Detection of Human Faces in Video Sequences Using Mean of GLBP Signatures

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Abstract. Machine analysis of detection of the face is robust research topic in human-machine interaction today. The existing studies reveal that discovering the position and scale of the face region is difficult due to significant illumination variation, noise and appearance variation in unconstrained scenarios. We designed work is spontaneous and vigorous method to identify the location of face area using recently developed You Tube Video face database. Formulate the normalization technique in each frame. The frame is separated into overlapping regions. The Gabor signatures extracted on each region by Gabor filters with different scale and orientations. The Gabor signatures are averaged and then local binary pattern histogram signatures are extracted. The Gabor local binary pattern signatures are passed to Gentle Boost categorizer with the assistance of face and non-face signature of the gallery images for identifying the portion of the face region. Our experimental results on YouTube video face database exhibits promising results and demonstrate a significant performance improvement when compared to the existing techniques. Furthermore, our designed work is uncaring to head poses and sturdy to variations in illumination, appearance and noisy images.

Keywords: Ensemble categorizer · Gabor wavelet · Human computer interaction · Local binary pattern · Normalization

1 Introduction

One of the most interesting fields of image analysis is the automatic identify the area of the human faces. The major applications of finding the face areas are face recognition, facial expression recognition, gender identification, face registration, human-machine interaction, surveillance, etc. Face discovery methods identify the faces in the video clips and provide the location and scale of all faces. But finding the region of the human face is a interesting task as the human face appearances are non-rigid and they appear in different backgrounds (simple,

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clutter) and have a high variability of different location, poses, expressions and illuminations (good and bad) [1,2].

To overcome these problems, the planned work is a new approach to identify the face region by Normalized mean of Gabor LBP signatures. The planned methodology is insensitive to head poses and strong to variations in lighting condition and noisy images. The residual portion of the paper is ordered as follows: Sect. 2 briefly evaluate the survey works. Section 3 defines the designed NGLBP signatures details. Section 4 shows the experimental results. Section 5, offers conclusion and plan for future task.

2 Survey Work

Detection of face techniques have been examined immense in the earlier. The methodology for identifying the face area utilizing skin color and the Maximum Morphological Gradient Combination image was exhibited [3,4]. The system failed when it manages with skin color areas including similar color background and region of dress. H. Sagha et.al designed a methodology for discovering sparse signatures using a genetic algorithm for multi view face detection. Notwithstanding, discovering these signatures was time intensive and wasteful by utilizing their strategies [5]. The Gabor Filter (GF) catches the properties of different orientation and spatial localization in the space and frequency domains was utilized in face detection [6–8]. The techniques using the LBP and Local Gradient Pattern (LGP) based signatures for detecting the faces was existed [9–11]. These techniques are sensitive to noise as the signatures at each location compare a central pixel with neighboring pixels. The detection of the facial components utilizing speeded up robust signatures presented in [12] could achieve only moderate performance. The extracts of Haar signature and a learning algorithm (Adaboost) are utilized in [13], where the methods suffer from global illumination variations. Kyungjoong Jeong et al. [14] carried out the work Semi - LBP (SLBP) signatures for face detection. These signatures are robust against noise. Though, higher detection rate could not be achieved.

A lot of existing detection systems utilized one type of signature. Though, for difficult works such as discovering the area of human face, a single signature set is not rich enough to capture all of the information required to detect the face. The robust detection always requires appropriate information on illumination, face appearance variation, and discriminating power of the signature set demanding more than one type of signature set. Finding and fusing relevant signature sets have thus become an energetic research theme in machine learning. Combining the GF and LBP signatures for face recognition is motivated for the work reported in [15]. We plan to combine GF and LBP signatures for discovering the portion of face.

The work considers the local appearance descriptors by Gabor Wavelet (GW) utilized in [6–8] and fusing it with Local Binary Pattern (LBP) signatures as used in [14] rather than working on individual signature set. The GF signatures convert facial shape and appearance information over a broader range of scales. The detection of LBP signature captures little appearance details and tolerance to illumination changes. Local spatial invariance is accomplished by locally pooling (histogramming) the resulting texture codes. The advantage of NGLBP signatures are utilized to capture the local structure corresponding to spatial frequency (scale), spatial localization, and orientation selectivity which are proved to be discriminative the face/non-face and robust to illumination, noise and appearance changes (Fig. 1).

