Optical Flow-Based Algorithm Analysis to Detect Human Emotion from Eye Movement-Image Data

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***Abstract*—One of the popular methods for the recognition of human emotions such as happiness, sadness and shock is based on the movement of facial features. Motion vectors that show these movements can be calculated by using optical flow algorithms. In this method, for detecting emotions, the resulted set of motion vectors is compared with a standard facial movement template caused by human emotional changes. In this paper, a new method is introduced to compute the quantity of likeness towards a particular emotion to make decisions based on the importance of obtained vectors from an optical flow approach. The current study uses a feature point tracking technique separately applied to the five facial image regions (eyebrows, eyes, and mouth) to identify basic emotions. Primarily, this research will be focusing on eye movement regions. For finding the vectors, one of the efficient optical flow methods is using the pre-experiment as explained further below.**

***Keywords*—human emotion, eye movement features, optical flow, motion vectors**

I. INTRODUCTION

One of the responses to emotional stimuli is the change of one's facial features. Recognizing these facial features is among one of the ongoing works within the face-processing vicinity of the study. Facial expressions contain a plethora of information about human emotion and plays a key role in communication between one another. According to psychological research, there are at least six emotions that are universally associated with their own unique facial expressions [1, 2]. It is of note that a variety of other emotions and their combinations have also been studied, but they remain unproven as universally identifiable. The six most common emotions are happiness, sadness, surprise, fear, anger, and disgust. In Fig. 1, six images of facial expressions, decided on from [2], representing said emotions, are shown.

Automatic facial expression recognition is crucial for intelligent and natural human-computer interaction. It has been created by using a variety of methods, each of which uses distinct types of data (still pictures versus video clips), varying facial feature extraction techniques, and employing different classifiers. Several photographs had been studied by Hong, *et al.* [3−5] to comprehend facial expressions. When compared to video footage, facial expression recognition from a single still image is less accurate since a single image provides significantly less information for facial expression recognition than a series of images. The advantage of using a series of images over a single image was demonstrated by Bassili, where he concludes that facial features become more decipherable when the data comes from dynamic photos instead of from a singular, static photo [6].

Figure 1. Six images with six universal facial expressions were chosen from [2].

In addition to having less information, it was observed that the extracted facial expression data from the singular images had much less precision when compared to the precision of the data that was obtained from video footage. One of the major factors was that there was less information to go off of from the singular image when compared to the footage. This factor is further cemented by Bassili's research [6].

Thus, the objective of this research is to identify which abnormal facial cues occur when certain expressions are shown. In addition, this paper also intends to give an in-depth and detailed look into certain facial movements. By analyzing the possible motions of facial expressions, and primarily focusing on eye movement, the true extent of a

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person's psyche may be explored. In this paper, a set of optical flow rules are used to determine facial movements for three primary facial expressions (neutral, happy, sad). Section IV and V describes techniques used in the study and is accompanied with the aid of using a dialogue of consequences and evaluation is done in Section VIII. Finally, conclusions are drawn.

One of the biggest advantages of our method is that it is unnecessary to determine the exact locations of facial features and only the approximate values are sufficient. The proposed optical flow-based movement data processing method applies the Horn-Schunck optical flow algorithm to train the eye movement behavior image dataset.

II. Research Objectives

The objective of this research is to induce human emotions in individuals in order to determine if specific facial movements could be detected and analyzed by the optical flow technique. Motion vector plots help represent this analysis. The test determines whether certain emotions can be described as a collection of facial movements that most people share when they are experiencing a certain emotion. 'Emotion vector maps' would then be established for specific emotions such as neutral, happy, sad and shock.

III. Related Work

A technique utilized by a multitude of scientists when determining emotions is based primarily on optical flow. Yacoob and Davis [7] used optical flow to study the movement of brows, eyes, nose, and mouth. In their study, they used a research desk to categorize six fashionable facial expressions, happiness, sadness, surprise, fear, anger and disgust. Barlett *et al.* [1, 8, 9] blended optical flow and predominant factor evaluation expressions (See Fig. 2)

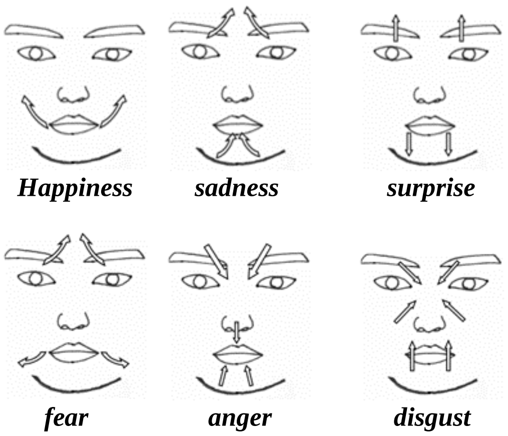


Figure 2. The movements of facial expression as suggested by Bassili [8].

