A Fusion Approach Based on HOG and Adaboost Algorithm for Face Detection under Low-Resolution Images

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Abstract: *Detecting human faces in low-resolution images is more difficult than high quality images because people appear smaller and facial features are not as clear as high resolution face images. Furthermore, the regions of interest are often impoverished or blurred due to the large distance between the camera and the objects which can decrease detection rate and increase false alarms. As a result, the performance of face detection (detection rate and the number of false positives) in low-resolution images can affect directly subsequent applications such as face recognition or face tracking. In this paper, a novel method, based on cascade Adaboost and Histogram of Oriented Gradients (HOG), is proposed to improve face detection performance in low resolution images, while most of researches have been done and tested on high quality images. The focus of this work is to improve the performance of face detection by increasing the detection rate and at the same time decreasing the number of false alarms. The concept behind the proposed combination is based on the a-priori rejection of false positives for a more accurate detection. In other words in order to increase human face detection performance, the first stage (cascade Adaboost) removes the majority of the false alarms while keeping the detection rate high, however many false alarms still exist in the final output. To remove existing false alarms, a stage (HOG+SVM) is added to the first stage to act as a verification module for more accurate detection. The method has been extensively tested on the Carnegie Melon University (CMU) database and the low-resolution images database. The results show better performance compared with existing techniques.*

Keywords: *Face detection, cascade adaboost, histogram of oriented gradients, low-resolution image.*

Received November 20, 2020; accepted January 10, 2022
https://doi.org/10.34028/iajit/19/5/4

1. Introduction

The goal of a face detection system is to accurately localize human faces in images or videos. The system needs to be robust and faces need to be accurately detected even under facial occlusion, as well as pose and illumination variations. Face detection is an essential pre-processing module in various systems including security systems, Human-Computer Interaction (HCI) and multimedia. Clearly, the performance of the face detection module affects the performance of the subsequent modules and the performance of the overall system. To this end, many different approaches of face detection have been presented and have been divided into four categories: Template-Based, Feature-Based, Appearance-Based and knowledge-Based methods [6]. Appearance-Based methods have shown to be amongst the most effective approaches due to their high accuracy rate and their capability of handling variations such as pose, illumination, and partial occlusion of the face [19]. Amongst the most popular approaches in this category is the work proposed by Viola and Jones [17], which used Haar-like features and the Adaboost algorithm to detect faces in images. It is considered as one of the most popular method to date. The advantage of using Haar-like features does not only rely on the flexibility of extracting features with a variety of types and scales, but also on the high speed of their extraction through the use of the integral image. The boosted cascade features as applied in Viola and Jones [17] is capable of rejecting non-face samples rapidly.

Many face detection methods suffer from the problem of high false alarms whereby non-face images are falsely detected as face images. The importance in the reduction of false positives at the final detection stage of any face detection system can be illustrated with an example related to the tracking module of a surveillance system (i.e., where the person being tracked is not cooperating). If the face detection module detects a false positive, the tracking module will keep tracking a non-face, failing as a result to track and recognize a potential suspect.

In low-resolution images the number of false positives increases because the quality of the images is not as clear as high quality images and as a result the performance of the detection decreases dramatically. There are a huge number of studies in face detection field but detecting human faces in low-resolution images has not been explicitly studied [6, 19].

The rest of the paper is organized as follows. Section 2 provides a brief review of the previous works on face detection under low quality images. Materials and methods are carefully analyzed in section 3. The proposed face detection framework is described in detail in section 4. The experimental results, conclusion and future works are presented in section 5.

2. Related Works

The first work in low-resolution face detection has been done by Torralba and Sinha [16]. To show the effects of image resolution, local context, contrast polarity and face orientation on detection performance, they focused on the task of face detection under impoverished conditions. In their method, ten subjects of MIT students were selected and presented with randomly interleaved face and non-face patterns and, in a 'yes-no' paradigm, were asked to classify them as such. Then the same sets of patterns with different resolutions were grouped in blocks. The presentation order of the blocks proceeded from the lowest resolution to highest. Their results showed that facial features were not effective enough for predicting face or non-face patterns; therefore, they used upper-body images to enhance face detection in low-resolution images.

