

Result Analysis of Robust Representation and Recognition of Facial Emotions Using Extreme Sparse Learning

¹Vishal Bhavsar,²Mr. Kailash Patidar,³Mr. ManojKumar Yadav,⁴Mr. Harsh Lohiya

¹M.Tech Scholar SSSIST, RGPV,²HOD CSE, SSSIST, ³Asst.Prof. CSE, SSSIST,⁴Asst.Prof. CSE, SSSIST

¹Computer Science & Engineering,

¹SSSIST, Sehore, India

Abstract : Facial Emotion detection under natural conditions is an interesting topic with a wide range of potential applications like human-computer interaction. Although there is significant research progress in this field, there are still challenges related to real-world unconstrained situations. One essential challenge is to find pose invariant spatio-temporal volumetric features to analyze the video sequence efficiently. Traditionally, facial emotion recognition systems have been evaluated on laboratory controlled data, which is not representative of the environment faced in real-world applications.

IndexTerms - Emotion recognition, Facial emotion, Pose invariance, Dictionary learning, Sparse representation, Extreme learning machine, Extreme sparse learning.

I. INTRODUCTION

Face recognition methods that work with focused images have complexity when presented with blurred data. The majority of the previous work tried to recognize facial expressions via static images and ignore the temporal information of an emotion in time domain due to expensive computational time or complicated temporal mode. Traditionally, emotion recognition has been performed on laboratory controlled data which is not representative of the environment faced in the real-world applications. The accuracy of an emotion recognition system generally depends on two critical factors: 1) how to robustly represent the facial features in such a way that they are robust under intra-class variations but are distinctive for various emotions and 2) how to design a classifier that is capable of distinguishing different facial emotions based on noisy and imperfect data. Automating facial emotion analysis offers a new modality for Human Computer Interaction (HCI) to make the interaction responsive to human emotion. Although all previous studies confirmed that data fusion from different modalities is more accurate and reliable for human affect analysis, it is an open issue how to integrate various data stream more effectively. For handling the illumination, there mainly two directions of pursuit depend on the 9D subspace model for face and extracting and identical illumination insensitive facial characteristic. Tan unite the strengths of the above two technique and suggest an integrated framework that comprise an initial illumination normalization step for face recognition under hard lighting conditions. A subspace educational approach using image gradient orientations for illumination and occlusion-robust face recognition has been proposed in. Practical face recognition algorithms must possess the capability to be aware of faces across reasonable variations in pose. Techniques for face recognition across pose can largely be categorized into 2D and 3D techniques. A good survey article on this subject can be found. It has been observed that since human faces have similar in general configuration, a relatively low dimensional subspace face is used to describe. Dimensionality decreasing subspace methods like Principle Component learning, Linear discriminated learning and Independent Component Analysis has been proposed for the job of face recognition. These approaches can be categorized into either generative or discriminative techniques. One of the major benefits of using generative approaches is that they are known as less sensitive to noise as compared to discriminative approaches.

Face recognition is an important research problem spanning numerous fields and disciplines. This because face recognition, in addition to having numerous practical applications such as bankcard identification, access control, Mug shots searching, security monitoring, and surveillance system, is a fundamental human behavior that is essential for effective communications and interactions among people. Due to its many potential applications, face recognition has become one of the most active topics in computer vision research [1]. However, despite the significant progress in the last decade, the design of recognition algorithms that are effective over a wide range of viewpoints, occlusions, aging of subjects and complex outdoor lighting is still a major area of research. While there is a significant number of works addressing these issues, problems caused by image degradations due to other factors such as blur, noise and sampling are mostly overlooked. This is particularly surprising as such image degradations also significantly affect the performance of face recognition systems and are often present in images and videos in real-world applications such as watch-list monitoring and video surveillance. Only recently has research community started to look at facial image. To the best of our knowledge, none of the existing methods can learn a non-linear classifier in the context of simultaneous sparse coding and classifier training..

II. EMOTION MODELS

Traditionally, facial emotion recognition systems have been evaluated on laboratory controlled data, which is not representative of the environment faced in real world applications. Although facial emotion recognition has been extensively studied in the past, most of the existing feature extraction approaches require frontal facial. Emotion is the projection/display of a feeling. Unlike feelings, the display of emotion can be either genuine or feigned. Affect is a key part of the process of an organism’s interaction with stimuli. Feeling is a sensation that has been checked against previous experiences and labeled. It is the body’s way of preparing itself for action in a given circumstance by adding a quantitative dimension of intensity to the quality of an experience.

