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A Novel Two-Stage Human Face Detection Method Based on Appearance and Local Shape Approaches

[1]Farhad Navabifar, [2]Rubiyah Yusof, [3]Rasoul Rahmani, [4]Mehran Emadi

[1,2,3,4]Centre for Artificial Intelligence and Robotics, Universiti Teknologi Malaysia, 54100 Kuala Lumpur, Malaysia.
[1,4]Department of Computer Engineering Mobarakeh Branch-Islamic Azad University, Mobarakeh, Esfahan, Iran.

Abstract: In the area of computer vision, face detection is the first step of any automated face processing system such as face recognition, face localization and face tracking. The goal of face detection is detecting faces in images or videos regardless of variations such as pose, illumination or expression. Face detection has many applications, including biometrics, surveillance, human-computer interaction (HCI) and multimedia management. Although many challenges still remain for the design of practical systems. One of the main problems for obtaining high performance face detection system is existence of high number of false alarms in the final face detection output. Since the performance of the face detection systems is evaluated by the detection rate and the false positive rate, reduction of the false positives may increase accuracy of the detection module, and also the performance of the subsequent modules of the overall system. In this paper, a combinational method is proposed based on Adaboost cascade and histogram of oriented gradients (HOG). The concept behind the proposed method relies on removing the false positives from the input image by adding a post-processing module, to obtain a higher performance. In the proposed method, at first, the majority of human faces are detected by main face detection module with a high detection rate which is Adaboost cascade algorithm, and then the detected face sub-windows will be forwarded to the post-processing module. In post-processing module, the HOG features and SVM classification are used, in order to remove the false positives. The experiments on CMU frontal and CMU profile datasets show superior performance of the proposed technique, compared with the existing works.

Key words: Face Detection, cascade Adaboost, Histogram of Oriented Gradients, Support Vector Machine.

INTRODUCTION

Finding objects using vision is one of the tasks that human performs routinely and effortlessly in their daily life. The demand of finding an object in still image or sequence of videos has been increased recently due to wide practical applications in multimedia, biometric systems, surveillance and human computer interaction (HCI). Face detection and recognition is one of the high applicable instances of the object recognition problem, which deals with finding and identifying appearances of human faces in digital images or video frames. Since face detection is the first step of any face processing application, the performance of the face detection module affects subsequent modules and the performance of the overall system. On the other hand, any increment in the detection rate results in increasing the false positives (Li and Jain 2011).

Face detection approaches are categorized into four groups including: Template-Based, Knowledge-Based, Feature-Based and Appearance-based methods (Yang, Kriegman *et al*. 2002). Amongst the approaches, Appearance-based methods have been shown the most effective approach in terms of accuracy and speed (Yang, Kriegman *et al*. 2002; Zhang and Zhang 2010; Navabifar, Emadi *et al*. 2011). One of the most popular methods in appearance-based approach which is state of the art in face detection, is the Adaboost cascade algorithm presented in (Viola and Jones 2001). They applied Haar-like features to capture and extract human facial features. Besides easily generating of different forms and size of these features, calculating the values of the features are simply due to integral image application. Generally, most of the areas in an image contain non-face samples and a few parts covered by human face; therefore, Viola and Jones utilized boosting cascade structure with the idea of immediately rejection of non-face samples. Nevertheless of the significant progress in the face detection field, the accuracy of the face detectors is not satisfactory due to existence of high number of false positives in images. Figure 1 shows correct detected face and false alarms in a sample image.

Corresponding Author: Farhad Navabifar, Centre for Artificial Intelligence and Robotics, Universiti Teknologi Malaysia, 54100 Kuala Lumpur, Malaysia
E-mail: nfarhad49@gmail.com

Fig. 1: Correct detected face and false alarms.

In this paper, a robust and fast face detection system is presented which consists of two stages. In the first stage, a modified cascade Adaboost algorithm, which is based on appearance approach detects all the possible faces in the images. Afterwards, a novel post-processing stage reduces the number of false alarms, which is based on local shape approach using the histogram of oriented gradients method. Furthermore, another classification is applied based on SVM classifier to remove all the non-face chosen patterns. The results obtained show a magnificent performance in terms of accuracy and computational cost.

