International Journal of Current Engineering and Technology
E-ISSN 2277 – 4106, P-ISSN 2347 – 5161

Available at http://inpressco.com/category/ijcet

Research Article

Drowsiness Detection using Facial Expressions

Ms. Thokal Nisha E. and Prof. Dr. Chobe S.V

Computer Engineering, DR. D.Y. Patil Institute of Technology, Pimpri, Pune, India, Savitribai Phule Pune University

Received 10 Nov 2020, Accepted 10 Dec 2020, Available online 01 Feb 2021, **Special Issue-8 (Feb 2021)**

Abstract

This project presents a method to automatically detect emotional duality and mixed emotional experience using Linux based system. Co- ordinates, distance and movement of tracked points were used to create features from visual input that captured facial expressions, head, face gestures and face movement. Spectral features, prosodic features were extracted using the web camera. Face API was used for calculation of features. A combined feature vector was created by feature level fusion and cascade classifier was used for emotion detection. Live participants and actions are to be used for recording simultaneous mixed emotional experience. As per calculated result system we generate the sound when driver any emotion driving the car. If we analysis then accident ratio is minimized on road.

Keywords: *Facial expressions, drowsiness detection, machine learning.*

Introduction

Emotion recognition has important applications in the field of medicine, education, marketing, security and surveillance. Machines can enhance the human-computer interaction by accurately recognizing the human emotions and responding to those emotions. Existing research has mainly examined automatic detection of single emotion. But psychology and behavioral science studies have shown that humans can concurrently experience and express mixed emotions. For instance, a person can feel happy and sad at the same time. In this research combinations of six basic emotions (happiness, sadness, surprise, anger, fear, disgust and neutral state) were used. The aim of this study is to develop features that capture data from facial expressions to identify multiple emotions. In case of single-label classification problem each annotated feature-vector instance is only associated with a single class label.

However, the multiple concurrent emotion recognition is a multi- label classification problem. In a multi-label problem, each feature vector instance is associated with multiple labels such as presence or absence of one of each six basic emotions. The multi-label classification is receiving increased attention and is being applied to a many domain such as text, music, images and video-based systems, security and bioinformatics. This system examined recognition of emotional ambivalence and mixed emotions. Additionally, the study examined two concurrent emotions (emotion duality) to limit the scope of the research based on availability of scenarios. This was done so that the experimental design was realistic. The subjects could express dual emotions with ease and observers could annotate the data without ambiguity. This study implemented a multimodal emotion recognition system with multiple check box input to facilitate the annotation of concurrent emotions in the user interface software.

Problem Statement

Sometimes it is found that in case of emergency or in case of long drive it may happen that the car driver may undergo in bad mental state due to personal busy schedule. Sometimes they may be too tired and realize its own drowsiness. In that case we require a system that perfectly recognizes the facial expression of driver and that system should be so much perfect that it will analyze the situation automatically and should take the necessary action. So, recognition of emotion and mood of the driver is a key technology through which driver assistance system judges the safety States itself.

Literature Survey

S. Patwardhan, "Augmenting Supervised Emotion Recognition with Rule-Based Decision Model", arXiv, 2016. Description: In this paper, we investigate the effect of transfer of emotion-rich features between source and target networks on classification accuracy and training time in a multimodal setting for vision based emotion recognition.

M. Liu, R. Wang, S. Li, S. Shan, Z. Huang, and X. Chen. Combining multiple kernel methods on riemannian manifold for emotion recognition in the wild. ICMI, 2014. Description: Emotional expressions of virtual agents are widely believed to enhance the interaction with the user by utilizing more natural means of communication. However, as a result of the current technology virtual agents are often only able to produce facial expressions to convey emotional meaning.