Furthermore, in this research, photo sequences of expressive human faces were used to estimate optical flows accurately, allowing them to better grasp human emotions. In this procedure, the face is segmented into 6 sections based on its facial capabilities and movements following an approximate estimation of the locations of facial features. Then, using Gautama and Vanhulle's [8] set of rules on optical glide, the particular motions of facial features are recorded, and the movement vectors are extracted by evaluation of the vector set. This assessment is completed by evaluating the reactions caused by certain expression of emotions on the face.

Besides that, supply vectors are a collection of vectors that show movement and distortion in the face as a result of representing emotions. To obtain supply vectors, a set of headshots are chosen whose movement vectors accurately represent facial traits, similar to Bassili's explanation [2, 8, 10]. The incorrect vectors are then deleted, and a couple of vector perspectives and their surroundings are saved for the rest. Fig. 3 shows an example of supply vectors that were utilized to detect happiness on a woman's face. Since there needed to be a minimum amount of picture sequences, six frames of a clip showing a happy smile are used in this situation. The vectors are then generated, and their miles are displayed inside the rest of the image. The vectors are then reviewed, and is placed in the first frame. This method was used for all simple emotions.

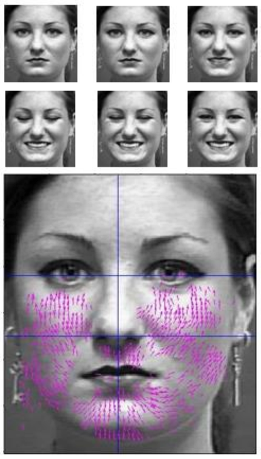


Figure 3. An instance of source vectors [11].

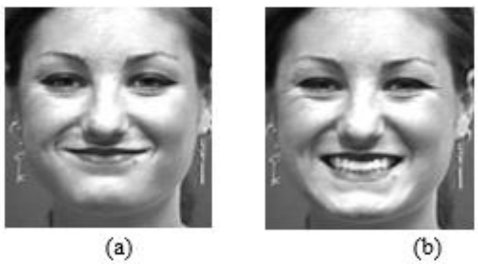


Figure 4. Two different images can be identified as happiness [11].

Note that the same emotion can have different forms in different subjects. Also, for some emotions, it is possible to have different facial movements in the same subject. An example is the two different expressions of happiness in the woman's face shown in Fig. 4.

IV. Our Work

In this study, video data from our experiments database is used, which comprises of three basic facial expressions (happy, sad, and shock). The database provides videos of subjects with audio-video interleave (avi.) file format. All videos display the sequences of facial expressions in frontal face view. The videos consist of approximately about 80 to 100 frames per second with a length of 4 seconds in a 640×480 resolution. The videos begin with the neutral expression to the most animated expression of one of the test emotions and then back to the neutral expression (refer to Fig. 5). This is then repeated with the other test emotions. The intensity of the facial feature movement is then measured using optical flow. For this research, we mostly focus on the eye section.

Figure 5. Sequences used to identify a happy expression.

Optical flow [12] is the estimation of an object's perceived motion between an observer and the scene. The optical flow allows for the measuring of motion between two image frames. The images of a subject's face with a clear view of their facial points serve as the optical flow's input. Two video frames are extracted each time the optical flow function is run, which are then utilized to measure the object's motion. Eq. (1), which is what the optical flow is restricted to, must be solved in order to construct the optical flow between two images.

$$I_x u + I_y v + I_t = 0 \tag{1}$$

where:

I_x, I_y and I_t are the brightness derivatives of the spatiotemporal images

u is the horizontal optical flow

v is the vertical optical flow

The video of facial expressions from our database is converted to grayscale format in the first phase. The purpose of converting the video to grayscale is to eliminate any superfluous pixels when extracting data. In addition, converting to grayscale helps simplify most of the calculations in the next step. Because of its ability to measure motion between two video frames, optical flow for video is computed. Before that, the background in the video was made black to get rid of noise in the video data.

