S-Log: Skin based Log-Gabor Approach for Face Detection in Video

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ABSTRACT: *Visual Surveillance systems have greatly increased in past few years. Several methods have been proposed in order to improve the efficiency of Face Detection but still remains a challenging task due to various illumination, poses and occlusion conditions. In this paper, we propose a novel method for Face Detection where a decision boundary is defined for skin classifier based on training dataset. Log-Gabor filter is used for feature extraction which is superior to Gabor filter as they can represent better frequency properties of the objects present in the video and SVM classifier is used for classifying it as face or non-face. The proposed method is tested on standard and our own collected video sequences, which shows good tolerance and is better than those of existing related algorithms.*

Keywords: Face Detection, Skin Segmentation, Log-Gabor Filter, False Alarm Rate, Detection Rate, ROC curve

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1. Introduction

Nowadays Face Recognition technology is taking a lot of importance and it is one of the most imperative topics in the field of face research. Face Detection is prior to Face Recognition. Face Detection is a separation of face and background and also determining the location and sizes of the faces [1]. Extracting faces from the video is a crucial task of many vision systems. It is a challenging task to detect faces in video sequences under different variations of illumination, pose and occlusion. These variations contribute to difficulties in designing effective video based detection and recognition system [2]. A variety of techniques has been proposed such as knowledge based methods, template matching, invariant based methods and appearance based methods. Knowledge based methods are rule based methods which encode human knowledge of what constitute a typical face. Invariant feature methods find common structural features which exist among faces under different ambient conditions. Template matching methods stores standard pattern of a face. Appearance based methods learn a model or a group of features from training images to acquire the variations in the facial appearance. The increase in the speed of processors during last few years has empowered the use of learning based methods for real time Face Detection. It is a two-class supervised classification problem in which set of features are obtained from the samples of the training set. Usually, Gabor filter is used in different scales and orientation for feature extraction. For example, in [3], Eight Gabor filters with two different wavelengths is used. In [4] performance is analysed using three scales and five orientations and four scales and six orientations. Chuan Lin [5] proposed a method to locate the faces which uses two-eye template and space. To improve the accuracy of the multi-pose and multi-expression Gabor filters are used. Rui Min et al. [6] proposed a method where Gabor Wavelets are used to extract the features, PCA method is used to obtain the feature vectors from both positive and negative example to reduce the dimensionality and SVM is used for classification. Deepak Ghimire et al. [7] proposed a method for detecting the face under unconstrained illumination condition based on skin and edge tone information. Skin tone percentage index and edge

information are used to separate face and non-face. Samita Rout et al. [8] proposed an approach which labels the pixel whether it is a skin or non-skin pixel using the back propagation model for skin detection and neural network based facial skin detector classifier. Decision boundary is used for classifying skin pixels. Ojo J.A. [9] proposed a new hybrid Face Detection algorithm that uses both skin segmentation algorithm and Gaussian skin distribution modelling method and then template matching is applied for the presence of the face. AbdellatifHajraoui [10] proposed a method for Face Detection which uses skin based and Gabor filters and showed good results when the face is in the image plane. DjamelEddineBenrachou [11] proposed a method based on Face Detection under drivers monitoring which uses Gabor filter for feature extraction and PCA for dimensionality reduction. In [12], a performance of Log-Gabor out-forms the Gabor filter for image based vehicle verification. Moving object detections proposed by Gopal Krishna et al. [13] based on Log-Gabor filter preserves the structure of the object. Gabor filter has a number of drawbacks when it has been applied in the broad range of applications. The bandwidth of Gabor filter is limited to one octave, so a large number of filters is needed to obtain wide spectrum coverage. Gabor filters concentrates on lower frequencies which may outcome with redundant information and high frequency of the images may not be captured. In this paper instead of the state-of-the-art method based on Gabor filters, the Log-Gabor function for skin based Face Detection is used. The drive to study is to experimentally prove the superiority of Log-Gabor filter over standard Gabor filters in this field and also efficient Detection Rate under illumination and pose.

