and nose). The facial components and facial feature points are extracted by some computer vision techniques that form a feature vector that represents the face geometry [5].

Recently, superior research results were reported on Active Appearance Model (AAM) by Kanade [6] group. However, there are two disadvantages of AAM to our research setting. First, this approach requires extensive dataset with large amount of manually tagged points of the face. Second, the accuracy of facial feature tracking significantly decreases in the faces that were not included in the training set.

Another approach is based on direct tracking of 20 facial feature points (e.g. eye and mouth corner, eyebrow edges) by particle filter [7]. This approach delivers good results for some facial motions, but fails in detecting subtle motions, that can be detected only by observing skin surface. The performance of this and similar approaches strongly rely on the accuracy of the facial feature points tracking. In practice, facial feature points tracking algorithm can not deliver the necessary accuracy for micro-expression recognition task.

In appearance-based methods, image filter, such as Gabor wavelets are applied to either the entire face or specific regions in the face, to extract a feature vector. This method was applied for spontaneous facial motion analysis and considered to be the most popular [8]. However, this method is based on analyzing the video frame by frame, without considering correlation between frames. In addition, applying this approach for facial surface analysis requires large datasets for training an enormous number of filters.

This paper focuses on effective facial data extraction, representation and facial expression recognition for micro-expression analysis and we skip face detection and face tracking step. For now we assume that examined frontal faces are located relatively in the same place. More detailed description of data capture will be presented in dataset section.

In this work we select 3D gradient oriented histogram for describing the facial motions, due to its ability to capture the correlation between the frames. Maraszalek [11] summaries several works that showed a good results in classifying motions in video signal using 3D gradient descriptors.
In Dollar work [9] local descriptors such as normalized pixel values, brightness gradients, and windowed optical flow were evaluated and compared for action recognition. Experiments on three datasets: facial expressions, mouse behaviour, and human activity, show best results for gradient descriptors [9]. Those descriptors, however, were computed by concatenating all gradient vectors in a region.

More advance approach of descriptor was proposed by Scovannere [10] where he use an extension of the SIFT descriptor to 3D data. For a given cube v(x,y,t), spatio-temporal gradients are computed for each pixel $\delta v_x(x,y,t)$, $\delta v_y(x,y,t)$ and $\delta v_t(x,y,t)$ respectively.

$$
\begin{aligned}
m_{3D}(x,y,t) &= \sqrt{\delta v_x^{\,2} + \delta y_y^{\,2} + \delta y_t^{\,2}} \\
\theta_{3D}(x,y,t) &= \tan^{-1}\left(\delta y_y^{\,2} / \delta y_t^{\,2}\right) \\
\phi_{3D}(x,y,t) &= \tan^{-1}\left(\delta y_t^{\,2} / \sqrt{\delta v_x^{\,2} + \delta y_y^{\,2}}\right)
\end{aligned} \tag{1}
$$

After that all pixels vote into the grid of histograms of oriented gradients using (1). For orientation quantization, gradients are represented in polar coordinates. This leads to problems of singularities at the poles since bins get progressively smaller. This problem is well represented through longitude and latitude grid of the globe.

Polyhedrons can be used as a possible solution to the singularity problem. Histogram computation is done by projecting gradient vectors onto the axes running through the centre of the polyhedron and the face centres and the gradient vector is computed for sub-blocks and not for every pixel [11].

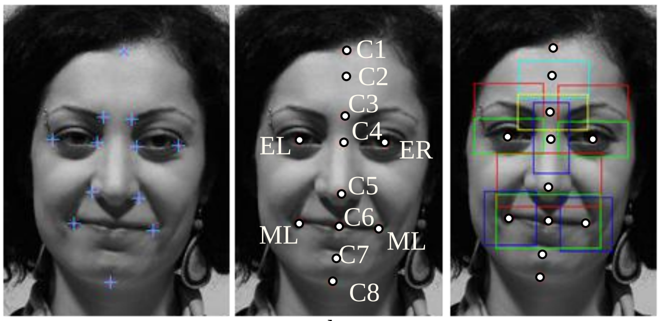
Both [10] [11] of the methods have the benefits of general descriptor but are lacking physical connection between the values of gradients histogram and the actual facial movements.

The proposed descriptor can be viewed as more specifically adapted for facial movements and allows us to examine the facial movements through observing gradient's histogram.