A. Categorical Model

Categorical model classifies emotions into discrete categories such as anger, disgust, fear, happiness, sadness and surprise which are considered as six universal emotions. The main benefit of categorical scheme of emotions is that human usually use these categories to express their emotional states in real life. The universality of these emotions was initially investigated by Ekman [11].

B. Dimensional Model

Dimensional representation considers multiple dimensions to describe an emotional state. Arousal and valence are two common dimensions that may construct a 2D emotion model to describe different emotional state. The theory of dimensional modeling of emotion was mainly introduced by Russel [12]. Additionally, dimensional spaces can provide the emotional intensity which can be used for evaluating the level of emotional reactions to outside stimulus. The majority of existing work on emotion recognition focus on dimensional emotions and less attention has been paid to dimensional model. The target-oriented systems select a single key frame involving the peak facial expression from a given sequence of images. Gesture-oriented approaches use temporal information in the sequence by tracking some specific facial feature points over all frames of a video sequence.

III. METHOD

In this research work proposes a face recognition algorithm that is robust to non-uniform (i.e., space-varying) motion arising from relative motion between the camera and the subject or facial expression change. The camera transformations can range from in-plane translations and rotations to out-of-plane translations, out-of-plane rotations, and even general 6D motion.

A hidden markov model (HMM) is a statistical markov model in which the system being modeled is assumed to be a markov process with unobserved (hidden) states. An HMM can be considered as a simplest dynamic Bayesian network [10]. In regular markov model the state is directly visible to observer therefore the state transition probabilities are the only parameters. In a hidden markov model the state is not directly visible, but the output dependent on the state is visible. Each state has probability distribution over the possible output tokens. Therefore sequence of tokens generated by on HMM gives some information about the sequence of state.

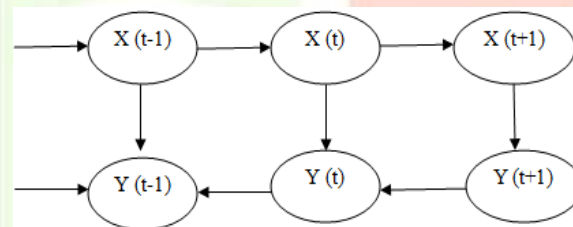


Fig.1 Architecture of Hidden Markov Model

The above fig.2 shows the general architecture of an instantiated HMM. Each oval shape represents a random variable that can adopt any of number of values. The random variable $x(t)$ is the hidden state at time t . (with $x(t)=\{x_1, x_2, x_3\}$) the random variable $y(t)$ is the observation at the t with $(y(t)=\{y_1, y_2, y_3\})$.

When we are using HMM for one dimensional gray scale face image. The significant facial regions (hair, forehead, eyes, nose, and mouth) come in natural order from top to bottom.

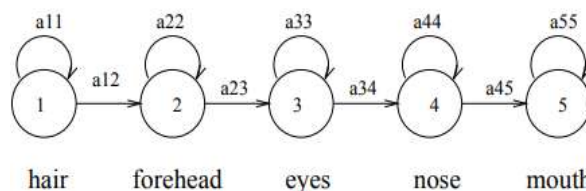


Fig.2 Left to Right HMM for face Recognition

In above fig.2 each of these facial regions is assigned to a state in left to right 1D continuous HMM. In 2D HMM we follow the embedded HMMs for facial image representation and recognition.

In fig.3 shows the flow diagram of proposed method. In this figure 3 firstly take object that is take input image for recognize. There are two types of object detection process. First one is the process of clicking the picture from camera and get image after that image taken for the another stage which is name as get image in which data or image clicking by camera are successfully stored. Another technique for detection of image is browse, in which image or pictures are taken from computer/laptop or any cloud server

where data should be stored. Then detection of object should be taken place. After that segmentation process is performing. Segmentation is the process of dividing or partitioning image into multiple sets or pixels.

