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Research Paper

Human intention detection with facial expressions using video analytics

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Abstract

The manuscript should contain an abstract. The abstract should be self-contained and citation-free and should not exceed 200 words. The abstract should state the purpose, approach, results and conclusions of the work. The author should assume that the reader has some knowledge of the subject but has not read the paper. Thus, the abstract should be intelligible and complete in it-self (no numerical references); it should not cite figures, tables, or sections of the paper. The abstract should be written using third person instead of first person.

Keywords: *Feature Tracker; Facial Expressions; Support Vector Machines; Emotion Classification.*

1. Introduction

Facial Expressions shows by the humans is one of the most powerful and natural way of communicating their emotions and motivational states [1]. The major modal quality of communication in human body is their facial expressions and eye movements. In recent years, information related to facial expressions has gained a substantial interest in research to track dynamic changes in human face movements. There are several real time applications like driver drowsiness detection, human interest in purchasing things while shopping.

In this paper, we propose a method which automatically infer human emotions through facial expressions for automatically inferring emotions by recognizing facial expressions in live video. Our method is based on support vector machines which helps the feature tracker to collect a set of values from images captures in video stream. These are later used to train an SVM classifier to recognize unobserved expressions.

2. Related work

Two reasons were the implementation of facial expression is difficult: 1) Inadequacy of large datasets of training images and 2) Expression classification is difficult because sometimes image captured can be static or motion image.

Data Extraction is performed with different factors and methodologies like using wavelet filters [2], eigen features [3] and FFT with energy computation [4].

Examining the Facial expression is the easier and practical method to detect human intention. There are several emotions examined in which few emotions are accepted universally across different environments such as anger, fear, happy, sad, surprise, disgust, sorrow. This mixture of emotions can be used as descriptors to detect facial expressions.

3. Overview of SVM model

In this paper, we propose a real time feature tracker for facial expressions which deals with localization and feature extraction in human expressions which is made spontaneously. The tracker extracts the position of facial feature from the video with multiple images and calculates the displacements between each frame of an expression. The calculates expressions values are given as input to the support vertical machine classifier altogether. The model will subsequently classify the feature displacement in real time based on the user request for every image in the video stream which is illustrated in Figure 1.

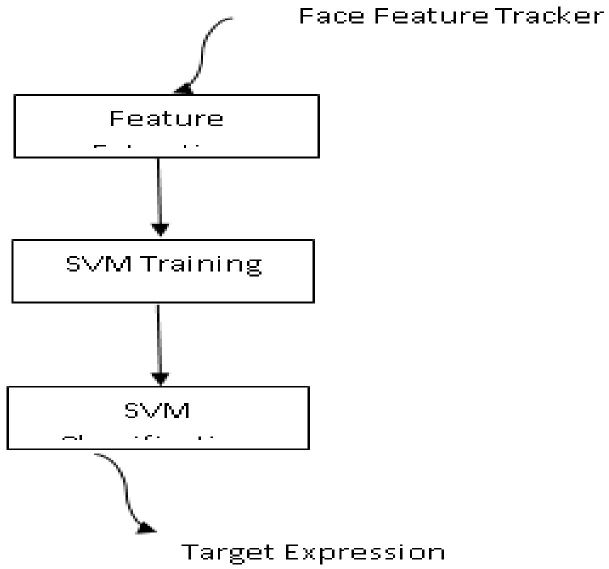

Fig. 1: Expression Recognition Using SVM Model.

By using a commercial video camera connected with personal system provides a well-defined frame rates by considering brightness conditions. For assumptions our model will accept the front view of the face and different head pose which works for randomly generated emotion classes. The common emotions accepted universally is considered for implementation purpose.

4. Face feature extraction and tracking

For real time video stream, feature displacement method is used. Face Feature extraction can be done by locating the position of the facial features in the video stream using tracker. The tracker uses filter to identify the position in consequent frames which is described in Figure 2.

Fig. 2: Face Feature Extraction by Adding Filters.

By considering the Euclidean distance, a feature displacement is determined in a video frame for each expression. Based on the features localized the motion patters are identified as shown in Figure 3.