3 Proposed Algorithm

In this section we explain these steps in our micro-expressions recognition algorithm. Input video signal is obtained from a high speed camera in order to capture micro-expressions. The algorithm has three steps: First, is division of the face to twelve regions and the extraction of facial cubes (section 3.1). Second, is descriptor computation based on 3D gradient orientation histogram at each cube (section 3.2). The last step is a classification of the descriptors (section 3.3).

3.1 Facial features regions



a. b. c.

Figure 1: a) Manually selected point on the first frame, b) Calculated region centres, c) Facial regions

The facial muscles structure and movements are complicated and recognising all facial movements at once is a difficult task. Unlike Bartlett [8] who applied bank of Gabor filters to all the face area at once, we divide the face to 12 regions of interest. Following the facial action coding system (FACS) [4] that decomposes facial expressions in terms of 46 component movements, we determined the most representative regions in term of facial motions. (FACS is the most widely used expression coding system in the behavioural sciences.)

Regions were selected in a way that would include only a limited number of muscles that can make influence on them. Therefore, during the classification step, every region will have a limited number of classes to distinguish from each other. The regions are selected manually using the following procedure: 12 points are marked on the first frame of the input video manually (Figure 1: a) , then the locations of the regions centres are calculated (Figure 1: b) as well as the average size of the eyes. Eye size has an important proportional value for face, as size of facial features and their location are regularized in proportion to it. It allows automatic adaption to variety of faces.

Table 1 summarizes all the names, sizes, and locations of the defined regions. The sizes of the regions are defined little bit bigger than a region of interest, to make sure that the important features will stay in the region in spite of small face movements and rotations. After we finish extraction of th regions, 3D facial cubes are created for every region.

The dimensions of the cubes are X ,Y and t (Figure 2). In other words facial cubes can be seen as cropped video of facial parts such as eyes, nose and etc.

In addition this approach removes the constraints of high accuracy tracking of facial features points.

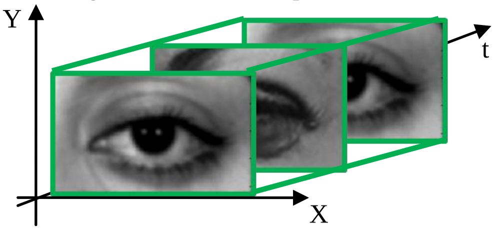


Figure 2: Facial cube

	Name	Centre Point	Size Height/Width [EyeUnits]
1	Forehead	C2	1 x 2
2	Left eyebrow	EL	2 x 2
3	Right eyebrow	EL	1 x 2
4	Left eye	ER	2 x 2
5	Right eye	ER	1 x 2
6	Between the eyes	C3	1 x 2
7	Upper Nose	C4	2 x 1
8	Lower Nose	C5	1.5 x 3
9	Mouth	C6	1.5 x 3
10	Left mouth corner	ML	1.5 x 1.5
11	Right mouth corner	MR	1.5 x 1.5
12	Chin	C7	1 X 1

Table 1: Facial regions names, region centres points and sizes

3.2 3D Orientation Gradients Histogram

In the case of 2D, given image I(x,y) the gradient magnitude and their orientation for each pixel is defined as follows:

$$m_{2D}(x,y) = \sqrt{\delta I_x(x,y)^2 + \delta I_y(x,y)^2}$$
$$\theta_{2D}(x,y) = \tan^{-1}\left(\delta I_y(x,y)^2 / \delta I_x(x,y)^2\right) \qquad (2)$$

where $\delta I_x(x,y)$ and $\delta I_y(x,y)$ stand for image partial derivative.

In 3D case of (x,y,t), there are number of ways to represent the spatio-temporal gradient vector as was discussed in the end of section 2. Here we propose a descriptor that is more specifically adapted for facial movement. It allows us to examine the facial movements through observing gradients histogram.