2. Proposed Approach

This paper describes Face Detection framework that is capable of achieving higher Detection Rate in video sequences. The proposed block diagram is shown in Figure 1. In the first step of our proposed method pre-processing is done where the input video sequences are skin segmented to obtain skin and non-skin pixels which reduce the search space for detecting the face. In the second step, the essential features are extracted using Log-Gabor filter on the image database. For the separation of the features obtained by the Log- Gabor filter bank SVM classifier is used which classifies it has face or non-face.

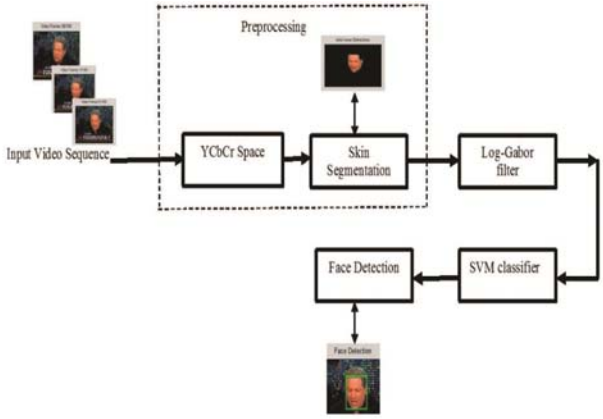


Figure 1. Block Diagram of the Proposed Approach

2.1 Face Detection

In the first step of our proposed method pre-processing is done for input video sequences and feature extraction is done using Log-Gabor filter and SVM classifier is used to classify face or non-face.

2.1.1 Skin-color Segmentation

In order to achieve fast system and computationally reduce the False Alarm Rate(FAR), skin color segmentation is used prior. We can model the distribution of skin and non-skin colors accurately where each pixel is marked as skin and non-skin pixels from the collection of images. Skin pixel segmentation is done using histogram based approach. RGB histogram is created for skin pixels and also for non-skin pixels of 32 × 32 × 32 in size. For each pixel color log likelihood is calculated for being a skin is [14]

$$log(H(r, g, b) / h(r, g, b)) \quad (1)$$

where H is the skin histogram, and h is the non-skin histogram. Each frame is read from the video and we compute the log likelihood of each pixel and then threshold the result to decide skin/non-skin. Figure 2 shows the result of the skin segmentation

process. The white areas in the images present in the frames show the face candidates. Not all the detected skin regions contain faces but it also corresponds to hands, neck and other parts of the body. The next step is to locate the face portion in each frame. To detect the portion of the face, the features that will only represent the face need to be considered. In our methodology, we are using Log-Gabor filter.

(a)Input Video (b) Skin Segmentation (c) Binary Image

Figure 2. Skin Segmentation Process

2.1.2 Log-Gabor Feature Extraction and Selection

According to above literature, it is clear that high Detection Rate in video based Face Detection is still a challenging problem. With this motivation, in the present work, an idea of Log-Gabor filter is explored to obtain more information in high frequency areas with desirable high pass characteristic. Gabor filters are used for obtaining localized frequency information. Gabor filters provide excellent spatial and frequency information but with the limitation when maximum bandwidth of Gabor filter is one octave. This is the main disadvantage as it limits the size of the features. By using the Log-Gabor function proposed by Field [15] are considered as Gaussian functions on the log axis which is a standard method of representing spatial frequency response of visual neurons. An effective representation of uneven frequency content of the images and redundancy in lower frequencies can also be reduced which is resulted by log axis. We can vary the bandwidth from one to three octaves. In our work we used logarithmic frequency instead of linear one by using Log-Gabor filter which provides arbitrary bandwidth and with optimization where features with high frequency information are captured. *Sigma* = 0.5 is initialized as the ratio of the standard deviation of the Gaussian describing the Log-Gabor filter's transfer function in the frequency domain to filter the center frequency. MinWavelength = 18 signifies the wavelength of the basis filter. *fo* = 1.0/min is the Centre frequency of the filter and *radius* = [0 : fix(data/2)] / fix(data/2) / 2. The Log-Gabor function has the function of the form.

$$logGabor(1 : data/2 + 1) = exp((- (log(radius/f\,o))^2)/(2 * log(sigma)^2)) \quad (2)$$

The images in the frame are resized to 100×100. The resulting Log-Gabor filter is then convolved with the Inverse Fast Fourier transform of the images in the frame which results in 100×151 feature vector array. Thus, the feature vector has 15,100 pixel values for computation.