The rest of this paper is organized as follows: Section 2 provides a brief review of the related works; the materials and methods are extensively described in Section 3; the proposed face detection framework is described in details in Section 4; the experimental results and the conclusion are presented in Sections 5 and 6, respectively.

Related Works:

A vast amount of research has been dedicated to enhance the face detection algorithm performance. One of the very significant jobs was performed by Rowley *et al*.(1998) which utilized a multi-layer neural network algorithm in the face detection. The proposed multi-layer neural network algorithm was applied in order to learn the spatial intensities and relationships of the pixels from face and non-face samples. Their proposed model consisted of two separate stages where in the first stage the multi-layer neural network algorithm classified the face and non-face patterns, while in the second stage the decision making was performed based upon merging multiple detection into a single face. For the purpose of training the algorithm, a set of 1050 face samples was collected from various scales, poses and intensities. In the second stage, the algorithm merged the overlapping faces detected between the outputs of the multiple network. Logic operators and voting were used for improving the performance. The proposed algorithm was tested on 24 images containing 144 faces where the results showed better performance compared with previous works.

Another fast and robust face detector algorithm, named Convolutional Face Finder (CFF), was proposed by Garcia and Delakis (2004). Their system was based on Convolutional Neural Network (CNN) architecture. The CFF method consisted of six layers where pipeline of simple convolution and sub-sampling modules were performed, and treated the raw image separately. Their results obtained showed a high accuracy with a low rate of false alarm, where the frontal CMU database was used to test.

Chen *et al*.(2009) presented a method for increasing the efficiency of a Genetic Algorithm (GA) based approach. Since the quality of the training set had some impacts on the classification performance, they would propose a method based on GA and manifold, in order to create optimal training set for obtaining a more robust face detection algorithm. Their proposed algorithm could obtain the accuracy of 90.73% on the MIT+CMT frontal face test database.

A parallel cascade structure for Real Adaboost algorithm was proposed by Wu *et al*. (2004). To overcome the pose variations problem, human faces were categorized into types. For each category, several classifiers are trained by Real Adaboost algorithm with forming a nesting-structured face detector. Although their proposed technique was slow, it could achieve 89.8 % detection rate with 221 false alarms, where the CMU profile face test set was used for the assessment purpose.

Huang *et al*.(2005; 2007) proposed a rotation invariant multi-view face detector algorithm. Their proposed algorithm consisted of a tree-structured multi-view face detector and a vector boosting algorithm.. They divided the entire face space into smaller subspaces utilizing a coarse-to-fine strategy. By simply rotating the detector 90°, 180° and 270°, their multi-view face detector algorithm covered +/-45° in plane and +/-90° out of plane rotations.. Their experimental results could obtain a high accuracy and good speed compared with other existing works.

Several experiments were performed in (Brubaker, Wu *et al*. 2008) on a novel cascade training algorithm based on the probabilistic prediction; to show the impacts of cascade learning, feature filtering and stronger weak hypotheses, on the performance of face detection algorithm. Their results showed a little impact for the different boosting methods such as Adaboost, Gentleboost and Realboost, and also ineffectiveness for using feature filtering techniques such as fast filters or slow filters. However, they found out that learning stronger weak hypotheses such as the combination of Viola-Jones features into CART trees can significantly enhance the performance.

Meynet *et al*.(2007) used Boosted Gaussian features which could improve the frontal face detection performance.. They used Adaboost algorithm for training the samples; however, they applied Gaussian filters for facial features extraction, instead of using Haar-like features. The CMU+MIT face test database was used to show that, although the performance of detection was improved relatively, their system is three times slower than Viola-Jones Adaboost algorithm.