Calculation of the 3D descriptor starts by given a video sequence v(x,y,t), its partial derivatives along x,y, and t are denoted by $\delta v_x(x,y,t)$, $\delta_y(x,y,t)$, and $\delta v_t(x,y,t)$ respectively. Then, each couple of partial derivatives $(\delta v_x, \delta v_y)$, $(\delta v_y, \delta v_t)$, and $(\delta v_x, \delta v_t)$ magnitude $m_{xy}(x,y,t)$, $m_{yt}(x,y,t)$, $m_{xt}(x,y,t)$ and orientation $\theta_{xy}(x,y,t)$, $\theta_{yt}(x,y,t)$, $\theta_{xt}(x,y,t)$ are computed using equation (3). We suggest following interpretation of each couple of partial derivatives: $\delta v_{xy} = (\delta v_x, \delta v_x)$ represents surface shape, $\delta v_{yt} = (\delta v_y, \delta v_t)$ represents vertical motion and $\delta v_{xt} = (\delta v_x, \delta v_t)$ represents horizontal motion from frame to frame. Note that all the calculated magnitudes and orientations are comparable as they computed in the original video sequence v(x,y,t).

Next, gradient orientation histograms are computed for every frame for δv_{xy}, δv_{yt} and δv_{yt} cubes. Figure 3 illustrates all the process.

$$m_{xy}(x,y,t) = \sqrt{\delta v_x(x,y,t)^2 + \delta y_y(x,y,t)^2}$$
$$\theta_{xy}(x,y,t) = \tan^{-1}\left(\frac{\delta v_x(x,y,t)^2}{\delta v_y(x,y,t)^2}\right)$$
$$m_{yt}(x,y,t) = \sqrt{\delta v_y(x,y,t)^2 + \delta v_t(x,y,t)^2} \qquad (3)$$
$$\theta_{yt}(x,y,t) = \tan^{-1}\left(\frac{\delta v_y(x,y,t)^2}{\delta v_t(x,y,t)^2}\right)$$
$$m_{xt}(x,y,t) = \sqrt{\delta v_x(x,y,t)^2 + \delta v_t(x,y,t)^2}$$
$$\theta_{xt}(x,y,t) = \tan^{-1}\left(\frac{\delta v_x(x,y,t)^2}{\delta v_t(x,y,t)^2}\right)$$

The δv_{xy} (surface shape) gradient orientation histogram contains 8 bins as shown in Figure 4.a. Figure 4.b exemplify the change of the δv_{xy} gradients magnitudes and orientation during the micro-expression.

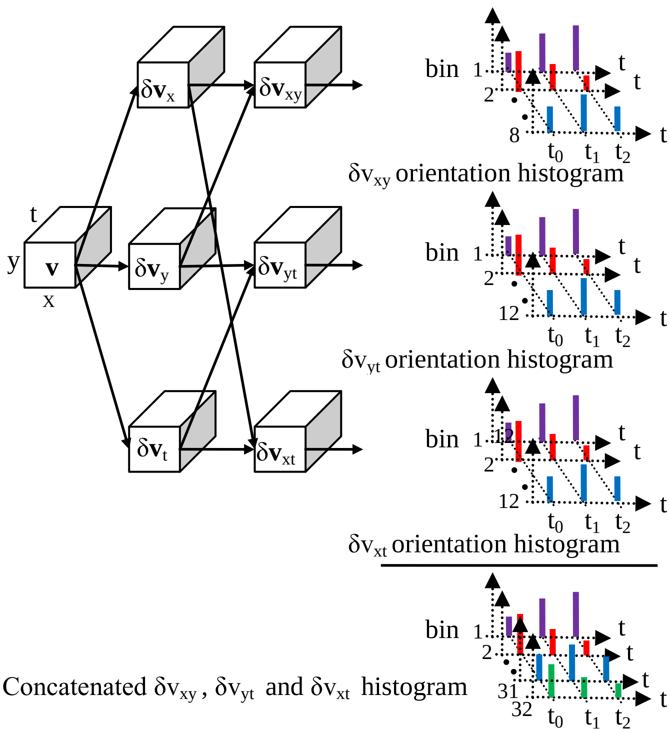
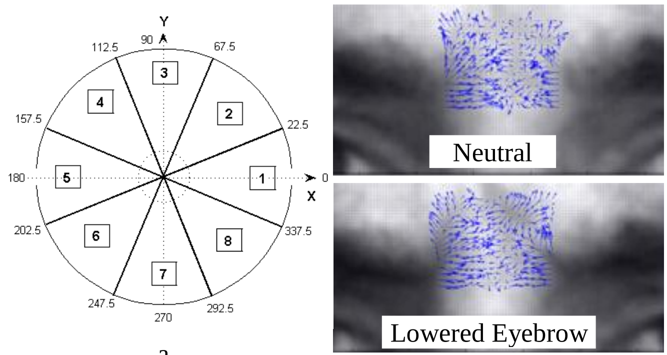