2.1.3 SVM Classifier

SVM is used for binary classification. SVM classifier separates the classes with maximum margin and chooses one particular solution. SVM learning algorithms analyse the data and recognize the patterns from a given set of training examples marking them into one of the two categories. SVM training builds a model which assigns new features to one of the two categories. Given with set of n points(vectors) $x_1, x_2 \ldots x_n$ and x_i is length of *m* and each belong one of the two classes either by +1 or -1. Our training set is $(x_1, y_1), (x_2, y_2) \ldots (x_n, y_n)$ for all i, $x_i \in R^m$ and $y_i \in +1, -1$, classifier is learned $f(x) = sign(w.x + b)$ such that

$$f(x) = \begin{cases} > 0\,, \; if \; y_i = +1 \\ 0\,, \; if \; y_i \geq -1 \end{cases} \quad (3)$$

Where y_i = +1 represents the face and y_i = -1 represents the non-face. SVM will minimise the similarity between the classification hyper plane and the subspace of the solutions in class 1. With new dimension, it examines the linear optimal searching hyper plane i.e. decision boundary separating the samples of one class from another. To find the optimal separating hyper plane SVM aims to maximize the margin.

$$maximize = 2/||w|| \tag{4}$$

$$f(x) = \begin{cases} y_i = +1, \; if \;\; w, x+b > 0 \\ y_i = -1 \;\; if \;\; w, x+b < 0 \end{cases} \tag{5}$$

3. Experiment

3.1 Experiment Setup

The proposed method is implemented on the i3 processor with MATLAB 10. The performance of the proposed system is evaluated using YouTube Celebrity Dataset [18] and McGill Face dataset [19]. In these datasets there are only a few face occurrences. We also used our own collected sequences of videos which differ in applications such as people counting and environmental conditions. Video sequences of the YouTube Celebrity Dataset, McGill Face Dataset and own Dataset is shown in Figure 3. Each of the videos is recorded under different illumination and poses in outdoor and indoor environment. Dataset considered in this paper consists of 16 video sequences of 25 frames/sec. Each of the video sequences consists of the persons ranging from one to ten. We have considered totally 20 frames from each video to record the result obtained from the proposed method. So totally we have 780 faces to be detected from all the video sequences. Each of the training images is resized to 100 × 100 in which faces are detected where small size scanning window is set.