Zheng *et al*. [20] presented a method based on a three-stage cascade Adaboost classifier using Modified Census Transform (MCT) for face detection on low-resolution color images. For the training set, they used 6000 face and 6000 cropped non-face images which were down-sampled 24×24, 16×16, 8×8, 6×6 pixels for different resolutions. To test the detector, they used the Georgia Tech face database, containing frontal and tilted images of 50 people at resolution of 640×480 pixels. Their experimental results showed that as the resolution of faces reduced in the test images, the number of false positives increased and the detection rate decreased. Furthermore, a 12-bit MCT could get a better performance than a 9-bit one.

The effect of low-resolution images on performance of face detection was analyzed by Marciniak *et al*. [12] They studied three approaches in face detection including human face skin color, geometric models and Haar-like features of Viola-Jones face detector over Yale database in five resolutions ranging from 640×480 to 50×40 pixels. Their experiments on skin color method showed that the algorithm generally detects faces properly, but the neck and sometimes blond hair could also be detected. Furthermore, face detection in this technique was extremely sensitive to image illumination. In the second method, they applied the knowledge of geometry which was based on the use of Hausdorff distance to find the location of the face in images. Their results demonstrated that this method could not deal with changes in rotation and also did not work properly in case of intensive side illumination. The third approach was based on using Haar-like features in Viola-Jones face detector to localize faces in images and also applying the histogram equalization resistant to changes in lighting. Their results represented that Haar-like method had the best detection rate and was robust against lighting and rotation of the head in low-resolution images. They got 90 percent detection rate on frontal and semi profile images without any information about the number of false positives [12]. A conventional neural network introduced by Li *et al*. [7] for face detection. The presented convolutional neural network cascade involves two different stages. In the first stage the background region of low resolution images, rejected quickly at multiple resolution and then evaluates a small number of challenging candidates in the last high resolution stage. To optimize localization effectiveness, and reduce the number of candidates at later stages, they introduce a CNN-based calibration stage after each of the detection stages in the cascade. To adjust the detection window position the output of each calibration stage is used for input to the subsequent stage. They achieved state-of-the-art detection performance on two public face detection benchmarks using a GPU for VGA-resolution images and 100 FPS. Liu *et al*. [9] applied deep learning for face attributes in the wild. They used two different architecture of networks including CNNs, LNet and ANet, which pre-trained differently and fine-tuned jointly with attribute tags. For face localization, LNet is pre-trained by heavy general object categories, while for attribute prediction, ANet is pre-trained by heavy face identities. The proposed framework outperforms the state-of-the-art with a large margin, but reveals valuable facts on learning face representation.

A fast and accurate face detector in unconstrained situation is proposed by Liao *et al*. [8] In the first stage proposed method they applied a new feature namely Normalized Pixel Difference (NPD) which is computed as the difference to sum ratio between two pixel values. This feature is able to reconstruct the original image and also scale invariant. In the second stage, a deep quadratic tree is designed to learn the optimal subset of NPD features, so that complex face manifolds can be partitioned by the learned rules. Furthermore, they explore that the normalized pixel difference features can be efficiently scaled and easily obtained from a look up table, which make their proposed structurer very fast. Experimental results show that the presented method achieves state-of-the-art performance in detecting unconstrained faces under different pose and occlusion scenes when tested on three public face datasets (FDDB, GENKI, and CMU-MIT).

Sinha [13] presented a fast method for efficient face detection using neural network for frontal faces. The method is based on localizing parts of image with corresponding scores of the sectors of the face that are being detected. Then to find face in image further processing is done in the likely face area. The detection time is very low because the neural network can identify parts of a face from a kernel and no need to use many kernel operations are required to successfully identify the face.