Figure 3: Descriptor calculation diagram for a facial cube

The upper image presents frame with neutral expression from "Between the eyes" cube (See Table 1). Lower image presents a frame with eyebrow lowered expression (FACS Action Unit 4 (AU)) at the next moment. Blue vectors on both images represent the gradients magnitudes of the surface. The changes of the surface can be observed by the changes in the gradients density, which is represented by blue vectors at the central part of the images. The gradient orientation histograms for δv_{yt} (vertical motion) and δv_{xt} (horizontal motion) contains 12 bins as shown in Figure 5. The figure illustrates the spread of the bins borders in the angle space between the Y and t axes, the spread between X and t axes is identical so all the following explanations concern both histograms .



a. b.

Figure 4: a) δv_{xy} orientation histogram b) AU4 with gradients magnitude.

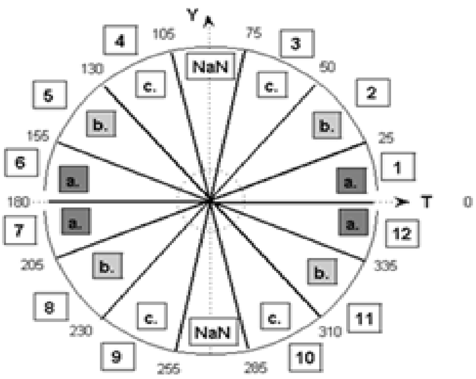


Figure 5: δv_{yt} and δv_{xt} orientation histogram

The angle space of δv_{yt} and δv_{xt} is split for 14 regions; normal 1 to 12 regions and two special NaN regions. Also, the normal 12 regions have three subgroups (a) , (b) and (c). The differences between the subgroups are described below.

NaN region: contains all the gradients vectors whose change rate in direction t is small, and they indicate no change between the frames in the corresponding pixel. So we do not include them in the histogram. We can exclude there pixels because image features of the pixels in this region are counted in δv_{xy} histogram.

(a.) region: contains gradients vectors which have small changes in x or y direction but have a significant change in t direction. It means that the corresponding pixels have a significant change only in their intensity between the frames.

(b.) region: contains gradients vectors with similar change rate in X and t (or Y and t) directions.

(c.) region: contains gradients vectors that indicate high rate change in Y direction and relatively small in t.

Then, with these group classifications the facial expression changes could be assigned to these regions. NaN region indicates no or little motions in the face between the frames. Region (a.) indicates big change in pixel intensity between the frames and can represent motions such as blinking and eyebrow movements. Regions (b.) and (c.) indicate different motions, appearances or disappearances of the skin folds on the face surface. During the histogram computation small vectors in all directions are excluded.

3.3 Descriptor

After computing histograms in δv_{xy} , δv_{yt} and δv_{yt} cubes for every frame, all histograms corresponding to the same frame are concatenated to one feature vector and normalised. This way the motion between every frame in the video v(x,y,t) is represented by 32 bins histogram vector (See Figure 3). In the experiments section we will show the results of k-mean cluster of the vectors for different facial cubes.

4 Datasets

One of the difficulties in establishing the research in facial expressions analysis is the need for an extensive dataset [17].

Until today, RU-FACS [12] is the only popular database of facial spontaneous expressions. The database consists of 100 subjects that participated in a 'false opinion' paradigm. In this paradigm, subjects first fill out a questionnaire regarding some issue, then asked to take the opposite stand from what they had reported before in the questionnaire. They were asked were to convince an interviewer, who is a retired FBI agent, that they are telling the truth. This paradigm has been shown to elicit a wide range of emotional expressions as well as speech-related facial expressions [13]. The subjects' faces were captured by four synchronized Dragonfly cameras by Point Grey, whose maximum frame rates with 640x480 resolution are 30fps. Only 33 subjects had been FACS-coded.