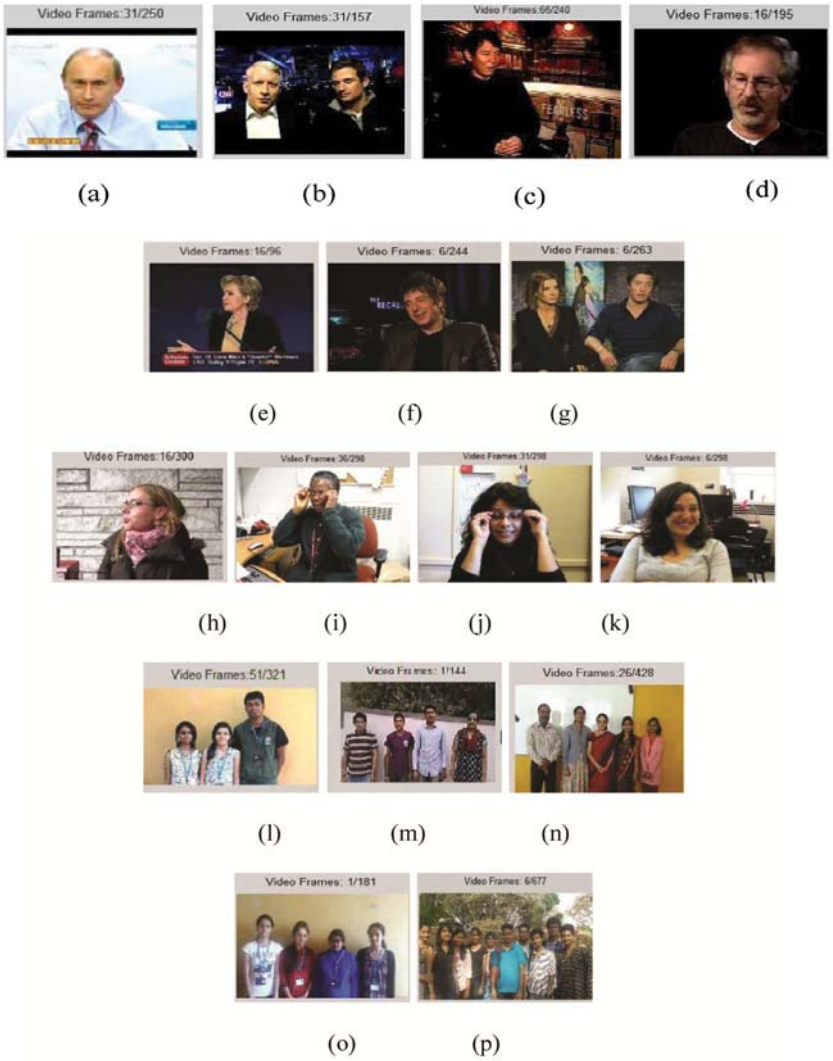
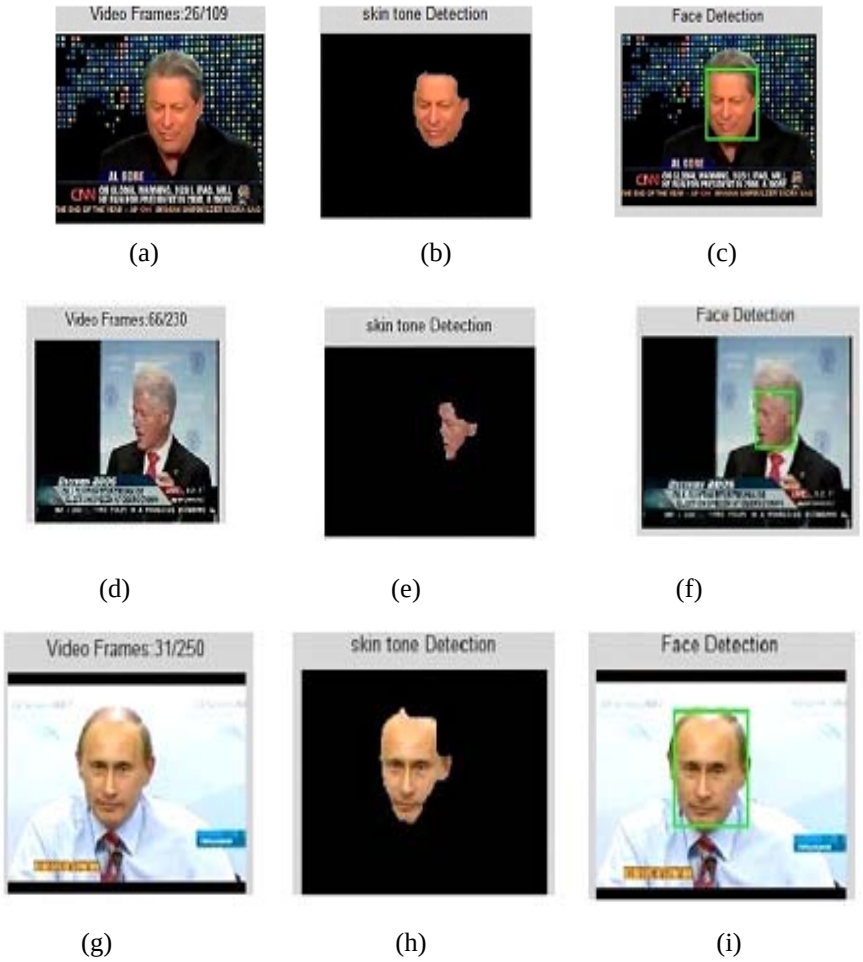


Figure 3. YouTube Celebrity Dataset: -(*a*, b, c, d, e, f, g), McGillFace Dataset: (h, i, j, k), Own Dataset:(l, m, n, o, p)