Sun *et al*. [15] Used deep learning to improve faster RCNN framework for face detection. Their research obtained high performance Receiver Operating Characteristic (ROC) curves among published works on FDDB. Zhang *et al*. [18] developed a fast and robust head and shoulder tracking algorithm for occluded face in ATM surveillance. Using novel energy function, Bayesian framework and Adaboost algorithm, they achieved 98.64% accuracy on face detection and 98.56% on occluded face detection. Machine vision quality assessments for robust face detection suggested by Soundararajan and Biswas [14]. They defined an index using weighted combination of predicted precision and recall for face detection under different image situation such as distorted and low resolution images. The proposed framework developed face detection performance while tested on IDEAL-LIVE distorted face database. Deep cascade approach proposed by Luo *et al*. [11] which applied bounding box regression to find potential faces in images. Using deep learning network, they designed high performance face detection. The structure of this paper is as follows: In the second section the research background is studied, and in the third part the proposed method is presented. The results are provided in the fourth section and compared with the previous works. In the final section the, the conclusions are presented.

Luaibi and Mohammed [10] presented a method based on HOG-DWT-PCA features with MLP classifier for facial recognition. Their study consist of four steps including face detection, preprocessing, feature extraction and classification. They achieved 99.1% and 94.5% accuracy on ORL and FERET databases respectively.

Elleuch *et al*. [3] Applied Histogram of Oriented Gradients (HOG) and Gabor features for Arabic handwritten script recognition. The proposed method used handcraft features form IFN/ENIT database as input of SVM algorithm to classify data. Their simulation results show good functioning on the suggested system based- SVM classifier.

In this section the most of the works focus on increasing the detection rate, however the number on false positives are noticeable. In low-resolution images the number of false positives increases because the quality of the images is not as clear as high quality images and as a result the performance of the detection decreases dramatically. In this paper the proposed method is designed to reduce the number of false positives and increase detection rate simultaneously.

3. Materials and Methods

3.1. Cascade Adaboost Classifier

Adaboost was proposed by Freaud and Schapire as an efficient algorithm of the ensemble learning fields. It is an iterative algorithm which obtains an ensemble of weak classifiers by evolving a distribution of weights over the training data. In each iteration of the Adaboost algorithm, the classifier h_t with the lowest weighted error is added to the ensemble. The decision of the ensemble after T iterations is defined as:

$$H(x) = \begin{cases} 1 & \sum_{t=1}^{T} \alpha_t h_t(x) \geq \theta \\ 0 & \text{Otherwise} \end{cases} \tag{1}$$

Where α_t is the Adaboost ensemble weight and θ is the threshold of the ensemble which is adjusted to meet the detection rate and false positive goals. More features are added to the ensemble when necessary to reach the expected performance.

Viola and Jones [17] Adaboost-based face detection algorithm is considered to be the state of the art of face detection due to selects the best weak classifiers, which are able to distinguish face from non-face features in an easy way. To construct each weak classifier, Viola and Jones applied a set of Haar-like features, each with a simple threshold on one of the extracted features. The Adaboost algorithm then selects a small set of the best classifiers (the ones with a low error rate). For a more accurate classification, weak classifiers are combined together to form a strong classifier. A set of Haar-like features are shown in Figure 1. The ability of creating a variety of these features, in terms of shape and size, made them popular for various detection problems including face 3D detection.

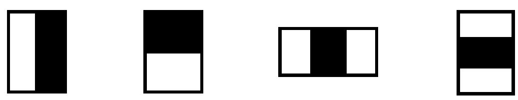

Figure 1. Haar-like features.