Schneiderman (2004) proposed an efficient cascaded object detection technique which used a combination of the feature-centric evaluation and high discriminative power features. To improve detection performance and computational cost. In general, the cascade-based methods such as Viola-Jones, apply window-centric evaluation to compute feature evaluation and lighting correction for each window, separately. Whilst, the proposed technique, applied feature-centric evaluation which re-uses feature evaluations among the overlapping windows.. To train the proposed cascaded technique, Adaboost algorithm with confidence weighted prediction was employed. The results obtained indicated that the proposed method could perform good in terms of detection rate with low false alarms over CMU+MIT test face database, comparing with the techniques proposed by viola-Jones and Schneiderman-Kanade. However, there were no results reported regarding the computational time and speed of the proposed algorithm.

Verschae *et al*.(2008) presented a unified learning framework by employing nested cascades of boosted classifiers for the purpose of object detection and classification. The main idea of the framework was using an integration of powerful learning capabilities along with effective training procedures. It made the detection and classification system resistant against the intra-class variability of the objects. It also helped the system to be robust in high speed training and testing tasks. In this method, rectangle and LBP features were trained by using bootstrap procedure with the goal of reduction of training time. The experimental results showed that using LBP features can reduce the training time; however, it has no effect on the performance, compared to using the rectangle features. The proposed method was tested using CMU+MIT, BioID, UCHFACE and FERET databases, the results showed a good performance achievement.

In another interesting research, Jun and Kim(2012) presented a human face detection system using evidence accumulation and local gradient patterns (LGP). LGP is insensitive to global intensity variations, which improves the discrimination power of the face/non-face histogram. In order to reducing the false positive rate, evidence accumulation method (EAM) was employed. The EAM technique accumulates the confidence values for several windows detected in different scales. The experimental results on CMU+MIT and FDDB databases verified that LGP+EAM method could show better performance compared with the previous works in terms of computation time, false positive numbers, and detection rate.

MATERIALS AND METHODS

Adaboost Cascade Classifier Overview:

Freund and Schapire (1995) presented Adaboost algorithm for learning samples. This algorithm is based on boosting theory, which combines several simple classifiers to construct a strong classifier, in order to classify objects. Viola and Jones (2001) applied Adaboost algorithm in face detection application which is an important reference in the field of face detection. Their proposed method has three contributions: The first contribution is applying integral image application for fast computing features; secondly, is the selection of efficient and small number of Haar-like features from a large set of Haar-like features with Adaboost algorithm and, the third is rejecting non-face samples rapidly by cascade structure are the next contributions. Viola and Jones used a set of basis functions, which is called Haar-like features that computes the difference of intensity in neighbor regions. Figure 2 shows the conventional form of these features. Thousands of these features can be generated in different scales and sizes due to its flexibility. These Haar-like features are used to build simple classifiers, which can discriminate face and non-face patterns. These classifiers are called weak classifiers because they cannot classify the data well. To construct strong classifiers, these weak classifiers combined with each other based on boosting theory. A weak classifier $\mathrm{h_j(x)}$, consists of a feature f_{j}, a threshold θ, and a parity p_j indicating the direction of the inequality sign:

$$\mathrm{h_j}(x) = \begin{cases} 1 & \text{if } \mathrm{p_j}\ f_{\mathrm{j}}(x) < p_j\,(\theta) \\ 0 & \text{otherwise} \end{cases} \qquad (3.1)$$

Where x is a weighted example, as well positive as negative.

Given one feature f_{j} and all the examples responses $f_{\mathrm{j}}(x)$, $i \in$ training set to this feature, the goal is, finding the threshold that separates the best positive and negative examples. This threshold obtained during training process.

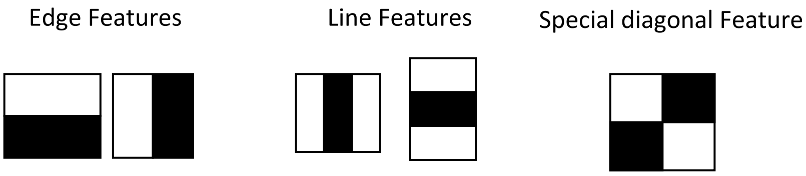

Fig. 2: Conventional Haar-like features.