3.2 Experimental Results and Comparative Study

There are two types of feature extraction methods, viz., holistic feature extraction method and local feature extraction methods. In holistic feature extraction methods, only one single feature is extracted from a whole image such as Principal Component Analysis (PCA) [20], Locality Preservative Projection(LPP) [21], Tensor Locality Preservative Projection(TLPP) [22], and Orthogonal Locality Preserving Projections(OLPP) [23]. The performance of this approaches mainly depend on the training set and is effected by the pose and illumination. In local feature extraction based method such as Gabor [24] and Local Binary Pattern [25-27] are robust to the uncontrolled conditions. They divide the images into sub-images and extracts the features and later combine them into a single feature vector. There are two major drawbacks in Gabor feature extraction. First one is the bandwidth is limited to one octave in order to prevent the high DC component. So large number of filters are needed to cover the preferred spectrum. The second one is Gabor filter may result in redundant information since it concentrates on a lower frequency and high frequency components may not be considered. There two major drawbacks of the Local Binary Pattern. One is speed decreases for the large database as it produces long histograms and other is as the effect of the centre pixel is not consider it may omit local structure. In existing approaches, the shape of the detected regions is not preserved but in the proposed approach the shape of the detected regions is same as the original video. Log-Gabor function reduces the redundancy of the local information and effective representation of the uneven frequency and the bandwidth can also be varied from one to three octaves. Hence, the proposed method overcomes the drawbacks of the existing methods in a more efficient way. A Log-Gabor-SVM based approach efficiently detected faces in standard and own dataset both with indoor and outdoor environment efficiently. Figure 4 shows successively video based Face Detection of YouTube Celebrity dataset and Figure 5 shows Face Detection on McGill Face and own dataset in different environment conditions. Figure 6 shows comparative results obtained from different existing methods and proposed method. In practical systems increase in Detection Rate may go along with an increases in False Alarm Rate. Our proposed method considerably reduces the False Alarm Rate and increases the Detection Rate when compared to other methods as shown in Table 3 and Table 4. The advantage of the proposed method is it preserves the texture of the detected region.



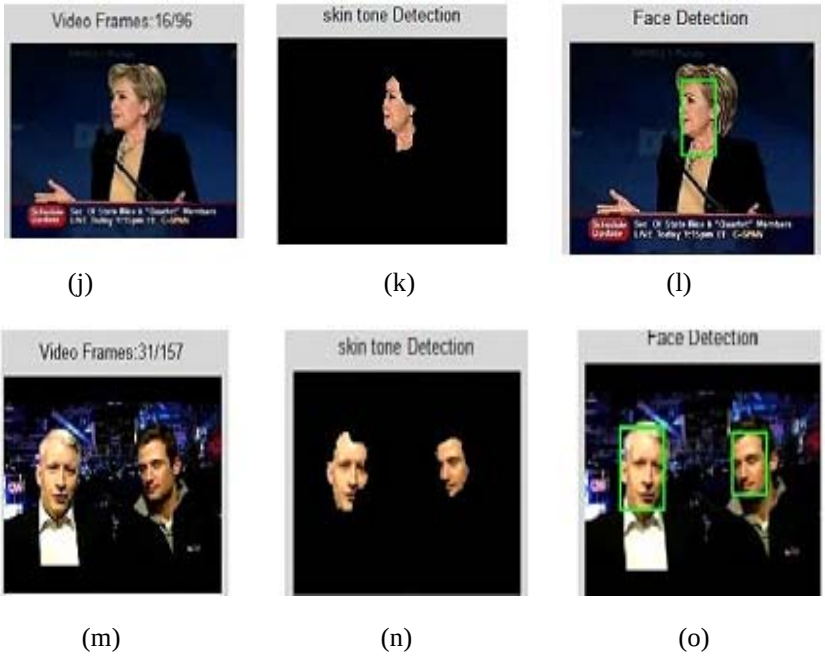


Figure 4. Results of Proposed method on YouTube Celebrity dataset: Frontal View(a, b, c), Pose Variation (d, e, f), Bright Illumination(g, h, i), Dark Illumination (j, k, l), Night(m, n, o)