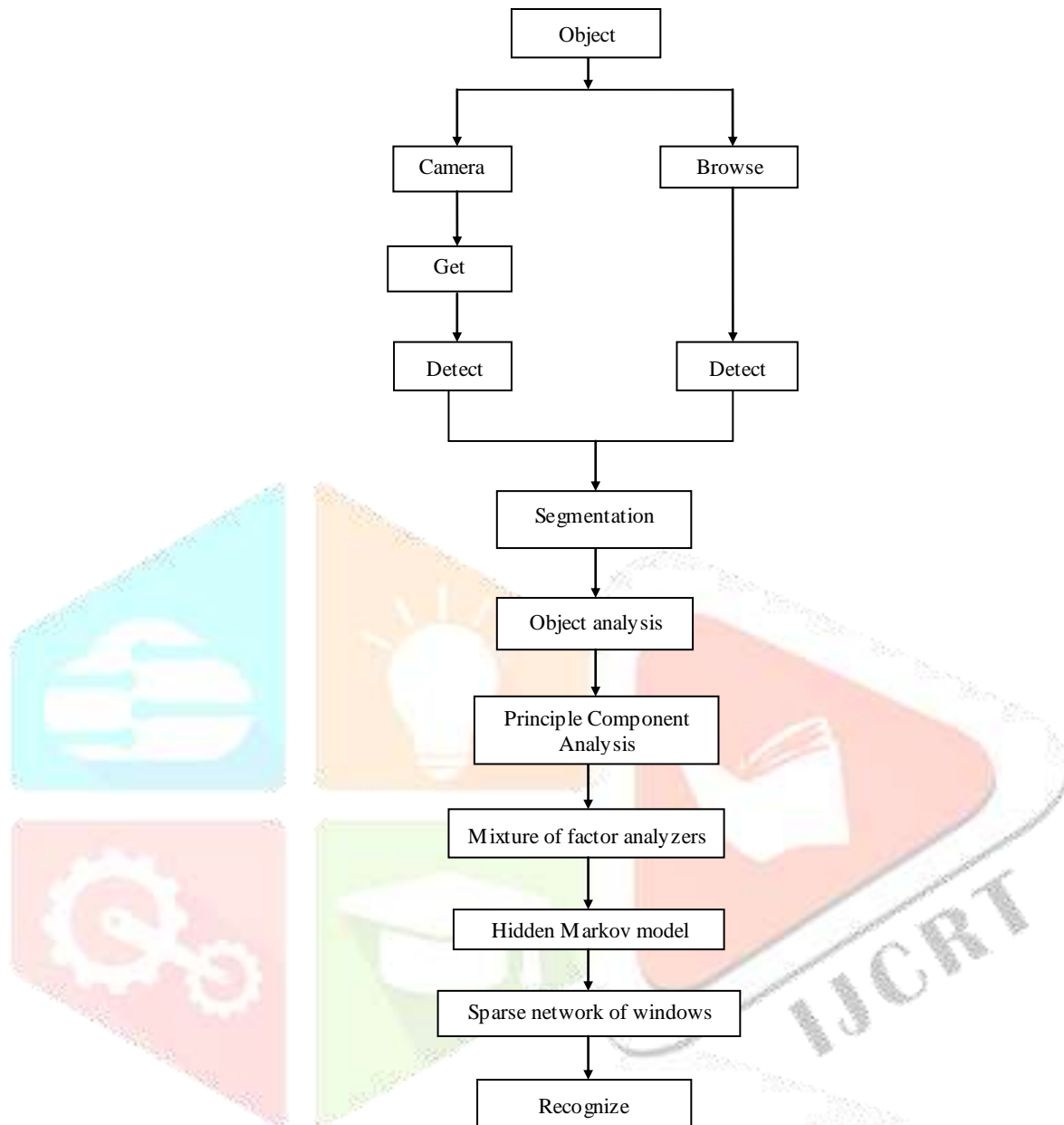


Fig.3 flow diagram of proposed method

After segmentation of image then analysis of object process is performing for detection edges, lines; trace borders after that PCA process that is principal component analysis which is a statistical procedure which is an orthogonal transformation to convert set of observed values. After this process mixture factor analysis and then hidden markov model (HMM) is a statistical markov model in which the system being modeled is assumed to be a markov process with unobserved (hidden) states. At last recognition of the output image.

IV. RESULT

In this section shows the result of proposed algorithm. The results figures are shown in below:



Fig.4 Preview image

Fig.4 represents the preview image. This image take an input image is capture from live camera, in which image or pictures are taken from computer/laptop camera.



