ISSN:0975-9646

I. Pavanendar et al, / (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 3 (5) , 2012,5141 - 5142

A Robust Facial Recognition System Based on Skew Gaussian Distribution

I.Pavanendar[1], P.Raja Sekhar[2], Y.Srinivas[3]

[1]M.Tech-CSE (CL), [2] Department of CSE,
Avanthi Institute of Engg & Tech, Narsipatnam, Visakhapatnam
[3] Department of IT, GITAM University,
Visakhapatnam,

***Abstract*—Facial recognition is considered to be the most vulnerable identification source for many of the criminal identification systems. In major security concerned areas, facial recognition is mostly used and the lack of security can be witnessed in issues like 26/11 Mumbai attacks, Washington attacks and other attacks. There are many algorithms that are developed for the effective analysis of the criminals based on facial recognition as the prime source of witness. However, the major drawback of any facial recognition algorithm is due to lightning conditions, occlusion and orientation issues and most of the available techniques are based on non-degenerative models, but generative models are much effective than non-degenerative models. Hence this paper highlights a model based approach for the effective identification of the face and thereby helping towards the criminal identification.**

***Keywords*— Criminal identification, Facial recognition, model based techniques, security issues, witness.**

I. Introduction

In the modern communication era biometric methods are predominantly used in many public and private places in order to counter attack the criminal possibilities. Among the various biometric methodologies used for security, facial recognition plays a predominant role since the face captured by the surveillance cameras can be utilized for the identification of the criminal. However, the major restriction with regard to the facial recognition includes orientation effects; lightning conditions and occlusion [1].In order to overcome these disadvantages, techniques like histogram equalization are used for image enhancement and in order to overcome the orientation effects certain restrictions such as converting the facial images to frontal views are to be considered [2]. Many algorithms and models have been derived for the effective identification of a plausible criminal using methods such as SVM [3][4][5], ICA[6][7], Gradient based[8], HMM[9][10]. However, these methods belong to degenerate models and generative model based techniques are more effective than degenerative models [S.K.Pal, N.R.Pal, (1993)][15]. It is also noted that the techniques based on SVM, which is a line classifier that classifies the data marginally and leads to miss classification if the facial pixels are along the marginal line, HMM is a stochastic model which needs a lot of training data for effective identification. In order to have an effective classification and identification of the faces, it is needed to model the pixels and identify the patterns of the pixels thereby fitting a model that can identify the faces exactly. In order to identify the faces effectively Gaussian Mixture Models are mostly used [11][12]. This is due to the assumption that the shape of the images be considered in nature are bell shaped and with this assumption symmetric distributions such as Gaussian are mostly preferred. However, in reality most of the realistic images are not Gaussian in shape and asymmetric in nature. In order to model the faces effectively it is therefore needed to approximate the pixels using asymmetric distribution instead of symmetric distribution. Hence in this paper we proposed facial recognition system based on Skew Gaussian mixture model which includes Gaussian distribution as a particular case. The rest of the paper is organized as follows: Section-2 of this paper deals with illumination, in section-3 Skew Gaussian mixture model is presented, section-4 deals with experimental results and the final section, section-5 concludes the paper.

II. Illumination Technique

One of the primary tasks for effective facial recognition is the illumination effects [13]. In order to overcome the illumination effects histogram equalization is utilized. It is defined as the frequency of occurrence of the gray levels and the number of occurrences of the gray levels [14]. In order to process the histogram equalization the input pixels are to be arranged so that the output pixels contain uniform intensity values which can be achieved by using the formula

$$I_l = [\textstyle\sum^{l}_{i=0} N_i] * I_m/N \qquad \text{--- (1)}$$

Where: I_l is the new intensity value of the i^{th} pixel
I_m is the maximum intensity level
N is the number of pixels.

III. Skew Gaussian Mixture Model

In most of the witnessed based criminal identification systems, facial recognition are considered to be the effective source of the input. The faces for recognition are captured from the CCT cameras and the input image may be either symmetric or asymmetric in nature in reality, the shape of the human structure differ from person to person, hence to model the faces asymmetric models are well suited[16]. Hence a Skew symmetric distribution is proposed. The probability density function of the Skew distribution is given by

$$F(y) = \sqrt{\frac{2}{\pi}}\, e^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2} \int_A^B \left(\frac{y-\mu}{\sigma}\right) \frac{e^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2}}{\sqrt{2\pi}} \qquad \text{--- (2)}$$

Where: in this paper we have considered A and B to be the minimum and maximum pixel values respectively, within the given facial image. The facial pixel values are modeled using the equation -2 and the probability density functions are generated.

IV. Experimental Results

In order to experiment the model, we have generated a facial database with images from both genders and preprocessed the faces using histogram equalization technique proposed in section-2, to overcome the lightning conditions. Each of the faces in the database are modeled using the Skew Gaussian mixture model given in equation-**2** and the corresponding probability density function values of each of faces are obtained. This process is considered to be the training phase, for testing purpose a database of 10 images were considered and for these images the probability density functions are calculated, and compared with the probability density functions of the training set for the most likelihood matches. If the likelihood match exists that image is to be notified as the image in the database. In order to evaluate the methodology we have considered metrics like FAR (False Acceptance Rate) and FRR (False Rejection Rate). The formulae for calculating FAR and FRR are given below

$$FAR= \frac{\textit{number of faces recognized wrongly}}{\textit{Total number of faces}} X\ 100 \text{ --- (3)}$$

$$FRR= \frac{\textit{faces that are rejected}}{\textit{Total number of faces}} X\ 100 \text{ --- (4)}$$

Fig. 1. Sample Database:

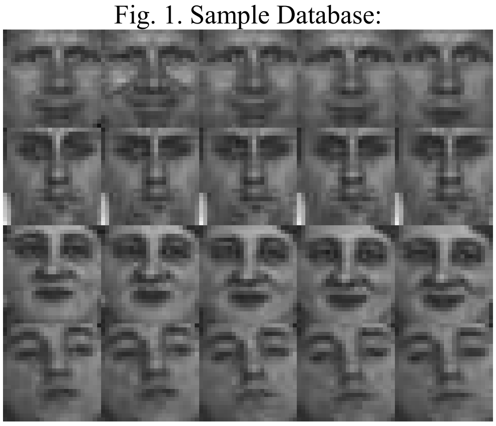

Table 1

Test Image	Output Images
	
	

The tabulated results using the above metrics are presented below:

Table 2

No. of Faces	FAR	FRR
30	2	2
40	3	2
50	3	2

From the above table, it can be clearly seen that the developed model performs better, even if the size of the test data is increased. This model will be very much useful for effective recognition of a criminal using facial recognition.

V. Conclusion

In this paper a novel methodology for facial recognition is proposed using Skew Gaussian distribution. The developed model is very much effective in the recognition of faces which are either symmetric or asymmetric in nature. The performance evaluation presented in the table-1 clearly depicts the strength of the model. The proposed model is very much useful in applications like biometric video surveillance and other concerned issues with facial recognition.

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