Other two well known FACS-coded datasets are: Cohn and Kanade's DFAT-504 [14] that contain 100 university students and Ekman and Hager dataset with 24 subjects. In both datasets the subjects were instructed to perform different expressions, while the emphasis was put on regular facial expressions (not micro-expressions). The facial expressions in those datasets were FACS-coded by two certified FACS coders. The lack of micro-expression dataset captured by high speed camera brought the need to create one.

We separated this task into two stages. First stage contained videos of posed facial expressions. This dataset will allow first evaluation of our algorithm. The second stage will include videos during 'false opinion' paradigm and other experiments with better simulation of hostile and dangerous behaviour. This paper focuses on the first stage.

For video capturing Grasshopper camera by Point Grey was used. Camera settings: 480x640 resolution, 200fps, RAW8 mode (in this mode minimum internal signal processing executed by camera allows 200pfs).

To have brighter experimental environment we followed the recommendations of McCabe [16] for mugshot and facial image. Three lights were used for shadow cancelation, left, right and upper point lights with diffusion sheets to minimise hot spots on the facial image. Uniform background approximately 18% gray was used and the camera was rotated 90 degrees (640X480) to maximise the amount of pixel on the face region. Dataset contains 10 university student subjects (5 Asian, 4 Caucasian, 1 Indian) (See Figure 6).

The participant were instructed to perform 7 basic emotions with low facial muscles intensity and to go back to the neutral face expression as fast as possible, simulating the micro-expression motion. Video facial cubes were extracted from all the faces in the dataset. Then, every cube was FACS-coded. We extended the FACS-coding by adding three time-tags to each AU as follows: i) “Constrict” - from a neutral expression towards one of the AU's (contraction of the muscles), ii) “In-Action” - expression it self (holding the muscles contracted) and iii) “Release” - from AUs towards neutral expression (release of the constructed muscles).

Figure 6: Subjects from our new dataset

5 Experiments

5.1 Micro-expressions classification

Currently, the algorithm is implemented in Matlab using "Piotr's Image&Video Toolbox" [15] without special emphasis on performance. However, parallel structure of the algorithm can get benefit from implementation on GPU environment. Such implementation is planned for the near future.

The algorithm has three parameters to be tuned. First, the values of 3D Gaussian smooth filter. During the tests it was found that to improve the performance, different values of the Gaussian filter have to be set to each group of facial cubes. Two other parameters are in histogram computation process. One is the magnitude cut-off threshold of the and the other is the size of the "NaN" bins (section 3.2).

The facial cubes from our dataset were divided to 8 groups: (a) forehead, (b) left and right eyebrows, (c)left and right eyes, (d) between the eyes, (e) lower nose, (f) mouth, (g) left and right mouth corner, (h) chin (Table 2).

Each group included facial cubes from 10 different faces and every frame was manually classified as one of neutral expressions, beginning stage of specific AU motion, ending stage of specific AU motion, and AU it self.

We used k-mean cluster methods. The number of clusters depends on the number of different motions that should be detected in each cube, it varies as 4 in (a), (e), (d),(e),(h) cubes; 7 in (b) cubes and 13 in (c) and (f) cubes.

The results indicate good classification precision in groups (a) forehead, (d) between the eyes, (e) lower nose are high. It is due to the small number of classes and they differ greatly from each other. The group (h) showed lower rates because of the beards on two faces in the dataset. Mouth group (f) shows the worst results. In many works on face expression recognition mouth movements were mentioned as the most challenging for classification.

In table 2 we report a classification precision for each class.

In addition, the result of almost all groups shows higher classification precision for beginning and ending part of the AU than AU itself. This indicates that the proposed descriptor is more suited for motion recognition and segmentation than for classification of the frames with "In-action" tags.

Facial Cubes	Neutral	FACS AU	Constrict	In-Action	Release
a) Forehead	0.95	AU2	0.93	0.95	0.91
b)Eyebrows	0.93	AU4	0.84	0.83	0.9
	-	AU5	0.86	0.83	0.85
c) Eyes	0.92	AU4	0.84	0.83	0.84
	-	AU7	0.86	0.8	0.81
	-	AU43	0.85	0.85	0.84
d) Between the Eyes	0.9	AU4	0.93	0.9	0.84
e) Lower Nose	0.94	AU10	0.95	0.93	0.95
f) Mouth	0.88	AU12	0.81	0.79	0.85
	-	AU24	0.81	0.67	0.79
	-	AU26	0.83	0.77	0.8
g) Mouth corners	0.83	AU13	0.85	0.81	0.89
h) Chin	0.89	AU17	0.83	0.83	0.84

Table 2: Classification results of micro-expression

As it was mentioned the dataset is designed includes videos that do not have head motions. However, some small head motions actually exist. In this experiment no special head stabilization was made this time.