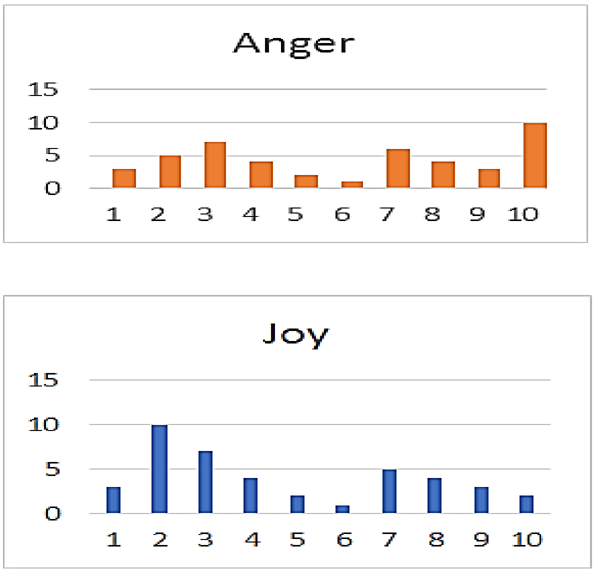

Fig. 3: Emotion Patterns for Face Feature.

5. Overview & classification

5.1. Overview of SVM

In General, the machine learning algorithm generates hypothesis function which can be used to forecast the future data.

S= ((X1Y1)……. (XiYi)), where Yi = {-1, 1}

SVM uses learning algorithms which separates the training data is formulated to use kernel functions that sets input vectors into feature space by avoiding external embedding. Based on the nearest training points called support vector gives kernels which is taken as decision function for expression classification.
SVM model is an integrated approach which allows domain specific kernel function that are used for classification. The expression classification is listed in Table 1 based on kernel functions.

Table 1: Kernel Function

Kernel Function	Equation
Linear	Xy
Polynomial	Yx.z+c
Radial Basis Function	Exp(-y|x-z|2)
Sigmoid	Tanh(yxz+c)

5.2. Classification of SVM for video stream

The SVM classifier is used for implementing the functionality of detecting the facial expressions in an object-oriented method. Before classification, the training data are collected and augmented which enables to retrieve the data for future classification. The data collected at several training sessions is taken and performs classification and it will be combined with the displacement by feature extraction phase.
During classification if unseen expressions are identified which is not in training set, then is also added in the training set to retrain the SCM classifier which will be added subsequently.
The SVM is then retrained. Unseen expressions to be classified pass the same feature extraction process and are subsequently assigned the label of the target expression that most closely matches their displacement pattern by the SVM classifier.

6. Evaluation

In this paper, we propose a model which evaluates the system by considering classification performance for basic emotions.Features were manually defined for each image and displacements were subsequently extracted from pairs of images consisting of a neutral and a representative frame for each expression.
We used the standard SVM classification algorithm together with a linear kernel. Table 2 gives the percentage of correctly classified examples per basic emotion and the overall recognition accuracy. Figure 6 shows the mean and standard deviation of the feature displacements for each basic emotion as extracted from the training data.

Table 2: SVM Classification Recognition Accuracy

Emotion	Percentage
Anger	82
Sorrow	84
Disgust	84
Fear	71
Joy	93
Surprise	99
Average	86

This approach can be evaluated using data training set during adhoc. This includes different users who will express emotions through facial expressions naturally in an unplanned setup in lighting conditions, move little far from camera with different pose. The resulting confusion matrix is shown in Table 3.

Table 3: Independent Person Emotion Recognition Accuracy

Emotion	Percentage
Anger	66
Sorrow	64
Disgust	66
Fear	66
Joy	91
Surprise	83
Average	71

Emotion recognition can be determined more accurately if the person is more expressive which in turn detects the intention of human across different places. More expressiveness in turn supplies more training datas which results in higher accuracy.

7. Conclusion and discussion

The goal of this paper to implement human intention detection with facial expressions using video analytics. We presented a method of facial expression recognition in video stream. With the properties of SVM learning system all the constraints are corelated in place of recognition speed and accuracy by real time environment.

In Future we extend the classification of our system in terms of variety of expression scenarios which include eye position, head pose in the video stream to achieve usable results. Some of these usable results which are achieved is more in adhoc.

Using automatic SVM model selection [5] to determine optimal parameters of the classifier for displacement-based facial expression data should also increase classification accuracy further.

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