To construct cascade structure several boosted classifiers are chained together with the aim of quick rejecting the majority of non-face windows while keeping almost all of the face patterns. The primary stages of the cascade is rejecting the majority of the negative samples with fewer number of features; however, in deeper node of the cascade a few hard examples should be tested by a large set of the best discriminant features. To obtain a high detection rate and minimum false positives, the number and size of the stages should be tuned during the training phase. The configuration of the cascade structure is depicted in Figure 3. The details of Adaboost cascade algorithm are indicated in (Viola and Jones 2001).

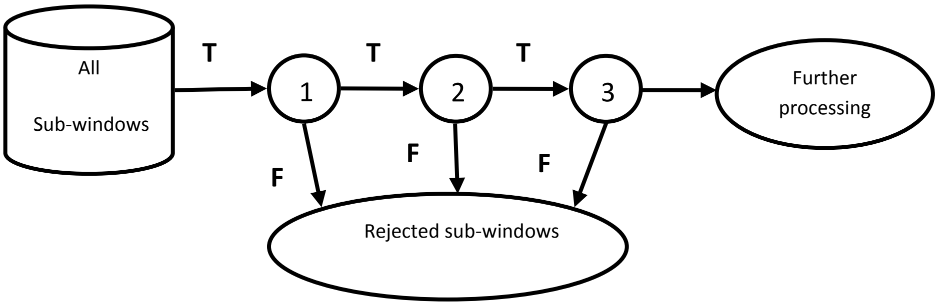

Fig. 3: Boosting Cascade structure.

HOG Feature Extraction Process:

Using HOG features for characterizing human facial properties attracted so much attention, recently. The importance of utilizing this feature for human face detection is not only the capability of HOG descriptors to capture edge and local shape of the objects, also its invariability against geometric and photometric transformations (Dalal and Triggs 2005; Sedai, Bennamoun *et al*. 2010). The accuracy of the HOG to extract features from objects compared with other existing features such as wavelet, makes it significant for applying in practical applications. For the first time Dalal and Triggs applied HOG features for detecting human in images (2005). Figure 4 shows schematic diagram of HOG feature extraction.

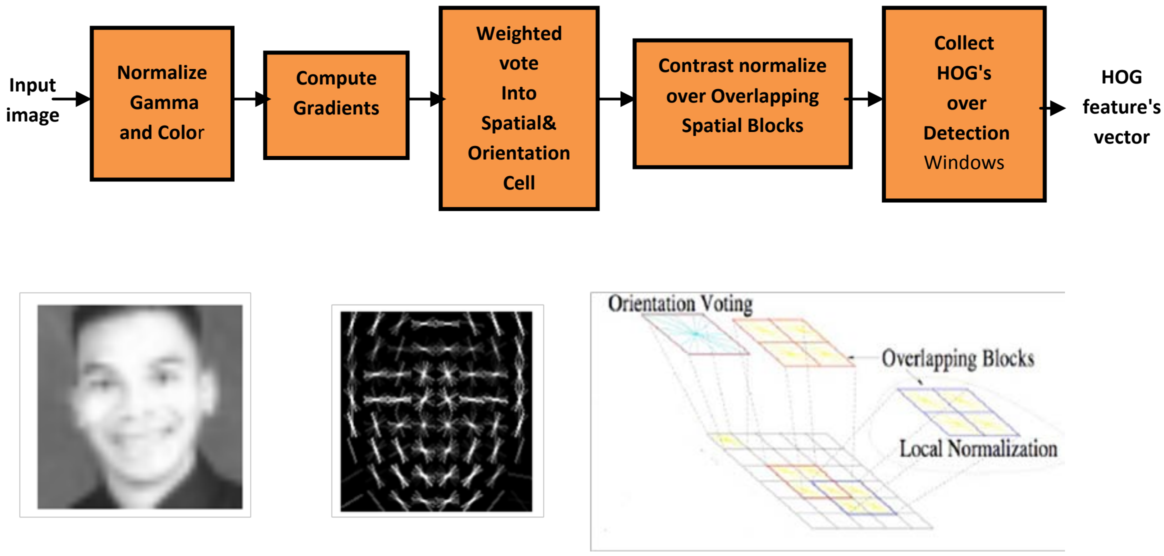

Fig. 4: Schematic diagram of HOG feature extraction.