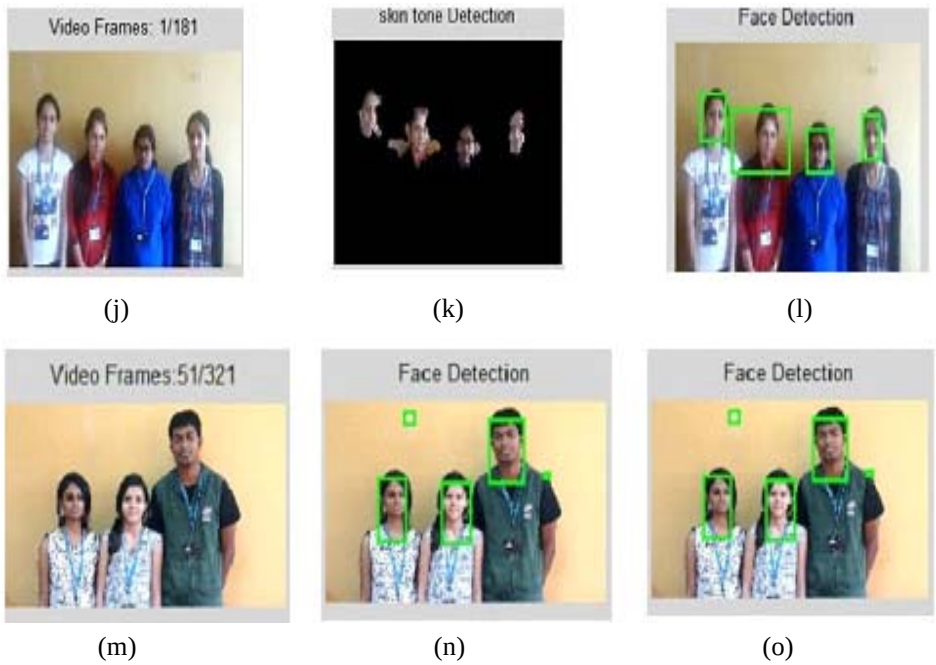


Figure 5. Results of Proposed method on McGillFace dataset: Pose Variation (a, b, c) and Own dataset: Sunset(d, e, f), Nonuniform Background(g, h, i), Twins(j, k, l), Indoor (m, n, o)

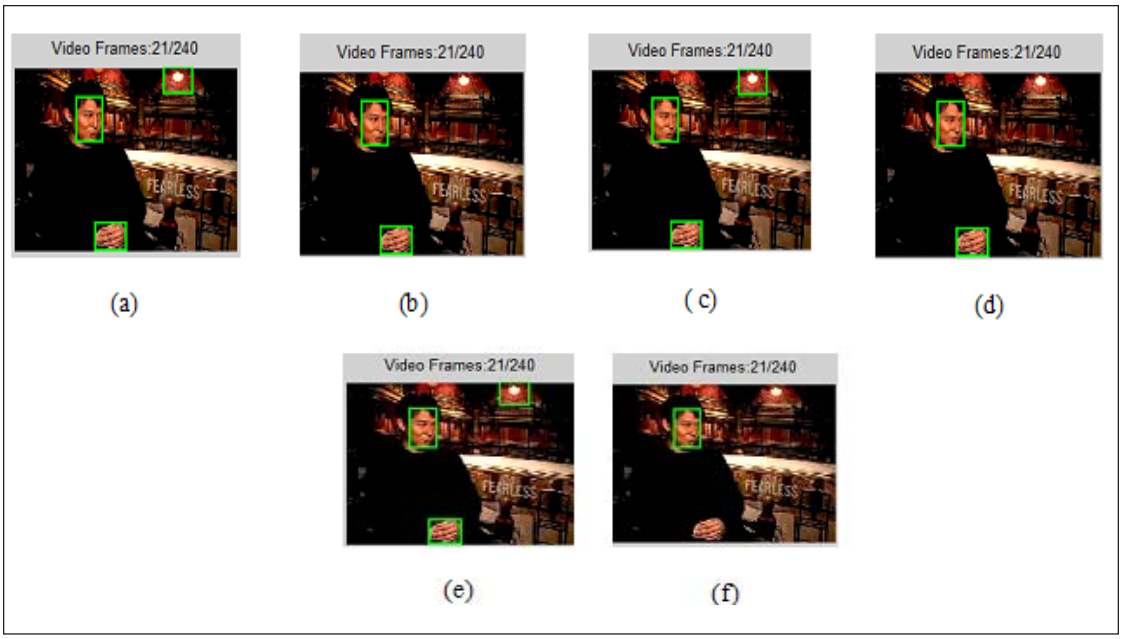


Figure 6. Comparative results of PCA (a), LBP (b), LPP(c), TLPP (d), OLPP (e), Proposed method (f)

3.2.1 Performance Measurement

The performance of our proposed is measured using the parameters: Detection Rate, False Alarm Rate; ROC curve; Time Complexity.