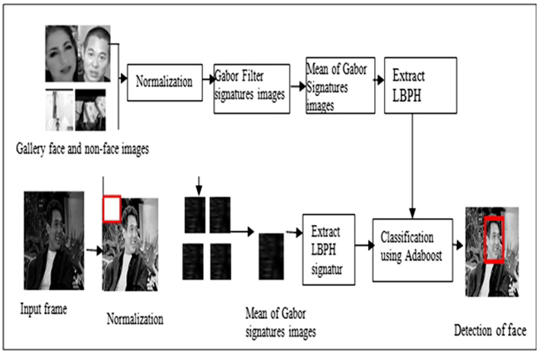

Fig. 1. Overview of the system diagram for identifying the location of face area where red color box (red color frame size is 30 × 30 pixels) (Color figure online)

3 Planned Work

The video with single subject contains multiple frames depicting the temporal variations in different poses, expressions and varying lighting conditions of the individual. The following steps describe the planned approaches:

1. Initially, normalization techniques are applied on each frame which adjusts the image intensity.
2. Subsequent, each frame is separated into intersecting regions and then local signatures are separated by using GF with different scale and orientation in each region. The Gabor filter signatures are most appropriate for face/non-face classification. The Gabor filter signatures are changed into mean of Gabor signatures. The Gabor signatures have the facial shape and appearance information over a range of coarser scales.
3. 59-LBPH signatures are separated from each region contains Gabor signatures.
4. The Gabor LBP signatures are distributed through the AdaBoost categorizer for the pixel wise classification with well-trained face and non-face signature.

The performance of the planned work NGLBP signatures is compared with the signatures extracted by conventional GF [14], LBP [9] and GLBP by deploying the Ensemble categorizers. For conducting and evaluating the work, YouTube (YT) video face databases [15] are taken. The succeeding sub-divisions reveal the technique in point.

3.1 Normalization

Due to the fact that variant light condition certainly reasons low finding rates and can be removed by illumination normalization, normalization techniques should be well measured in an automatic detection system. So the histogram normalization technique [16–18] was applied on each frame to compensate for different lighting conditions. As the little- contrast image's histogram is narrow and centered toward the middle of the gray scale, if we distribute the histogram to a wider range, the quality of the image will be improved. So we can do it by adjusting the probability density function of the original histogram of the image so that the probability spread equally. It is utilized to produce an image with distributed brightness levels over the image. Initially, each frame is extracted and represented as set of frames f1, f2, ...f_k from video V, where k is the number of frames. The gray levels of the k_{th} frame is first equalized by

$$f_k = E(r_k)\sum_{i=0}^{m}\frac{n_i}{n} \qquad m = 0,1,...L-1 \tag{1}$$

where E denote the equalization function, n is the total number of pixels, n$_i$ is the number of pixels with gray level r_i and L is the number of discrete gray levels.

3.2 Signature Extraction of Gabor Filter

Following the intensity normalization, Gabor filters offer the greatest simultaneous localization of spatial and frequency information. The Gabor wavelet (GW) that catches the properties of orientation selectivity, spatial localization and optimally localized in the space and frequency domains was used in face detection [16–18, 21]. The extracts of Haar feature and a learning algorithm (Adaboost) are proposed in [22], where the methods suffer from global illumination variations. KyungjoongJeong et al. [14] carriedout the work Semi - LBP features for face detection. Among all the features, the Gabor features [19] are good for solving the computer vision problem such as face detection to provide better accuracy with head poses and appearance variations. Hence, we concentrate on Gabor features. However the Gabor features are limited due to their sensitivity to illumination variations and noisy images. But the performance, quality of a face detection system can be vulnerable to variations in illumination levels; which maybe correlated to the conditions of their surroundings. Therefore, we propose the use of a novel method known as NGF features which is insensitive to variations in lighting condition and noisy images. The 2D Gabor filter is agreed [8] and it could be mathematically stated as:

$$\psi(a,b,\sigma,\theta) = \exp\left(-\frac{(A^2+\gamma^2B^2)}{2\sigma^2}\right)\cos\left(\frac{2\Pi}{\lambda}A\right) \tag{2}$$