In this diagram, at first, a normalization process is done for correcting gamma factor of the input image using histogram equalization. In the second step, the gradients of the image are calculated. Afterwards, the image is divided into several sub-windows which are called cells and then, histogram of oriented gradients of each cell is provided. The cells are grouped into the larger windows (Blocks) in order to decrease the illumination variations. These blocks are overlapped to ensure consistency across the whole image without loss of the local shape variations. In the last step HOG features are collected as a feature vector.

Support Vector Machine Approach for Classification:

The concept behind the principle of Support Vector Machine (SVM) is based on a linear separation in a high dimension feature space where the data have been previously mapped; in order to take into account the eventual non-linearities of the problem.

Given a set of training data: $D=\{(x_i, y_i | x_i \in R^p, y_i \in \{1, -1\}\}_{i-1}^{n}$

Each boundary is determined by the location of support vectors that satisfies:

$$y_j \lfloor W^T X_j + b \rfloor \equiv 1 \quad ; j = 1, N_{sv} \qquad (3.2)$$

Where W is the normal vector and N_{sv} is the number of support vectors. Vapnik (1995) proved that during the training process, the optimal hyperplane maximizes the margin selected by the algorithm. SVM is considered as one of the best supervised learning algorithms that utilizes a set of hyperplanes to classify samples, which is used for patterns classification and regression analysis. In the case of the face detection (binary classification), the linear SVM classifier is used due to its high generalization ability and its ability to minimize the empirical classification error.

Proposed Face Detection Method:

In this section, the proposed face detection algorithm is described. It consists of two modules which are shown in Figure 5, where the overall structure is illustrated.

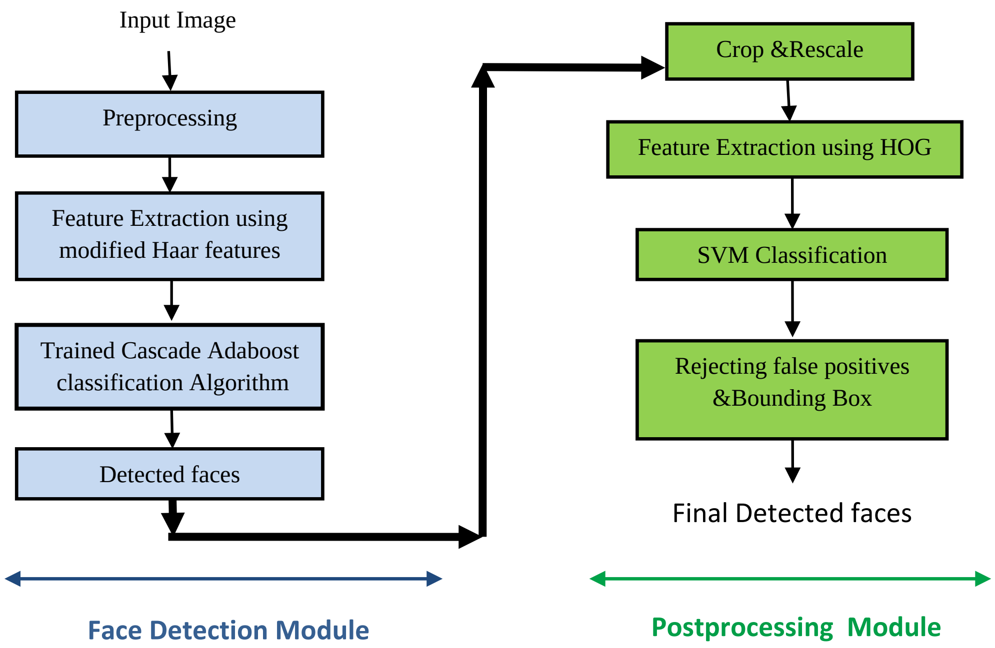

Fig. 5: Overall structure of the proposed method.

In the first stage a preprocessing step is applied, in order to make the image information more appropriate. Afterwards, the Haar-like features of the input image are extracted .The cascade Adaboost structure which is trained previously in the training task, classifies face and non-face sub-windows. Finally the detected faces are bounded into a box.