A. S. Patwardhan, "Augmenting Supervised Emotion Recognition with Rule-Based Decision Model", arXiv, 2016. Description: This paper presents a method to automatically detect emotional duality and mixed emotional experience using multimodal audio- visual continuous data. Coordinates, distance and movement of tracked points were used to create features from visual input that captured facial expressions, head, hand gestures and body movement. Spectral features, prosodic features were extracted from the audio channel.

SE. Kahou, C. Pal, X. Bouthillier, P. Froumenty, C. Glehre,R. Memisevic, P. Vincent, A. Courville, Y. Bengio, RC. Ferrari and M. Mirza. Combining modality specific deep neural networks for emotion recognition in video. Proceedings of the 15th ACM on International conference on multimodal interaction, 2013. Description: This paper presents the initial implementation of a system of multimodal recognition of emotions using mobile devices and the creation of an affective database through a mobile application. The recognizer works into a mobile educational application to identify user's emotions as they interact with the device.

A. S. Patwardhan and G. M. Knapp, "Multimodal Affect Analysis for Product Feedback Assessment," IIE Annual Conference. Proceedings. Institute of Industrial Engineers-Publisher, 2013. Description: In this paper, we investigate the effect of transfer of emotion-rich features between source and target networks on classification accuracy and training time in a multimodal setting for vision-based emotion recognition.

Proposed System

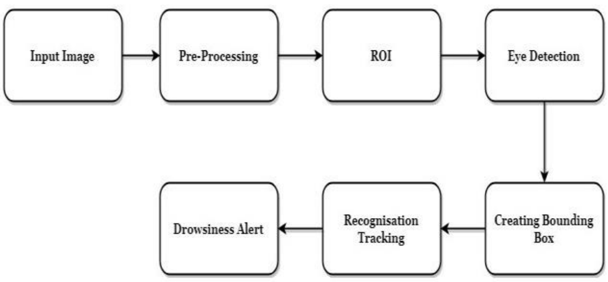

Fig 1. Block diagram

Image Processing Module

This module will aim at processing the acquired video images. The processing will target to detect the drivers face from the video stream; once the face is detected, the region of interest that is the eyes will then be located from the facial features. The state of the eye will then be computed using the pixel intensity difference and a threshold value.

Drowsiness Detection Module

This module determines the drowsiness levels of the driver based on the statistical information obtained the predecessor stage.

Fisher face algorithm

Facial recognition using fisherface method. In general, face recognition system in this study can be seen in following figure.

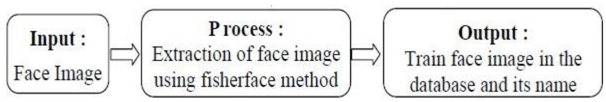

Image Data

4.1. Image of the photograph result. Here is a sample of photos photograph with each individual represented by a minimum of 5 samples of face images with different positions and different expressions

4.2. Image Data Training.

To know the success of the system created, then the system will be trained in the first with several images as follows:

Input: Face Image **Process:**

Extraction of face image using fisherface method **Output:**

Train face image in the database and its name

4.3. Image Data testing.

Feature generation process with fisherface method

Assumed: Size of rectangular face image with height = N and width = N and consists of h samples image, *a b h*,, , and C class *c x* , *x* , *x* 1 2 .

PCA

- Conversion training image 1, 2, . . with size N x N into vector form with length size N ^
- Calculate the average of all face images or written as,
- Compute vector eigen (***eigVecs***) and value eigen (eigenVals) by using the method svd of thematrix **A.** Sort eigvecs then
- reduction with the pca method, pe. pe is ***eigenfaces***

LDA Calculate the average of each person / class

Projection back *VeSbb with Pe* eigenfaces then formed (***Pe * VeSbb***) Output as **Fisherfase**.

Normalization Fisherface
Pe*VeSbb*N Find the transpose of the normalized **Fisherfaces**,
Pe*VeSbb*Nt
Calculate Weights for each training image into a normalized fisherface, U =
Pe * VeSbb * Nt *
The result of the above process is the weight of each training image in the form of eigen vector which will be used to find similarity with face image which will be recognized by using Euclidean distance formula.