$\mathbf{A} = \mathbf{a}\cos\Theta + \mathbf{b}\sin\Theta$; $\mathbf{B} = -\mathbf{a}\sin\Theta + \mathbf{b}\cos\Theta$

where orientation Θ, the effective width σ, the wavelength λ is the spacing factor between filter in the frequency domain, the aspect ratio $\ddot{Y}$. We propose the GF procedure by dividing the k^{th} frame f_k into overlapping regions 'B' represented as. The number of regions are (m − 30) × (n − 30) and m and n are the number of rows and columns in each frame respectively. Typically, each 'B' size is 30 × 30 within a frame, its convolution with a Gabor filter Ψ is stated as follows.

$$GF_k, B, \sigma, \Theta(\mathbf{a}, \mathbf{b}) = f_{k,B}(\mathbf{a}, \mathbf{b})\ \Theta\ \Psi\ (\mathbf{a}, \mathbf{b}, \sigma, \Theta) \tag{3}$$

where Θ is the sign for convolution. Eight scales σ, ε (5 to 19 with increments by 2) and four orientations θ (−45°, 90°, 45°, 0°) are utilized in the Gabor filters. The given 'B' region within a input frame f_k is filtered with the Gabor filters as in Eq. (3), ensuing in a series of Gabor filtered images with signatures such as bars and edges usefully emphasized for improved identifying the location of the face. Then extracted signatures are converted into Mean (M) of Gabor signatures in each region. The performance of the planned mean of GF signatures is compared with the Standard deviation (S) and Variance (V) of GF signatures in each region as

$$G_{k,B,M}(a,b) = \frac{1}{\sigma * \theta}\left(\sum_{\sigma=1}^{8}\sum_{\theta=1}^{4} GF_{k,B,\sigma,\theta}(a,b)\right) \tag{4}$$

$$G_{k,B,V}(a,b) = \left(\sum_{\sigma=1}^{8}\sum_{\theta=1}^{4}\left(GF_{k,B,\sigma,\theta}(a,b) - \left(\frac{1}{\sigma * \theta}\left(\sum_{\sigma=1}^{8}\sum_{\theta=1}^{4} GF_{k,B,\sigma,\theta}(a,b)\right)\right)\right)^2 / \sigma * \theta\right) \tag{5}$$

$$G_{k,B,V}(a,b) = \left(\sum_{\sigma=1}^{8}\sum_{\theta=1}^{4}\left(GF_{k,B,\sigma,\theta}(a,b) - \left(\frac{1}{\sigma * \theta}\left(\sum_{\sigma=1}^{8}\sum_{\theta=1}^{4} GF_{k,B,\sigma,\theta}(a,b)\right)\right)\right)^2 / \sigma * \theta\right)^{1/2} \tag{6}$$

As a result, each region contains M, S, and V of Gabor signatures.

3.3 Signature Extraction of LBP

The Gabor signatures of each region size are 30 × 30 resolutions. Then GLBP is defined by a binary coding function [19] to the obtain Gabor signatures in each region. Let $G_{k,B}$ (a, b) be the Gabor signatures in 'B' region within k^{th} frame around pixel (a, b). The center value of 3 × 3 matrixes is compared with another eight values and an 8bit code is coined, which will be the value at each pixel position(a, b). Let M to represent the matrix as:

$\mathbf{M} = G_{K,B}(\mathbf{a}, \mathbf{b})$

The value by using the planned method GLBP is obtained as:

$$f_{GLBP}(a,b) = \sum_{a=0}^{2} \sum_{b=0}^{2} T(a,b) 2^{8}$$

$$where \quad a \neq 1 \quad and \quad b \neq 1 \tag{7}$$

and

$$T(a,b) = \begin{cases} 1 & M(a,b) \geq M(1,1) \\ 0 & else \end{cases} \tag{8}$$

After fixing the value using GLBP technique for each pixel related with a region, a 59-bin histogram is applied to capture the signature for the each region. A histogram (H) of the region $f_{G,L,B,P}$ can be defined as:

$$\begin{aligned} & h_L = h_L + I(lower_L < f_{GLBP}(a,b) \geq higher_L) \\ & 1 \leq a \leq m-30, \qquad 1 \leq b \leq n-30, \qquad 1 \leq L \leq 59 \end{aligned} \tag{9}$$

$$I(A) = \begin{cases} 1 & A \quad is \quad true \\ 0 & A \quad is \quad false \end{cases} \tag{10}$$

where L is the number of bins for the values formed by the GLBP function. The interval of each bin is represented by the range lower L and higher L.