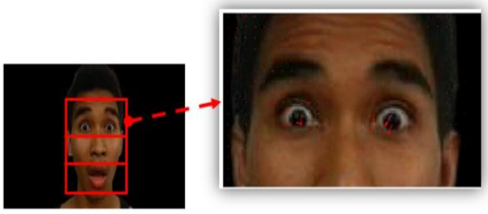


Figure 6. Segmentation of ROI in this research.

At the same time, two video frames are used, one of which is the subject's initial state, which is the neutral face, and the other is a non-neutral facial expression with a strong level of expression strength. To help observe the movements of facial characteristics, a Region of Interest (ROI) was given a focus. For example, the ROI of gaze is used to assess human task performance [13–16]. To assess the amplitude of optical flow, the segmentation process, which divides the face into numerous ROIs, must be done. The segments are divided into 3 sections, which are: (1) the area around the eyes and brows, (2) the cheeks, and (3) the lips. For this study, we will concentrate on one essential area: the eyes and brows. Fig. 6 depicts the ROI segmentation in this study.

The magnitude of each facial feature is measured by computing the displacement of the current and previous position for each frame using Eq. (2).

$$\tilde{v} = \sqrt{(x_i - x)^2 + (y_i + y)^2} \tag{2}$$

Finally, the facial expression in the video is analyzed. The framework can be seen in Fig. 7.

Figure 7. The facial expressions analysis framework.

V. Motion Vectors Computations Using Optical Flow Techniques

Optical flow shows how a photograph changes as a result of movement over the span of seconds. Higher-degree processing that can solve movement issues requires the calculation of optical flow. Calculating optical flow can be done in a variety of ways. Barron *et al.* [8, 17, 18] examined nine distinct strategies, serving as a consultant for a variety of approaches, including differential, matching, energy-based, and phase-based ones. They evaluated these algorithms on a variety of popular photo sequences.

The optical flow method [19, 20] is an important method for evaluating photographs of movement and has a wide range of applications in system vision and image processing. The optical flow calculation of a moving subject can be used to assess the motion statistics of facial features. The set of rules for the Horn-Schunck optical method requires a dense optical flow subject based entirely on grayscale consistency assumptions. The optical flow computations may be incorrect if the brightness is not always invariant or if a moving subject is deformed. Using the traditional optical flow approach will invariably result in a flawed optical flow subject, which will have an impact on the success rate of computing facial features.

In this paper, based on the extended optical flow constraint equation, a novel approach for estimating the detection of changes in facial expression based on the Horn-Schunck method for calculating optical flow is presented. The approach is used to calculate the optical flow field of facial expression sequences. The experiment results show that the performance of this approach is better than the normal method [21, 22]. On top of that, we propose an optical flow method for moving images because the characteristics of optical flow are more than suitable at handling abrupt movement [23, 24]. Due to its ability to extract the velocity and angle, the optical flow method has been utilized in earlier research. As a result, this method will determine the displacement and intensity density for each frame of the movement video. The Horn-Schunk algorithm (HS), which has decent performance and is straightforward, is one of the traditional algorithms in an optical flow.

Previous research [25] has compared different optical flow fields from Horn-Schunck, Lucas Kanade and Brox's warping techniques. The set of rules of the Horn-Schunck method aims for higher impact smoothing with the aid of presenting denser fields as compared to other techniques. Within the wide variety of item displacements, it offers steady fields of optical flow. However, the fields are very sensitive to mistakes derived from their neighboring points [22]. Therefore, we use the Horn-Schunck method to estimate the optical flow wished in our set of rules.

VI. METHODOLOGY

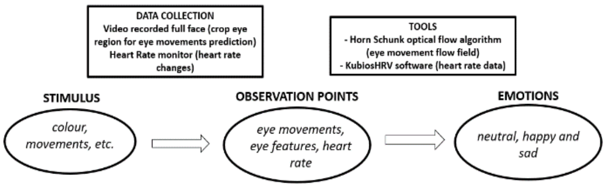


Figure 8. Underlying model.

Fig. 8 above shows the underlying model for the whole research process. In the first step, heart rate data and eye movement video are preprocessed to remove artifacts. Next, the flow field is calculated from the processed eye movement data. Horn-Schunk's optical flow algorithm was chosen to extract the eye movement flow field. Finally, three fusion strategies are explored to improve the performance of the proposed emotion prediction algorithm.