The proposed method is able to increases the detection speed and can result in a high detection rate. There exists a number of false positive detections which is due to variations in pose and environment illumination. To empower the cascade Adaboost algorithm against pose and illumination variations, the following modifications are applied:

In order to enhance the proposed algorithm in terms of handling the pose variations, several rotated and asymmetrical Haar-like features are added to the existing feature set. Figure 6 shows some of these features.

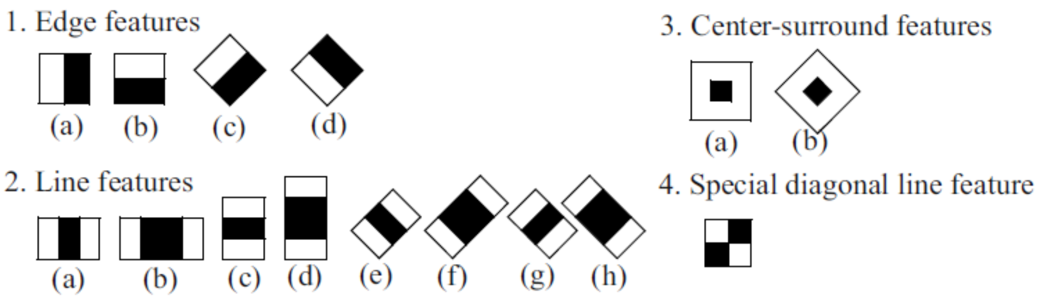

Fig. 6: Rotated and asymmetrical Haar-like features used in our algorithm to improve the robustness of the face with respect to pose variations (Lienhart and Maydt 2002).

In addition, a set of new face and non-face training samples are created from the original training set, to be used in order to improving the robustness of the proposed algorithm against changes in illumination and variable pose situations.

The second stage of the proposed algorithm acts as a post-processing module which is shown in Figure 5. The aim of the post-processing module is to reduce the false positives rate to improve the overall performance of the system. The inputs of this stage are the detected faces from the Cascade Adaboost which all are cropped and rescaled into a 36×36 image size. (If the HOG module were used on its own as a shape-based face detector, it would have been computationally expensive (particularly when processing large resolution images)). The goal of the rescaling and cropping the images is to make sure that the post-processing module processes reduced-sized sub-windows. Afterwards, based upon the HOG method, a feature vector will be extracted. Indeed, the HOG module is very computationally expensive for being used on its own as a shape-based face detector algorithm. A full description of the different steps of the proposed algorithm is presented for a given image of 36×36 pixels, as follows:

Cell size=4×4; Block size=8×8; Number of histogram bin=6; Block stride=4×4.

The output parameters are selected as follows:

Total number of histograms in each block=6*4=24;

Total number of block= (36/4-1)*(36/4-1) =64;

Feature vector dimension=64*24=1536.

Then, the face and non-face images are classified using a linear support vector machine (SVM) system. High generalization ability and capability of minimizing the experimental classification error are the major points for employing SVM technique (Cortes and Vapnik 1995; Navabifar, Emadi *et al*. 2011). A database of 36×36 samples containing face and non-face images is used in order to train the SVM classifier. To show the detected faces in the given image, they are bounded by a box.

Although the HOG and SVM module is quite capable of discriminating the face and non-face samples, their combination is very computationally expensive and cannot be utilized as a united technique. This is due to the exhaustive search of a vast number of sub-windows of the original input image.

Experimental Results and Analysis:

To evaluate our results, two sets of database including the CMU+MIT frontal and the CMU profile datasets have been used due to their popularity, accessibility and image's diversity.

The CMU+MIT(Dataset#3) (Schneiderman and Kanade 2000) test database contains 130 gray scale images with 507 upright face which are collected from different sources such as internet, newspapers and magazines (with low resolution), analog camera and hand drawing. The CMU profile test database consists of 208 gray scale images with faces in profile position(Schneiderman and Kanade 2000).