The GLBP histogram holds data about the report of the local micro-patterns such as edges, spots and flat areas, over the whole image, so could be utilized to statistically define image characteristics. We gained 59 - GLBP histogram bins for each region in the frame.

3.4 Classification

Adaboost algorithm as utilized in [19, 23, 24] for object detection reveals a low false positive performance and hence organized in our work for classification in face/non-face region. Initially the gallery set is formed using the NGLBP signatures from the collection of gallery images having both face and non-face images and stored in database (DB1). The signatures of the each frame are classified in face/non-face region with DB1 utilizing pixel wise classification of boost algorithm. The signature of the each block with in a frame are classified into face and non-face region with training set using boost algorithm [25,26]. Finally the location of face region is obtained from each frame.

$$\mathbf{F} = \mathbf{2} * \mathbf{P} * \mathbf{R}/\mathbf{P} + \mathbf{R} \tag{11}$$

The detection of human face is described in the algorithm as given below.

Algorithm for detection of face region

Input: Given an input video (V), Set scale $\sigma = 8$ and orientations $\theta = 4$, DB - training database

Output: F - face region
V = f1, f2, ..., f_k Collection of frames, K is the number of frames
f(a, b) Resize the input framefinto 110 × 110 pixels.

$$f_k = E(r_k) = \sum_{i=0}^{m} \frac{n_i}{n} \qquad m = 0,1,\ldots\ldots.,L-1$$

(Apply normalization)

Block ← 1 represent block, where r and c are the rows and columns of input image respectively, input image is divided into overlapping blocks, (block_height, block_width) = size (block), each block size is of 30 * 30 pixels

Iterate 1:
a = 1:r; b = 1:c f_b(a, b) = f (a:a + block_height −1, b:b + block_width −1)

Iterate 2: s = 1 to σ ; o = 1 to θ

$$\psi(a,b,\sigma,\theta) = \exp\left(-\frac{(A^2+\gamma^2 B^2)}{2\sigma^2}\right)\cos\left(\frac{2\Pi}{\lambda}A\right)$$

A = $a\cos\Theta + b\sin\Theta$
B = $-a\sin\Theta + b\cos\Theta$
$GK_{k,B,\sigma,\Theta}(a,b) = f_{K,B}(a,b)\Theta\Psi(a, b, \sigma, \Theta)$

$$G_{k,B,M}(a,b) = \frac{1}{\sigma*\theta}\left(\sum_{\sigma=1}^{8}\sum_{\theta=1}^{4} GF_{k,B,\sigma,\theta}(a,b)\right)$$

$$G_{k,B,V}(a,b) = \left(\sum_{\sigma=1}^{8}\sum_{\theta=1}^{4}\left(GF_{k,B,\sigma,\theta}(a,b) - \left(\frac{1}{\sigma*\theta}\left(\sum_{\sigma=1}^{8}\sum_{\theta=1}^{4} GF_{k,B,\sigma,\theta}(a,b)\right)\right)\right)^2 / \sigma*\theta\right)$$

$$G_{k,B,V}(a,b) = \left(\sum_{\sigma=1}^{8} \sum_{\theta=1}^{4} \left(GF_{k,B,\sigma,\theta}(a,b) - \left(\frac{1}{\sigma * \theta} \left(\sum_{\sigma=1}^{8} \sum_{\theta=1}^{4} GF_{k,B,\sigma,\theta}(a,b) \right) \right) \right)^2 / \sigma * \theta \right)^{1/2}$$