The cascade structure consists of several stages of trained classifiers using Adaboost algorithm. This structure reflects the fact that the majority of the image area covered by non-face windows. As such the cascade attempts to rejects as many of the negative sub-windows as possible at the earliest stage, while positive sub-windows are passed to the next stage for further processing. To achieve a high detection rate with low false alarms and minimum computation time, the number of stages and the size of the stages should be adjusted during the training task. The false positive rate of the cascade is defined as:

$$F = \prod_{i=1}^{k} f_i \tag{2}$$

Where F is the overall false positive rate of the cascade classifier, k is the number of classifiers, and f_i is the false positive rate of the i th classifier. The detection rate is:

$$D = \prod_{i=1}^{k} d_i \tag{3}$$

Where D is the overall detection rate of the cascade classifier, k is the number of classifiers and d_i is the detection rate of the i th classifier. To construct a high performance cascade structure, the maximum acceptable rate for d_i and minimum acceptable rate of f_i are selected by the user. The cascade is trained by the Adaboost until the target detection rate and false alarms are met for each layer. If the overall target false positive is not yet met, then another layer is added to the cascade.

In order to increase the speed and improve the detection performance, many of the negative sub-windows are rapidly rejected by the cascade classifier at the earlier stage, while positive sub-windows are passed to the next stage for further processing as shown in Figure 2. This process is repeated at each stage of the cascade, and the current samples are forwarded to the next stage, for a more accurate classification. However some hard examples which have not been correctly classified by the previous stages still remain. These hard examples appear in the final output as false alarms. The type of features, the number of training samples and the choice of the training algorithm affect the detection performance.

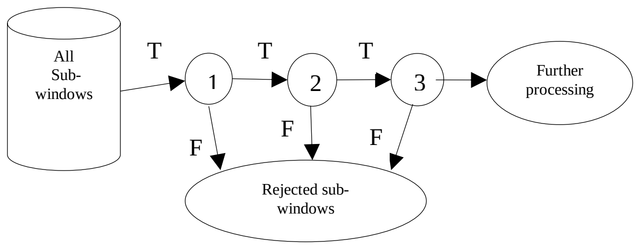

Figure 2. Schematic diagram of the cascade structure [3].

3.2. HoG Feature Extraction and SVM Classification

3.2.1. Feature Extraction Using Histogram of Oriented Gradients (HoG)

The basic concept behind the Histogram of Oriented Gradient approach is to describe the shape of an object based on the distribution of the local intensity gradients. This approach has recently attracted attention particularly with applications in the areas of object recognition, detection and pose estimation. This is due to two main reasons. First, this gradients structure has the capability to satisfactorily characterize the local shape and to capture edges. Second this representation is relatively invariant to local geometric and photometric transformations [17]. These characteristics allowed the HOG to provide an excellent performance compared to other existing feature sets such as wavelets. Dalal and Triggs [2] used HOG to detect humans in images for the first time in their work in. An overview of the HOG feature extraction process is depicted in Figure 3. In their first step, for a better clarification of the edge of the input image, a preprocessing of the image is performed to normalize the gamma correction factor of the image. This can simply be done using histogram equalization. After the normalization process and in the second step, the gradients of the windows are computed. Several gradient detectors can be used. Commonly, the [1, 0,-1] detector is utilized due to its simplicity and speed. For color images, each RGB channel is computed separately and the largest value is selected as the gradient for that pixel. In the third step, the image is divided into small sub-windows (cells), and histograms of oriented gradients are accumulated for that cell. To decrease the effect of illumination changes, the cells are grouped into larger windows, called blocks and each block is then normalized to ensure the low contrast regions are stretched. To ensure consistency across the whole image without loss of the local shape variations, the blocks are overlapped. Finally, the histogram of oriented gradients is collected as a feature vector.

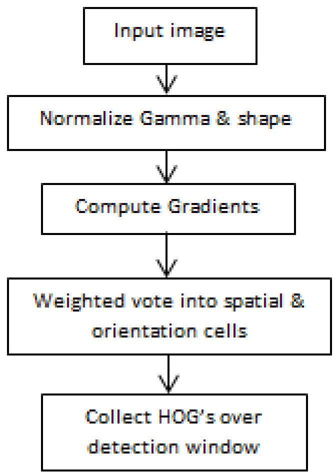

Figure 3. Overview of HoG feature extraction.