The training Adaboost cascade is run on 5000 faces and 8500 non-faces of size 19 × 19, taken from the CMU training database. In order to make algorithm robust against lighting variations and image's rotation, several new face samples have been generated using some changes in face patterns and then added to the training samples. To train SVM classifier, 5000 face and 8000 non-face samples with the size of 36×36 are selected from CMU training database and then are applied on SVM^{light} library, which is an implementation of Vapnik's Support Vector Machine (Vapnik 1995) . Using SVM^{light} library has two significant advantages. Firstly, it uses a fast optimization algorithm and solves classification and regression problems (Joachims 1999). Secondly, this algorithm has scalable memory requirements and therefore can handle problems with several thousands of support vectors efficiently. Experimental results show that our proposed method obtains a high detection rate with fewer false positives compared with existing works.

Table 1: Accuracy table of the Adaboost cascade algorithm and the proposed method in terms of detection rate and number of false positives on the CMU+MIT frontal test database.

Detection method	Correct Detected Faces	False Negative	False positives	Detection rate (%)
Adaboost Cascade	468	39	143	92.3
Proposed method	467	40	47	92.2

As shown in Table 1, the proposed method achieved high detection rate, furthermore decreasing the number of false positives compared with Adaboost cascade algorithm is noticeable. The above results emphasize the role of post-processing module in increasing the detection performance.

Table 2: Accuracy evaluation of the Adaboost cascade algorithm and the proposed method on the CMU profile test database.

Detection method	Correct Detected Faces	False Negatives	False positives	Detection rate (%)
Adaboost Cascade	412	29	160	93
Proposed method	410	31	91	93

As shown in Table 2, the number of false positives decreased significantly at the same detection rate for both techniques. The result shows the effect of post-processing unit in improving the detection accuracy.

Table 3: Face detection results on the CMU+MIT test set (130 gray scale images, 507 faces).

	False Positives					
Detector	10	19	31	50	95	167
Viola-Jones [2001]	76.1%	-	89.7%	92.1%	93.2%	93.7%
Garcia-Delakis [2004]	90.5%	-	91.5%	-	-	93.1%
Versache-Solar-Correa[2008]	-	88.0%	90.1%	-	-	-
Jun-Kim (LGP+EAM) [2012]	~90%	-	-	~93%	~94%	~94.5%
Proposed Method	89.4%	-	90.2%	93.1%	93.9%	94.8%

Table 3 shows the rate of detection versus different number of false positives on CMU frontal face database. It can be concluded from the results that our proposed method improves the detection rate while keeping low false alarm rates compared with popular and recent works.

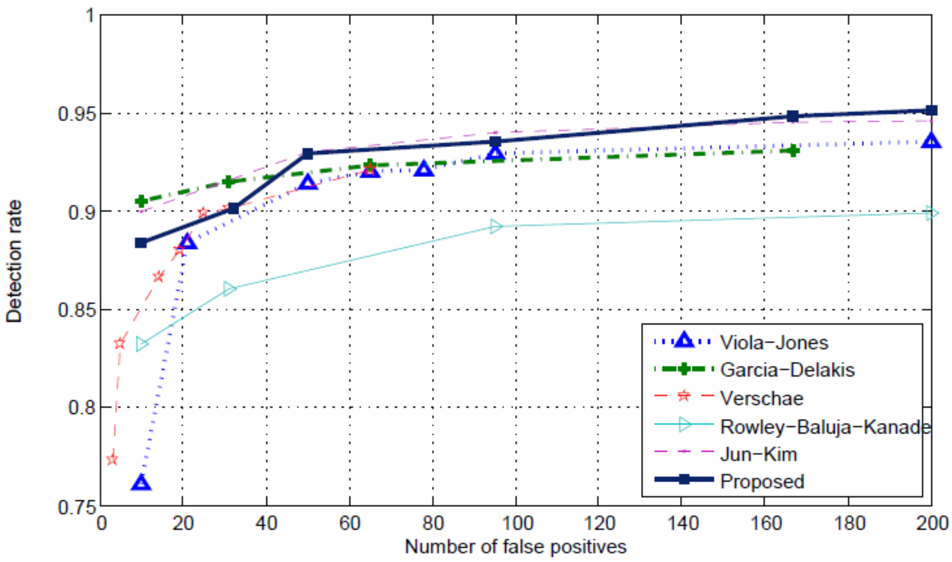

Fig. 7: ROC curve of face detection on the CMU+MIT face database.