$M = G_{K,B}(a,b)$
Extract LBP feature

$$f_{GLBP}(a,b) = \sum_{a=0}^{2} \sum_{b=0}^{2} T(a,b) 2^8$$

$$where \quad a \neq 1 \quad and \quad b \neq 1$$

$$T(a,b) = \begin{cases} 1 & M(a,b) \geq M(1,1) \\ 0 & else \end{cases}$$

$$h_L = h_L + I(lower_L < f_{GLBP}(a,b) \geq higher_L)$$

$$1 \leq a \leq m - 30, \qquad 1 \leq b \leq n - 30, \qquad 1 \leq L \leq 59$$

$$I(A) = \begin{cases} 1 & A \quad is \quad true \\ 0 & A \quad is \quad false \end{cases}$$

End iterate 2
F = Classify the face or non-face region using Adaboost classifier algorithm (f_{GLMP},DB)

End Iterate 1

4 Experimental Results and Discussion

To evaluate the performance of our planned method, YT video datasets were utilized for the experiment. YT video clips contain 47 celebrities. Some of the videos are low resolution and recorded at high compression rates. This leads to noisy, low-quality image frames. The dataset consists of about 1910 video clips, each containing hundreds of frames. Out of the 1910 video sequence studies, 1870 of them consists of only one person and the remaining have more than one person. For gallery purpose, 805 face images and 1023 non-face images are collected from ORL, Yale databases and background imaged respectively. Figure 2 shows some samples of the gallery images.

Fig. 2. Sample of gallery images a) face, non-face images

4.1 Performance of Signature Extraction

We collected the gallery images, which comprise of face images and non-face images. The gallery images are rescaled into three types of resolution such as 25 × 25, 30 × 30 and 35 × 35 pixels for finding the location of face. Initially signatures are extracted such as NGLBP, GLBP, LBP and GF from each gallery image. In our experiments, the orientation and scale of Gabor filters imposed on images are two key parameters that determine the effectiveness of the extracted texture signatures. Figure 3 compares the detection results obtained using 2, 4, 6 and 8 orientations of Gabor filters (the number of the scales is fixed at 8) in each

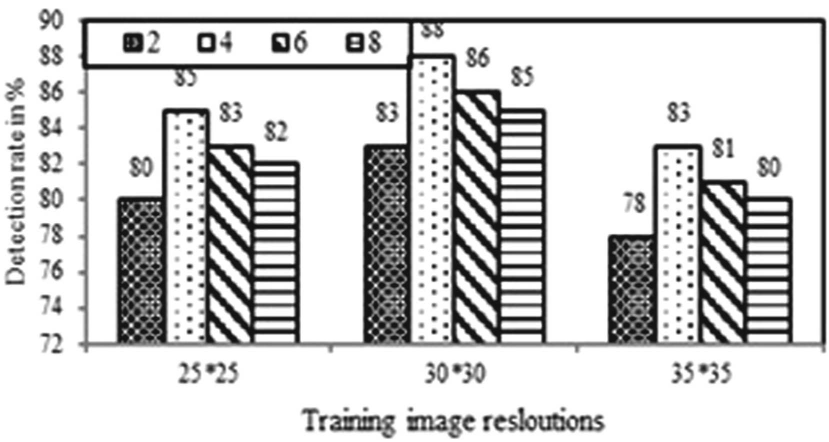

Fig. 3. Four sets of orientation in YT database

resolution gallery images using GA categorizer. The four sets of orientations are (90°, 0°), (−45°, 90°, 45°, 0°), (−45°, −22.5°, 0°, 22.5°, 45°, 90°) and (90°, 67.5°, 45°, 22.5°, 0°, −22.5°, −45°, −67.5°), correspondingly. It can be seen that utilizing the default 4 orientations makes highest accuracy of 89percent among the four sets of orientation values. This result suggests that Gabor filters require at least 4 orientations to be able to capture most of the discrimination information.