A. Data Acquisition

For the image acquisition phase, an experimental paradigm is designed to acquire the emotional eye movement signals. A subject is shown four videos with a short gap in between each video. The first video clip displayed, "Happy," is a comedy video in which an animated short is played featuring brightly colored characters playing around accompanied by upbeat music on a clear background which is intended to trigger a happy feeling. The second video on the list, "Neutral," is a video that shows a short clip from a film that displays peaceful and beautiful scenery. The third video, "Sad," shows a clip of a mother crying tragically after losing her daughter. The fourth video, "Shock," shows a clip of a firefight during World War 1.

B. Preprocessing

During this phase, the entire human eye movement image will be extracted and stored in a ".net" file using the MATLAB software. Preprocessing breaks down the visual input into discrete frames that can be processed further. The format used in processing the video file is ".avi."

C. Feature Extraction

Then, for the human eye movement data, the Horn-Schunk optical flow algorithm will be applied to extract the velocity-based features. This application was made based on MATLAB software. The details of this application are described below.

1) Optical flow

The optical flow methodology was selected as the approach for the interpretation of facial expressions. This method involved assessing the magnitude and direction of facial motion. In recent years, optical flow has emerged as a useful tool in the analysis and tracking of motion features in video sequences. The traditional approach assumes the motion between two image frames at the pixel level. The conventional method assumes pixel-level mobility between two image frames. The motion of an object in three dimensions (3D) is projected into a two-dimensional (2D) plane. It is assumed the type of motion sought is distributed over a sequence of several neighboring frames. In practice, this assumption is reasonable as the motion is gradually spread out across several frames. This presumption is valid in practice because the motion is gradually dispersed over numerous frames. Although the large motion of vehicles and human beings is easier to detect, the precise movements of a human body organ are harder to capture.

For this work, it was assumed there is a brightness consistency across neighboring video frames. Hence the brightness of neighboring image pixels does not change over time. Therefore, in Fig. 9, an example of an optical flow analysis can be seen, where the 'neutral face' seen in image A is compared to an image of the 'expressive face' (image B) creating a vector map (quiver diagram) - Image C. The red arrows in Image C are 'flow vectors', with their length being proportional to the velocity of the expression.

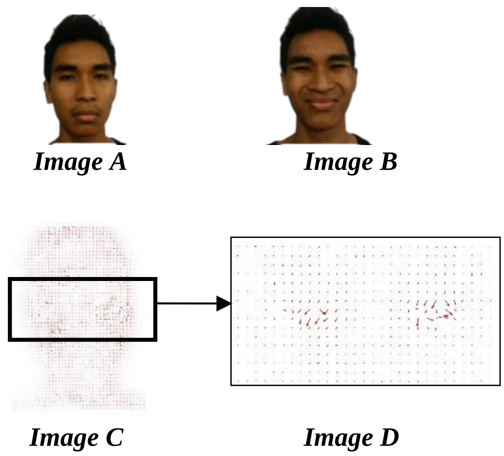


Figure 9. Image analysis by optical flow (flow field diagram).

The base 'neutral face' image A on the left is compared to the 'happy face' image B and the vector map image C is created. Image D is an enlarged portion of the complete vector map, or flow field diagram, showing individual vectors, which are too difficult to see in image C.

VII. EXPERIMENTAL PROCESS

A. Stimuli

An experimental paradigm is designed (as shown in Fig. 10) to acquire the eye movement signals as the subject experiences various emotions. Each trial begins with the word "begin" appearing on the screen to signal the beginning of the stimuli video, which is followed by a brief beeping warning tone. Afterwards, four different emotional stimuli videos with a duration of sixty seconds each are displayed. When the stimuli video ends, the subject is allowed to relax for fifteen seconds to attenuate the current induced emotion. The process is then repeated with another video until all four videos are shown.

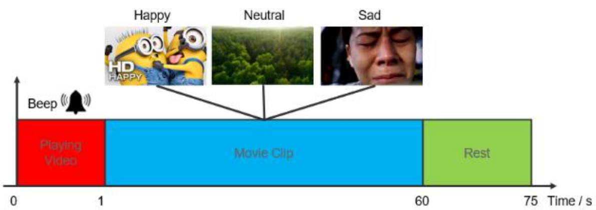


Figure 10. The experimental paradigm of each trial. The horizontal axis indicates the duration of the experiment.