Figure 7 evaluates the proposed method and several face detectors in form of the ROC curve. Clearly, with an increase in the detection rate, the number of false positives has increased correspondingly, but our proposed method achieved a higher detection rate. Furthermore, with the same detection rate, our proposed method has less false positives.

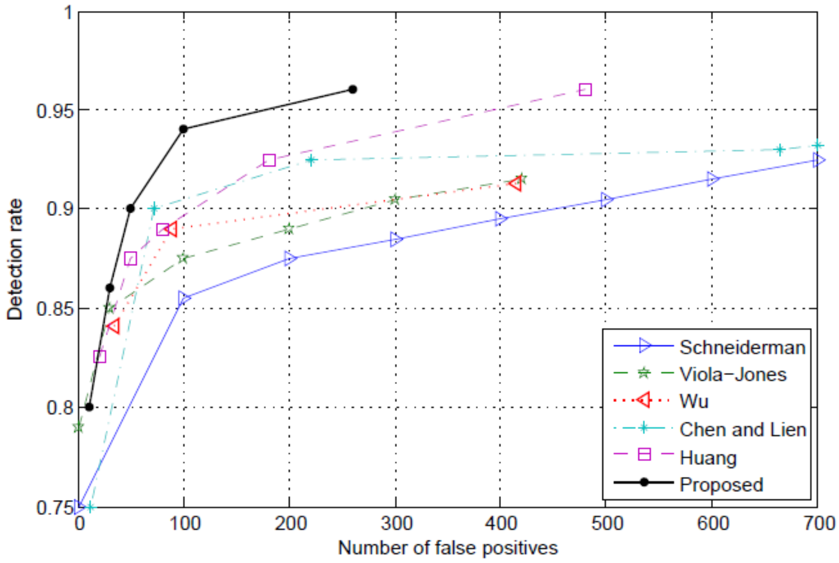

Fig. 8: ROC curve of face detection on CMU profile test set.

Figure 8 shows the operation of several face detectors and the proposed face detection system on CMU profile test set. As shown in this Figure, the proposed method has high detection rate with lowest number of false positives, which is greatly significance, compared with existing works.

Table 4 shows an evaluation of the average computation time for several different face detection methods on a few thousands images of size 320×240. The average computation time includes the total time for loading image, preprocessing and post-processing.

Table 4: Comparison of average computation time for several face detectors.

Detector	Average computation time (ms)
1-Schneiderman-Kanade	42,132.0
2-Rowley-Baluja-Kande	1053.3
3-Jun- Kim (LGP)	10.12
4-Viola-Jones	70.22
5-Proposed	11.74

We obtained the average computation time for items 1 to 4 of Table 4 from the paper of Jun and Kim (2012). As shown in this Table our proposed method achieved low computation cost. This experiment has been done using a computer system with 2.83 GHz quad core Intel processor with 8 GB memory on Windows Vista operating system. It should be noted that the computation time is much related to the type of the processing hardware such as the type of CPU and the quantity of memory.

Figure 9 shows several sample images extracted from the CMU+MIT database and CMU profile images and personal photos, which have been used to test our proposed method. This results proved that proposed face detector are able to detect human face in different scale, different position and under different illumination.

Conclusion and Future Direction:

In this paper, a novel face detection method is presented. The concept behind this method relies on further removing false positives from the image while keeping high detection rate. For this purpose, at first, the possible human faces are detected in the image using Adaboost cascade algorithm. This algorithm was trained with a set of modified training examples which makes algorithm robust against illumination and pose. Then, the detected faces are forwarded into post-processing module with the aim of further removing false positives using HOG features and SVM classification. Experimental results on two test datasets, the CMU+MIT and the CMU profile, show that our proposed method achieves a high detection rate as well as a very low number of false positives compared with the recent works. Our future work will focus on using the proposed method for detection of other objects.

Fig. 9: Detected faces on sample test images.

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