3.2.1.1 False Alarm Rate and Detection Rate

Detection Rate and False Alarm rate is obtained using the confusion matrix which contains predicted and actual classification [28] as shown in Table 1.

True Positive(TP) is the number of positive faces correctly identified. False Positive (FP) is the number of negative faces wrongly identified as positive. True Negative(TN) is the number of negative faces classified correctly. False Negative (FN) is the number of positive faces that were wrongly classified as negative. According to the definition of False Alarm Rate (FAR), involves TN, which is actually not computed for Face Detection, thus we can consider the Equation (6) for computing FAR. Equation (7) is used for computing the TPR or Detection Rate.

$$FAR = FP/(FP + TP) \quad (6)$$

$$TPR = TP/(TP + FN) \quad (7)$$

As shown in Table 2 our proposed method results with corresponding True Positive(TP), False Positive(FP) and False Negative (FN) with the calculated values of False Alarm Rate(FAR) and Detection Rate(DR) for the different video sequences. Each of the results in Table 2, is considered for 20 video frames. The last row in the Table 2 indicates results recorded for total number of faces from all the 16 videos, considering only 20 frames/video. Our proposed method decreases the False Alarm Rate and increases the Detection Rate when compared with the other subspace learning approaches [20-24] as shown in Table 3 and Table 4 respectively. Last row in both the Table 3 and 4 indicates False Alarm Rate and Detection Rate recoded for 16 videos considering 20 frames/video.

		Predicted	
		Positive	Negative
Actual	Positive	TP	FN
	Negative	FP	TN

Table 1. Confusion Matrix

3.2.1.2 ROC Curve

We also measured the performance of the proposed method using the Receiver Operating Characteristic (ROC)[29]. We plot the ROC graph with False Positive rate on X-axis and True Positive rate on Y-axis between 0 and 1. In the graph (0,1) indicates there are no false positives and all are true positives and (1,0) indicates none are true positives. Setting up the pair of (TP, FP) we plot on the ROC graph. ROC curve gives a graphical method for finding the trade-off between the False Positive rate and True Positive rate for our proposed method in comparison with the other existing methods. The observation made from the graph is a method is better than another method if it has a larger area and a method performs random guessing if the Area Under Curve is equal to 0.5. Figure 7 shows that our proposed method is comparatively better than other methods.