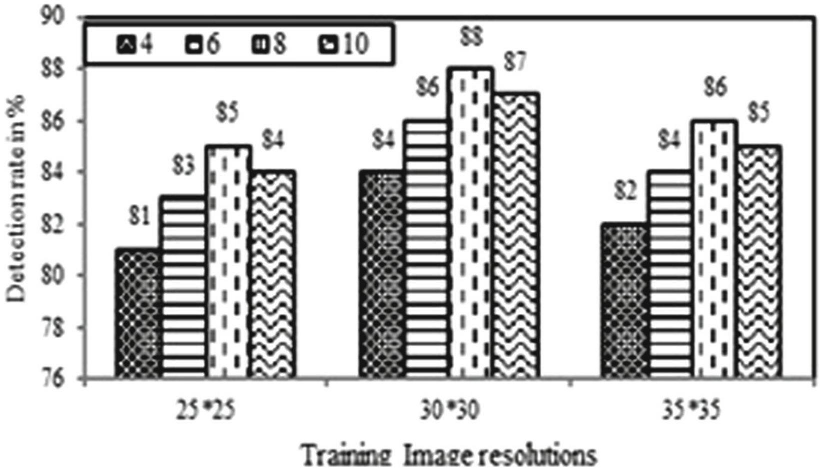

Fig. 4. Four sets of scales in YT database

Figure 4 compares the accuracies obtained using 4, 6, 8, and 10 scales of Gabor filters (the number of orientations of Gabor filters is fixed at four) in each resolution gallery images using GA categorizer. The four sets of scales are composed of (5:2:11), (5:2:15), (5:2:19), and (5:2:23) pixels correspondingly. The results also confirm that the default 4 orientations and 8 scales of Gabor filters are the optimal parameters for detecting the face area. In both Fig. 3 and Fig. 4, 30 × 30 resolution gallery images shows the best result.

Table 1. Compares the accuracies obtained using GW and NGW

Extracting Signatures	Detection rate in %				
	Mean	Std	Variance	Skeweness	Kurtosis
GW	80	79	81	82	81
NGW	85	84	84	84	83

Table 1 compares the accuracies obtained using mean, standard deviation, skewness and variance signatures in gallery images of 30 * 30 resolutions. From the result, it can be observed that mean of Gabor signatures result in better detection of face in 30 × 30 resolutions gallery images.

4.2 Performance of Categorizer

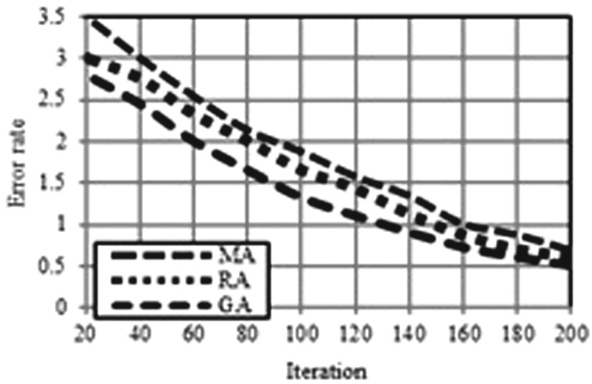

Fig. 5. Error rates from three Adaboost algorithms

The NGLBP signatures are trained through variant Adaboost categorizers such as RA, GA and MA in 30 × 30 resolution gallery images. They are compared for error checking with 100 boosting iterations as shown in Fig. 5. From the analysis GA returns the lowest error rate and is selected as the detection algorithm for our system.

4.3 Performance of NGLBP

Figure 6 shows the receiver operating characteristic curves (ROC). The curve is made by YT databases with GF, LBP, GLBP and NGLBP signatures are tested in GI, BI, N and MS. Figure 6 depicts the relationship between a number of false positives and the detection rate. The NGLBP signatures highlight higher performance of 3 videos respectively. The LBP signatures higher performance of 3 lower performance by 2 performance by 1.5 individual signature under all types of videos. The averages of all types of videos for identifying the location of face region rate considerably improved to about 4 reported for utilizing NGLBP signatures over using individual signature set in different video conditions.

Detection of the face includes calculating the Sensitivity, Precision and F measure the results are shown in Table 2, which indicates the number of video sequences with GI, BI, N and MS. It can be seen that the GF and LBP signatures perform poorly owing to their sensitivity to various illumination variations