Fig.5 Source image

Fig.5 elaborates a source image.



Fig.6 face detect image

Fig.6 shows the face detect image in test dataset.



Fig.7 detected face image

Fig.7 shows a detected face image. In this applied proposed algorithm for the face detection.

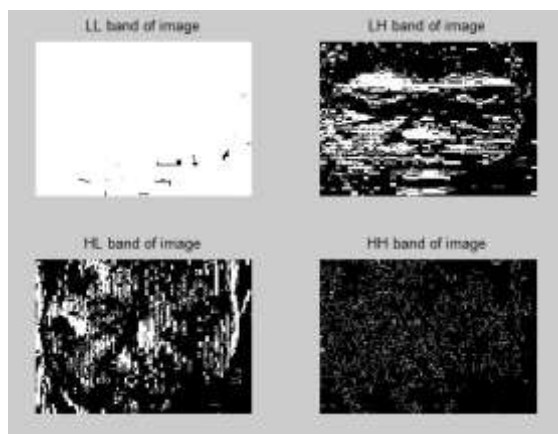


Fig.8 segmentation image

Fig.8 Shows segmentation image. Segmentation process is performing. Segmentation is the process of dividing or partitioning image into multiple sets or pixels. In this figure image is segmented in four band LL band, LH band, HL band and HH band.



Fig.9 Recognized face image

Fig.9 presents the output image. This image recognize in output section. This is an output image.

V. CONCLUSION

In this research work proposed a methodology to perform face recognition for real time detection. In this showed that the set of all images obtained by non-uniformly blurring a given image using the TSF model is a convex set given by the convex hull of warped versions of the image. Capitalizing on this result, we proposed a hidden markov model and PCA face recognition algorithm. The limitation of our approach is that significant occlusions and large changes in facial expressions cannot be handled. The proposed approach has novelty in both the feature extraction and recognition. We have performed extensive experiments on both acted and spontaneous emotion databases to evaluate the effectiveness of the proposed feature extraction and recognition schemes under different scenarios.

REFERENCES

- [1] Shojaeilangari, Seyedehsamaneh, et al. "Robust representation and recognition of facial emotions using extreme sparse learning" *IEEE Transactions on Image Processing* 24.7 (2015): 2140-2152.
- [2] Wang, Panqu, and Can Xu. "Robust face recognition via sparse representation"
- [3] Kim, Do Hyoung, Sung Uk Jung, and Myung Jin Chung. "Extension of cascaded simple feature based face detection to facial expression recognition" *Pattern Recognition Letters* 29.11 (2008): 1621-1631.
- [4] Gu, Wenfei, et al. "Facial expression recognition using radial encoding of local Gabor features and classifier synthesis" *Pattern Recognition* 45.1 (2012): 80-91.
- [5] Aleksic, Petar S., and Aggelos K. Katsaggelos. "Automatic facial expression recognition using facial animation parameters and multistream HMMs" *IEEE Trans. on Info. Forensics and Security* 1.1 (2006): 3-11.
- [6] Zheng, Wenming, et al. "Emotion recognition from arbitrary view facial images" *Computer Vision—ECCV 2010* (2010): 490-503.
- [7] Wright, John, et al. "Robust face recognition via sparse representation" *IEEE trans. on pattern analysis and machine intelligence* 31.2 (2009): 210-227.

[8] Bacivarov, Ioana. “Advances in the modelling of facial sub-regions and facial expressions using active appearance techniques” Diss. 2009.

[9] R. Niese, A. Al-Hamadi, A. Farag, H. Neumann, and B. Michaelis, “Facial Expression Recognition Based on Geometric and Optical Flow Features in Colour Image Sequences” Computer Vision, IET, vol. 6, pp. 79–89, 2012.

[10] A. Snchez, J. V. Ruiz, A. B. Moreno, A. S. Montemayor, J. Hernandez, and J. J. Pantrigo, “Differential Optical Flow Applied to Automatic Facial Expression Recognition” Neurocomputing, vol. 74, no. 8, pp. 1272–1282, 2011.

[11] P. Ekman, “Strong Evidence for Universals in Facial Expressions: a Reply to Russell's Mistaken Critique” Psychological Bulletin, vol. 115, pp. 268-287, 1994.