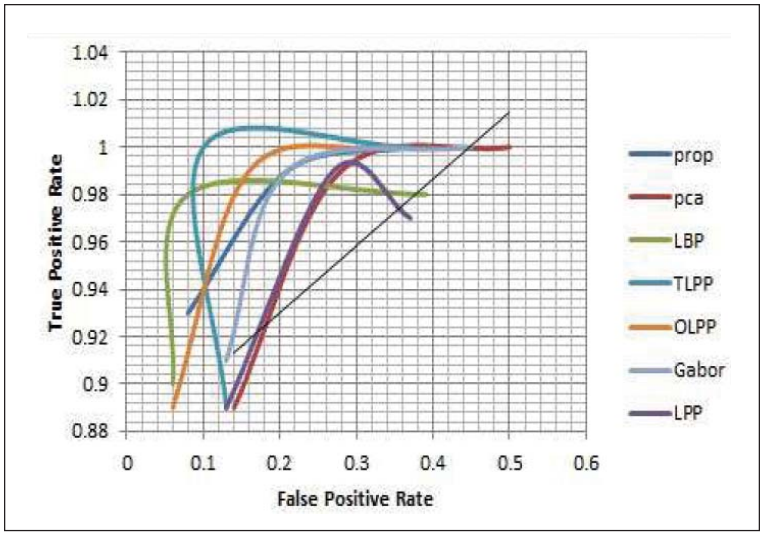


Figure 7. ROC Curve for Proposed method in comparison with other methods

3.2.1.3 Time Complexity

We measure the processing time to detect the face in the video sequence for the proposed approach in comparison with the other existing approaches. Our proposed method pays less focus to the non-skin color and, as a result, pays more attention to the skin color. Thus, there is a faster computation when compared to the other methods as shown in Table 5.Table 5 shows the computation time measured in seconds. The last row indicates computation time taken for 16 videos considering only 20 frames/video. However, our proposed method efficiently retains the processing speed by placing more emphasis on the skin color and less emphasis on the non-skin color by increasing the Detection Rate and decreasing the False Alarm Rate.

Input Video	Number of Faces	Number of TP	Number of FP	Number of FN	False Alarm Rate(%)	Detection Rate(%)
(a)	20	19	1	1	5	95
(b)	40	40	0	0	0	100
(c)	20	20	0	0	0	100
(d)	20	20	12	0	37.5	100
(e)	20	20	3	0	13.0	100
(f)	20	20	0	0	0	100
(g)	40	40	34	0	45.9	100
(h)	20	20	4	0	16.6	100
(i)	20	20	25	0	55.5	100
(j)	20	20	5	0	2 0	100
(k)	20	20	14	0	41.1	100
(l)	60	60	4	0	6.25	100
(m)	80	80	0	0	0	100
(n)	100	90	0	10	0	90
(o)	80	78	1	2	1.2	97.5
(p)	200	179	39	21	17.8	89.5
16 Videos	780	746	142	34	15.99	95.64

Table 2. False Alarm Rate and Detection Rate for the Proposed Approach

Dataset	PCA(%)	LBP(%)	LPP(%)	TLPP(%)	OLPP(%)	Gabor(%)	AMLPP Approach(%)	Proposed Approach(%)
YouTube Celebrity	28.68	8.29%	27.82	10.8	16.74	21.83	27.80	21.83
McGrillFace	50.31	39.69	37.09	37.0	34.42	45.57	37.5	37.5
Own Video	14.10	6.38	13.94	13.91	6.22	13.43	12.02	8.28
16 videos	24.0	12.12	20.8	16.5	13	20.6	19.0	15.99

Table 3. False Alarm Rate

Dataset	PCA(%)	LBP(%)	LPP(%)	TLPP(%)	OLPP(%)	Gabor(%)	AMLPP Approach(%)	Proposed Approach(%)
YouTube Celebrity	99.44	98.33	99.44	100	99.44	99.44	99.44	99.44
McGrillFace	100	98.75	97.5	100	100	100	98.6	100
Own Video	89.03	90.19	89.03	89.2	89.80	91.73	92.3	93.65
16 videos	92.5	92.9	92.3	92.8	93	94.3	94.5	95.64

Table 4. Detection Rate

Dataset	PCA	LBP	LPP	TLPP	OLPP	Gabor	AMLPP Approach	Proposed Approach
YouTubeCelebrity	.9966	.6681	.7873	3.7946	1.1475	.1531	1.2873	.2624
McGrillFace	.4822	1.118	.1902	4.7249	1.246	.4876	2.1802	.3517
Own Video	.2706	1.016	.1641	6.0378	.9042	.3012	1.1621	.2082
16 videos	.5831	.9342	.3805	4.8524	1.0991	.3139	1.3205	.2741

Table 5. Computational Time

4. Conclusion

The proposed methodology is implemented and experimented on both standard and own datasets. In contrast, with the other existing approaches a new descriptor Log-Gabor method is proposed. These filters provide effective representation of uneven frequency content of the images and redundancy in lower frequencies can also be reduced when compared with existing approaches. Two main aspects have been observed: First is it emphasizes on the skin color thus reducing the False Alarm Rate and second is features with high frequency information is efficiently captured and preserves the texture of the detected region. The experiments enclosed in this paper prove that there is a considerable increase in the Detection Rate and decrease in the False Alarm Rate. A large number of false alarm are detected but are eliminated during the skin segmentation. The performance of Face Detection can be improved in circumstances such as occlusion present in faces which will be considered in future work.

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