5.2 Time measurements of micro-expressions

The results in Table 2 illustrate the ability of proposed algorithm to recognize three phases of the expression: the “Constrict” phase, “Release” phase and “In-Action” phase. The ability to extract this information is important for future classification methods. Moreover it is important for physiology analysis of micro-expressions. We believe, this time-measuring ability will be useful for the implementation of micro–expressions for hostile intent and danger demeanour detection.

Figure 7 presents the values of (1,5) bins in δv_{xy} histogram, and the values of (1,6),(2,5),(9,10) bins in δv_{yt} histogram during the AU4 micro-expression. Note that (1,5) in δv_{xy} is considered to be a representation of constructed muscles and (1,6),(2,5),(9,10) in δv_{yt} are represent the motions of the muscles. Three main phases of motion can be easily observed: “Constrict” - constriction of the muscles from 31 to 43 frames that lasted approximately 0.065s, “In-Action” - holding the muscles constructed from 44 to 73 frames, the expression it self that continued 0.15s and “Release” - the release of the muscles from 74 to 85 frames that lasted approximately 0.055s.

6 Conclusion

Micro-expressions are found to be useful behaviour source for lie indication and can be used for danger demeanour detection. In this paper, we presented a novel approach for facial mirco-expressions recognition using 200fps high speed camera of for capturing the face motion.

In order to initiate the research of detecting micro-expressions using high speed cameras, a new dataset was created. We presented the recognition results of 13 different micro- expressions . The unique feature of our approach is the ability to measure the duration of the three phases of micro-expressions (“Constrict” - constriction of the muscles, “In-Action” - muscle construction and the “Release” - release of the muscles).

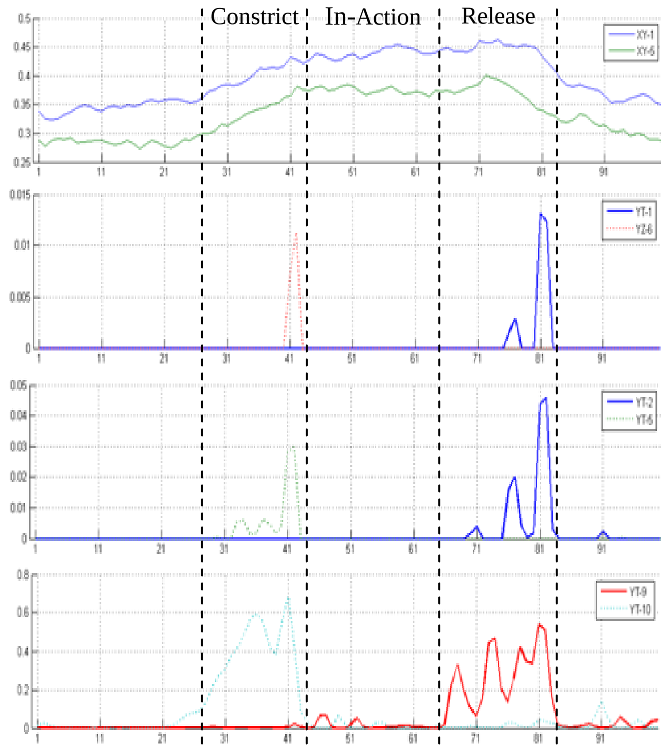


Figure 7: Values of 1,5 bins in δv_{xy} and (1,6),(2,5),(9, 10) bins in δv_{yt} histograms during AU4

Future extensions include face tracking and testing of the system with a wider variety of faces. More sophisticated generic classification algorithm will be applied in near future in order to adapt more varieties of micro-expressions.

In conclusion, in the academic sense, the use of micro-expressions for hostile intent detection is still unknown. In practice, the manual analyses of micro-expressions are widely used by secret services and homeland security departments around the world. However, due to the nature of micro-expressions it is difficult to detect or investigate them manually, this leading to the need for an automatic system.

This work is a step towards creating such a system.

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