B. Subject

For the experiment, ten healthy subjects (five females and five males, aged 24 ± 1) are individually involved to sit about 40cm away and in front of the screen. On the desktop are stereo loudspeakers, and an appropriate volume has been empirically initialized for the sound. Before the experiment, all subjects are informed of the purpose and the procedure of the experiments and are given a preview to two to three of the video clips in order to be familiar with the experimental environment and instrument. Additionally, they will be questioned about how comfortable the lighting, temperature, and other factors are, such as the distance between the subject and the screen. If the user finds any of the settings uncomfortable, the factor will be adjusted according to the subject's feedback.

C. Laboratory Set-up

The experiment was conducted in an air-conditioned laboratory. Simultaneously, the previous system tracks eye movements using only the PC's webcam. Both the initialization of the system and the selection of the required parameters are automated. Tests were conducted on a 14-inch screen. A Logitech HD webcam was used to record the subject at a resolution of 1920×1080 pixels with a frame frequency of 15 frames per second with the lens facing towards the subject positioned approximately 40cm in front of the screen.

D. Experimental Process

All ten subjects watched four stimuli videos each. Subjects were seated on a chair approximately 40cm away from the screen, directly facing it, and were instructed to look at the computer's screen. This process assisted in determining the link between emotion and associated physiological changes. Subjects were given a remote control for the speakers and were told to adjust the volume at any time to a comfortable level during the films. The camera was then turned on, the first stimuli video began, and the researcher left the room. The videos were shown in a random sequence to negate predictability.

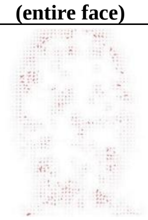
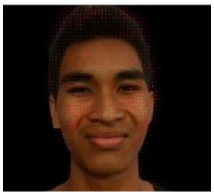
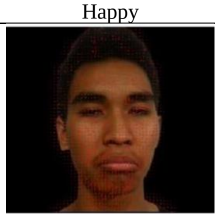
VIII. Results and Discussion

Table I depicts the result of applying our algorithm to the image sequences. The left column shows the facial expression and other cells show the numbers of suitable vectors earned for each of the emotions. One of the properties of this method is that it does not categorize an emotion absolutely but shows the amount of similarity it has with the other three basic emotions. In addition, our algorithm can determine facial expressions with only three to four frames in a sequence. This means that even if most of the frames were unused, the method can still work.

Moreover, to make the result of the flow vectors in the flow field clearer, the *t* value in Eq. (3) is created which is the maximum value of optical flow minus the minimum value of optical flow for all image sequences from each video of experiments. Hence, the *t* value for every frame in all experiments was calculated and the highest value of the frames was selected as the reference image.

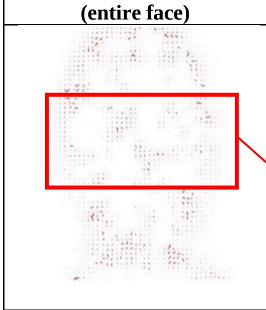
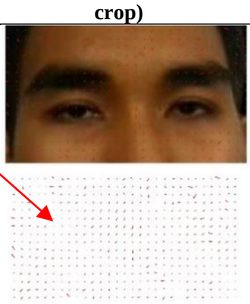
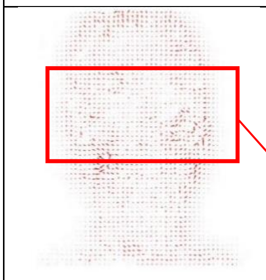
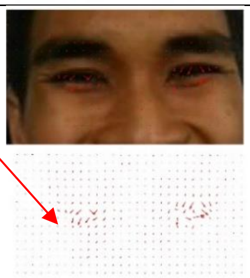
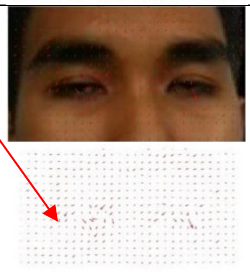
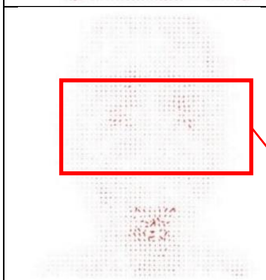
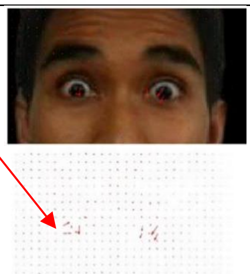
$$t \text{ value} = \text{maximum optical flow} - \text{minimum optical flow} \quad (3)$$