Identification or recognition algorithm.
The identity classification steps are as follows:

- Conversion of the face image tested by the size of N * N into the column vector form i N^2 r
- Normalization of facial image input to the image of training by finding the value of different matrix *inp* by subtracting the average value of training image.
- Calculates the weight of the test image by multiplying the eigenval transpose matrix
- Calculate the distance of the difference between the image testing with training face image using euclidean distance.

The result of the identification is the image that has the smallest distance with the test image displayed by the system.

Proposed algorithm

Face Recognition System The proposed model for face recognition system is the main modules used are: 1) Dataset Generation: In this stage, face dataset of the user is created, in which images of each user are taken and the attributes used are user ID and username. The Linear Discriminate Analysis performs a class specified dimensionality reduction. In order to find the combination of features that separates best between classes to within-classes scatter.
Fisherfaces heavily depends on the input data.
The idea is simple: same classes should cluster tightly together, while different classes are as far away as possible from each other in the lower-dimensional representation.

1. Compute the average (Euclidean distance) of all faces.
2. Compute the average of each face.
3. Subtract (2) from (1)
4. Build two scatter matrices- within the class and between classes.

user is created, in which images of each user are taken and the attributes used are user ID and username. The Linear Discriminate Analysis performs a class specified dimensionality reduction. In order to find the combination of features that separates best between classes to within-classes scatter. Fisherfaces heavily depends on the input data. The idea is simple: same classes should cluster tightly together, while different classes are as far away as possible from each other in the lower-dimensional representation.

1. Compute the average (Euclidean distance) of all faces.
2. Compute the average of each face.
3. Subtract (2) from (1)
4. Build two scatter matrices- within the class and between classes.

Result and Discussion

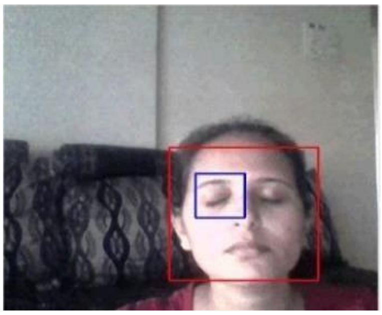

Fig 1. Simple example for drowsiness detection

Driver drowsiness detection is a driver safety technology which helps prevent accidents caused by the driver getting drowsy. Various studies have suggested that around 20% of all road accidents are fatigue-related, up to 50% on certain roads.

Conclusion

This system work presents a comprehensive and simultaneous detection of Emotion and its application in all driving system. The proposed system is found a novel approach to assist the driver and safeguard the vehicle by switching into auto mode driving need. It is very well helpful for detection of an emergency to switching vehicle control from manual to automatic mode.

References

[1]. S. Patwardhan, "Augmenting Supervised Emotion Recognition with Rule-Based decision Model", arXiv, 2016.

[2]. A. S. Patwardhan and G. M. Knapp, "Affect Intensity Estimation Using Multiple Florida Artificial Intelligence Research Society 0Conference, May. 2014.

[3]. A. S. Patwardhan and G. M.Knapp, "Multimodal Affect Analysis for Product Feedback Assessment," IIE Annual Conference. Proceedings. Institute of Industrial Engineers-Publisher, 2013.

[4]. S.E. Kahou, C. Pal, X. Bouthillier, P. Froumenty,C. Glehre,R. Memisevic, P. Vincent, A. Courville, Y. Bengio, RC. Ferrari and M. Mirza. Combining modality specific deep neural networks for emotion recognition in video. Proceedings of the 15th ACM on International conference on multimodal interaction, 2013.

[5]. A. S. Patwardhan and G. M. Knapp, "Multimodal Affect Analysis for Product Feedback Assessment," IIEEE Annual Conference. Proceedings. Institute of Industrial Engineers-Publisher, 2013