3.2.2. Support Vector Machine Classification

Vapnik proposed support vector machine, which is considered as one of the most appropriate proper machine learning, which is used for classification of patterns and regression analysis [1]. SVM is a supervised learning algorithm that applies a set of hyperplanes to classify examples. The best hyperplane is the one that maximizes the margin. High generalization ability of SVM and its ability to minimize the empirical classification error makes it proper for binary classification projects such as face detection. The idea behind the SVM for face/non-face classification is to create a hyperplane decision surface between positive and negative decision boundaries. Given a set of training data:

$$D=\{(x_i, y_i | x_i \in R^p, y_i \in \{1, -1\}\}_{i-1}^{n} \tag{4}$$

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

$$y_j[W^T X_j + b] \equiv 1 \; ; j = 1, N_{sv} \tag{5}$$

Where N_{sv} is the number of support vectors and W is the normal vector. The optimal hyperplane maximizes the margin selected by the algorithm during the training process.

4. Proposed Face Detection Method

In this paper, a two-stage face detection system is proposed using a cascade Adaboost and histogram of oriented gradients. Figure 4 shows the overall structure of the proposed method.

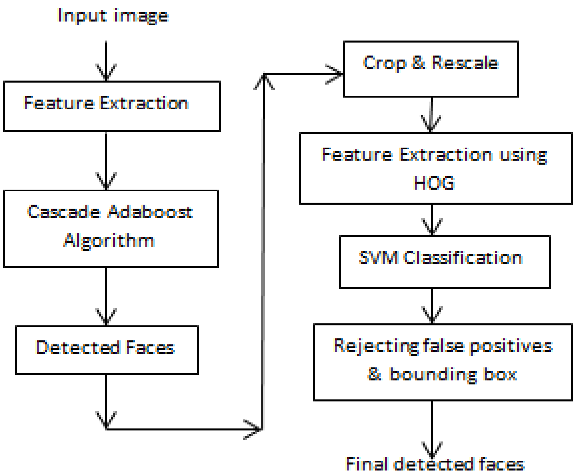

Figure 4. Configuration of the proposed method.

In the first stage, a strong classifier is constructed from the cascade Adaboost algorithm based on Haar-like facial features during the training phase. During the testing phase, Haar-like features are first extracted from the input image. The faces in the input image are then detected using the cascade Adaboost structure. The Adaboost-based face detection has three major attractive characteristics. The first is the use of the integral image to compute the Haar-like features which makes the process very fast. The second characteristic is consideration of small number of effective Haar-like features from a large set of Haar-like features to generate the classifiers. The third characteristic of Adaboost is the combination of weak classifiers in cascade which reduces the computation time and the false positive rate. This method is applied in our proposed face detection approach. It reduces the detection speed and results in a high detection rate. Due to pose and illumination variations, the output image may detect non-face objects resulting in a number of false positives. To ensure that the cascade Adaboost algorithm is robust against partial variations in pose and illumination, the following changes were applied in the algorithm.

In addition to the standard basic Haar-like features, several modified Haar-like features were added to the feature set in order to increase the ability of the algorithm to handle faces under pose variations. Some of these features are shown in Figure 5.

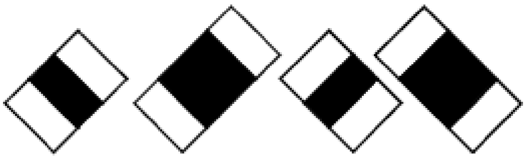

Figure 5. Modified haar-like features (rotated and asymmetric).

Furthermore, to improve the robustness of the method against pose and illumination variations, several new face and non-face training samples were generated from the original training set. These samples are used during the training process.