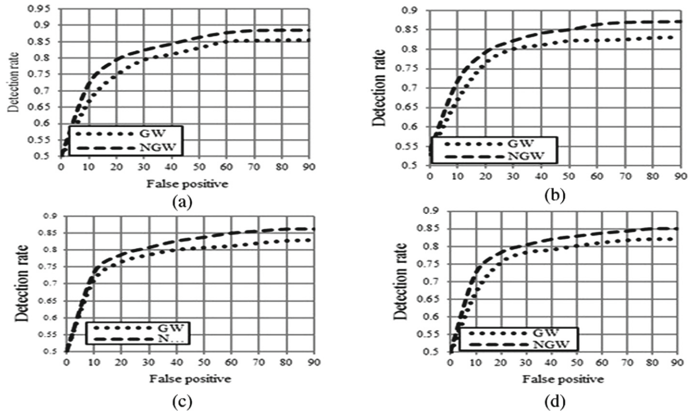

Fig. 6. Roc curve false positive rate vs. Detection rate a) Good Illumination b) Bad Illumination c) Noisy images d) Multiple Subject

Table 2. Result for identifying the location of face

author	Signature Extraction	Categorizer	Sensitivity in (%)				Precision in (%)				F measure in (%)			
			No. of videos				No. of videos				No. of videos			
			625	420	542	35	625	420	542	35	625	420	542	35
			GI	BI	N	MS	GI	BI	N	MS	GI	BI	N	MS
	GF	Gentleboost	84	80	78	79	85	80	82	81	84	80	79	80
	LBP	Gentleboost	85	83	80	82	87	82	83	84	85	82	82	83
proposed	GLBP	Gentleboost	87	85	83	85	88	84	85	86	87	84	85	86
	NGLBP	Gentleboost	90	88	86	87	90	85	87	88	90	86	87	87

Table 3. Time complexity for comparing our designed approach with existing approach

Signature Extraction	Signature extraction for gallery Images (compilation time in ms)	Testing Videos for face detection (compilation time in ms)			
		GI	BI	N	MS
LBP [9]	25	974000	789300	1213450	632211
GF[14]	28	982120	801342	1238691	637625
GLBP	28.5	983450	812420	1256302	638823
NGLBP	29.5	985629	816458	1259000	639000

and common appearance respectively, while NGLBP signatures give much better performance. Figure 7 shows the sample result. The size of the bounding box is determined using the scale on the detected face on the video sequences. The LBP and GF signature would fail to detect the face in the different poses and noise image respectively. GLBP signature would fail to detect the face in the BI variation. From Fig. 7, we can show that our plannedNGLBP signatures are robust against noise and illumination and differences pose variations and expressions. This seems to suggest that a combination of normalization, Gabor and LBP signatures result in better detection of face. In our work by using Intel Core i5 @ 3.20 GHz, 8 GB RAM with Matlab 2013a. Table 3 show that the time complexity for identifying the location of face region.

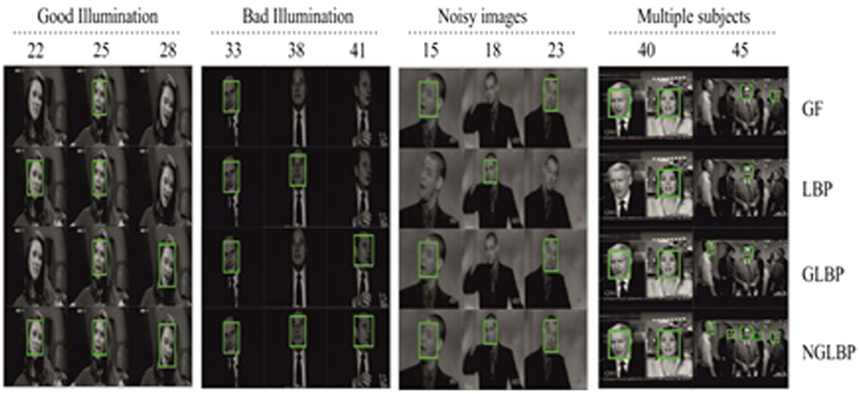

Fig. 7. Sample detection of face result in YT databases

5 Conclusion and Future Work

This paper investigated the benefits of NGLBP signatures for strong discovery of face area in video sequences under uncontrolled scenario. The experimental results showed that the planned method is successful when compared to the existing methods. The advantage of NGLBP signatures is amazingly uncaring in appearance varieties through illumination, expression, and noise in the images. NGLBPsignatures are not just robust to the varieties of image condition, additionally in encoding discriminate information, i.e. face/non-face area in spatial and frequency domains. The NGLBP test results exhibit that signature finds the best execution of revelation of face applications on the YT databases. In future work on the face regions are utilized for facial expression recognition.

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