order to find the velocity of moving objects. The idea of motion detection is based on finding amount of difference in two consequent frames of a video sequence.

A set of comparative experiments was prepared utilizing Horn-Schunck facial expression video sequences. Four facial expressions such as normal, happy, shocked and sad were sampled to be recognise in this work. From the facial expression video file, we have collected variable length consecutive frames from each video sequence. The collected frames are then realigned with the size of 480 x 272 pixels. To evaluate the performance of the proposed system, we applied a total of 30 to 90 image sequences per expression for training and testing each expression respectively.

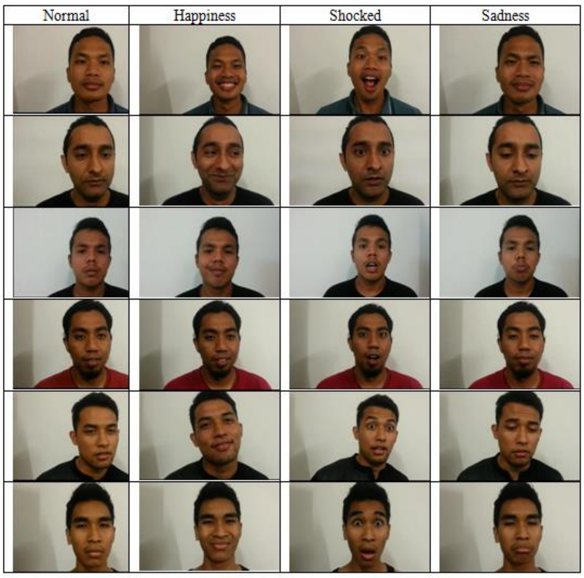


Figure 3. Facial expression sequence for the four categories of normal, happy, shocked and sad

Various techniques have been developed for automatic facial expression recognition, which differ in the kind of data used (still images vs. video sequences), feature extraction methods used, and classifiers used. Figure 3 shows the shows a snapshot of the user interface containing the pre-processed image sequence which was used for the extraction and classifying process.

The database consists of 100 subjects, both male and female, with four expressions of themselves, which are normal, happy, shocked and sad. After all the image sequences had been pre-processed, 30 image sequences were categorized by emotional expression (normal, happy, shock and sad) Figure 3, which were some of the image sequences for each category. All categorized image sequences were used as the input data for the tracking algorithm.

3.4. Facial expression classification

After the feature points were tracked and the velocity of the points calculated (facial expressions feature data). The next step of the classification process identifies the facial expressions of each sequence into the four categories: normal, happy, shocked and sadness category. To classify the different facial expression region neural network is used as classifier that is just one of many possible choices for learning the class separation boundaries. The classification process compared the optical flow plot of selected image frames from the video file which were calculated for each of the four expressions categories: normal, happy, shocked and sad.

In computer science and relative fields, artificial neural networks are computational models inspired by animal central nervous system (in particular the brain) that are capable of machine learning and pattern recognition. They are usually presented as systems of interconnected neurons that can compute values from inputs by feeding information through the network. The feature vector is given as input the neural network. Neural network involves a series of algorithms that attempt to identify underlying relationships in a set of data by using a process that mimics the way the human brain operates.

4. Result and Discussion

The experiments were conducted here using 100 different persons, to find a solution of the problem of facial expression of face recognition. For this study, feature extraction algorithm called Horn-Schunck optical flow algorithm has been used. For these experiments 100 different face images are of varying expressions with a total of 4 different poses which are normal, happy, shocked and sad. This work has been simulated using MATLAB (R2010a) [15] in a machine of configuration. Horn-Schunck optical flow showed its superiority over all the feature extraction methods by means of achieving the highest recognition rate.

Other than that, flow vectors are the collection of vectors which shows motion and deformation expressed in the face due to emotion representation. To obtain flow vectors, a series of facial images is chosen which its motion vectors show facial expression correctly similar to Horn and Schucnk optical flow algorithm [2,3]. For example, when we want to save flow vectors of happiness, more fibrous vectors appear in the flow field. Table 2 shows an example of flow vectors which used for detection of normal face, happiness, shocked and sad. In this case, four frames of a different faces' image are programmed as the input image sequences. This procedure is run for all of basic emotions.

Moreover, to make result for flow vectors in the flow field more clearly, *the t value* (1) is created which is value of maximum optical flow minus the minimum value optical flow for all image sequences from each video of experiments [27]. 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.

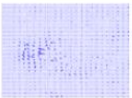
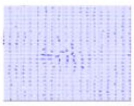
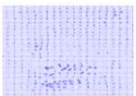
t value = maximum optical flow – minimum optical flow (1)

Referring to the Table 1, we can identify the average value represented by every facial expression that is derived from (1). Through this average value, we can make a rough analysis on the optic flow change which occurred with the existence of two frames of facial expression images with different rates. Table 1 shows that Expression 3 has an optical flow value that is the highest compared to Expression 1 and Expression 2. This proved that Expression 3 has much movement in the facial expression, compared to Expression 1 and Expression 2. This is also proven in most of the study [1], [11], [23], [25], [26], [28] including this experiment that, when much movement in the face occurred, it will show the highest optical flow value.

Table 1. Results of average value

Info	Experiment 1	Experiment 2	Experiment 3
Minimun OF	-1.013	-1.121	-1.136
Maximum OF	+1.105	+1.140	+1.175
*t*value (Maximun OF – Minimum OF)	+2.135	+2.261	+2.311

Table 2. Results of Average Value

Video	Selected Frame	Optical Flow Plot	*t* value
Expression 1 (normal)			+1.083 (lowest value)
Expression 2 (happiness)			+1.115 (medium)
Expression 3 (shocked)			+1.118 (highest)
Expression 4 (sadness)			+1.1131 (medium)

In conjunction with values in Table 1, Table 2 shows that Expression 3 has an optical flow value that is the highest compared to Expressions 1, 2 and 4. This proves that Expression 3 has much movement in facial expression, compared to Expressions 1, 2 and 4. Meanwhile Experiment 1 has an optical value stream that is the lowest compared to Experiment 2 and Experiment 3. This showed that (Experiment 1 < Experiment 2 < Experiment 3).

5. Conclusion

In this paper, we introduced an efficient algorithm for facial expression detection based on Horn and Schunck optical flow technique to extract the necessary motion vectors, and consequently, determining the faces of varying expressions like normal, happy, shocked and surprise.

Recently, facial expression change detection has been a challenging issue in the pattern recognition field. At present there are still many problems need to be further addressed. In conjunction with that issue, we have proposed an approach based on the extended optical flow constraint and the approach has been applied in facial expression recognition, and the experimental results show that the performance of this approach is better than the normal method.

We have proposed a video-based using Horn and Schunck optical flows for facial expression change detection. We have illustrated the performance of our proposed method applied to sequential image frames for facial expression recognition problems. The experimental results show that optical flow improves the feature extraction task. Furthermore, optical flow processed sequential facial expression images can provide superior recognition rate over the other feature extraction approaches [26].

For classification of these features neural network is used as classifier which provides better results and few false detections are observed in the presence of significant noise. Also training the neural network to separate the given input data into classes is little difficult.

Based on the experiments that has been conducted, the average values of the facial expressions were identified. Through this average value, researchers can make a preliminary analysis of the optic flow changes which occurred with the existence of two frames of facial expression images that are derived from two different rates.

In the future, we will consider classifying the expressions so that we can determine human behavior by applying Horn-Schunck algorithm and will be integrated with thermal sequences images data illumination with different facial action units in order to produce accurate results.

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