TABLE I. Image Frames with Optical Flow Field the Entire Face

Image Frames	Optical Flow Field (entire face)	*t* value
 Neutral		+1.083 (lowest value)
 Happy		+1.115 (medium value)
 Sad		+1.113 (medium value)
 Shock		+1.118 (highest value)

By referring to Table I, we can identify the average value represented by every facial expression that is derived from Eq. (3). Through this average value, we can make a rough analysis of the optical flow change which occurs from the existence of two different frames of facial expression images with different rates. By using this average value, we can perform a cursory examination of the difference in optical flow from the result of the presence of two frames containing images of various facial expressions. Table I shows that the shocked emotion has the highest optical flow value compared to the other three human emotions. The finding in this experiment has also been observed in other studies [26, 27], in which when more movement in the face occurs, the optical flow value will be higher. Tables I and II show the results of applying our method on only the first, middle and last frames of the different facial expression image sequence seen in Fig. 11, as well as the optical flow field of the entire face and an eye crop.

TABLE II. OPTICAL FLOW FIELD BETWEEN THE ENTIRE FACE AND EYE CROP

Optical Flow Field (entire face)	**Optical Flow Field (eye crop)**	***t* value**
		+1.090 (lowest value)
		+1.105 (medium value)
		+1.140 (medium value)
		+1.175 (highest value)

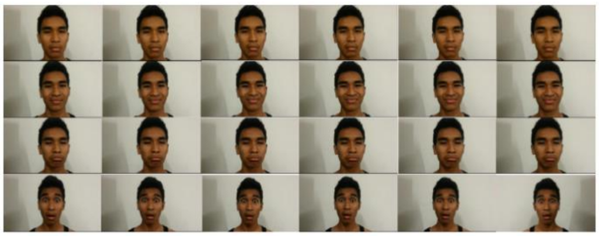


Figure 11. Some instances of emotion representation for neutral, happiness, sadness, and shock, respectively.

The slowness of the optical flow algorithm, the difficulty of detecting emotion when faced with significant head motion and the problems related to the optical flow techniques when the lighting is not properly adjusted are the biggest disadvantages of our algorithm.

TABLE III. RESULTS OF AVERAGE VALUE

Human Emotions	***t* value for Optical Flow Field (full-face)**	***t* value for Optical Flow Field (Eye crop)**
Neutral	+1.083	+1.090
Happy	+1.113	+1.105
Sad	+1.115	+1.140
Shock	+1.118	+1.175

In conjunction with values in Table III, it is shown that the human emotion ‘shock’ has the highest *t* value for the optical flow field when compared to human emotions ‘neutral,’ ‘happy’, and ‘sad’. This proves that the human emotion ‘shock’ involves more facial movement compared to other human emotions. Meanwhile, human emotion ‘neutral’ has the lowest *t* value for the optical flow field compared to the human emotions.

Both results, whether it’s the *t* value for optical flow field of the entire face or the *t* value for optical flow field of only the eyes, show that the human emotion ‘shock’ produced the highest *t* value when compared to the other three human emotions tested. In addition, the results also prove that only three frames are sufficient to detect human emotions. These results make high-performance facial recognition based on optical flow techniques effective and feasible.

IX. CONCLUSION

In this research, we presented an efficient facial expression detection method based on the Horn-Schunck optical flow method for extracting the essential motion vectors and, as a result, determined the optical flow of various expressions of different emotions such as neutral, happy, sad, and shock.

For detecting changes in facial expression, we suggested a video-based method based on the Horn-Schunck method for optical flows. The performance of our suggested technique for facial expression identification was then demonstrated using sequential image frames. The method used showed an increase in facial feature extraction, according to the results of the experiments. Furthermore, when compared to other feature extraction methods, optical flow processed sequential facial expression photos can yield a higher recognition rate.

Future work will include the use of more subjects to obtain a larger sample of eye movement points, as well as a more detailed study of pupil dilation in relation to where the eyes are fixated. Also in our future work, we will further our exploration in physiological changes using human heart rate variability based on facial expression. To increase the overall accuracy level, the experiment's findings could be added to the results.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Tuan Khalisah Tan Zizi, and Suzaimah Ramli conducted the research, analyzed the data and authored the paper. Muslihah Wouk, Muhd Afizi Mohd Shukran authored the paper. All authors had approved the final version.

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