The subsequent module of our proposed approach acts as a verification stage, with the goal of decreasing the false alarm rate and improving the overall performance rate. In this stage, the output of Cascade Adaboost face detection are cropped and rescaled into a 36×36 image size as shown in Figure 4. 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 purpose of the cropping and rescaling is to guarantee that the verification module only processes reduced-sized sub-windows which have been detected by the previous stage. Then a feature vector is extracted based on the histogram of oriented gradients method following the description of section 3. Given an image of 36×36 pixels we use the following input parameters (selected after extensive empirical tests):

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

The output parameters are selected as follows:

Total number of histograms in each block:

$$6\times4= 24$$

Total number of block= $\left(\frac{36}{4}-1\right)\times\left(\frac{36}{4}-1\right)=64$

Feature vector dimension= 64×24=1536

A linear Support Vector Machine (SVM) is then trained to classify face and non-face images. For the purpose of this paper (i.e., binary classification), SVM is one of the most appropriate proper classification tool due to its high generalization ability and its ability to minimize the empirical classification error [4, 5]. To train the SVM classifier, a database of 36×36 face and non-face samples is used. Finally, each verified detected face is bound into a box, and regions, which are identified as false positives, are removed from the input image.

Despite the high capability of the HOG and SVM module to discriminate between face and non-face samples, their combination cannot be used as a unique system for face detection, due to the heavy computational cost caused by the exhaustive search of a large number of sub-windows of the original image.

5. Experimental Results

The proposed method was implemented on a 2.83 GHz quad core processor with 8.00 GB of RAM on a Windows 10 operating system. It was coded using OpenCV and Visual studio programming. To evaluate our results, two databases, the CMU+MIT dataset and the manual prepared low-resolution images dataset have been used.

The CMU+MIT test database consists of 130 gray scale images with 507 upright face. This subset is called CMU125 (Dataset#3). The images were collected from a wide variety of sources including the internet, newspapers and magazines (with low resolution), analog camera and hand drawing. The manual prepared low-resolution database consists of 1000 human faces, taken from Closed-Circuit Television (CCTV) footage of the internet and CCTV of CAIRO (Center for Artificial Intelligence and Robotic) Center of Universiti Teknologi Malaysia (UTM).

Experimental results explore that our presented method achieves a high detection rate with minimum false alarm compared with existing works. The detection rate is defined by the following relation:

$$\text{Detection rate} = \frac{\text{True positives}}{\text{True positives} + \text{false Negatives}} \quad (6)$$

Table 1. Evaluation of the proposed method on cmu+mit database.

Detection method	Hits	Misses	False positives	Detection rate (%)
Cascade Adaboost	475	32	143	93.5
Proposed method	473	34	88	93.4

Table 1, evaluates the operation of the Cascade Adaboost algorithm and our proposed method when tested on the CMU+MIT test database. The results show an improvement in the performance using the rejection of false positives in the verification stage.

To evaluate the proposed method on low-resolution images, at first, a rich database was prepared. This database contained 1000 images (550 human faces) captured from CCTV footage of CAIRO (Cener for Artificial Intelligence and Robotic) Center of UTM (Universiti Teknologi Malaysia) and CCTV images and videos from the internet. The DPI of all the images was lower than 96.

Table 2. Evaluation of the proposed method on low resolution images containing human faces.

HIT	Miss	Detection rate (%)	Number of false positives
483	67	87.8	92

Table 2 shows that the proposed method obtained a 87.8% detection rate with 92 false positives when tested on low-resolution images database.

Table 3. The effect of verification module (hog+svm) of the proposed method no reduction of false positives.

Methods	Detection rate (%)	Number of false positives
Proposed method without verification module	87	175
Proposed method with verification module	87.8	92

Table 3 demonstrates the effect of verification module on performance of the proposed method. As shown in this table, 47 percent of the false positives were removed by the verification module.

To compare the existing works, Table 4 was prepared. In order to evaluate the proposed method, three different works were applied in prepared low-resolution images database (human faces taken from CCTV), which are highlighted in gray in Table 4.

Table 4. The comparision table for low- resolution face detection algorithms.

Methods	Test database	DR (%)	FP
Marciniak *et al*. [12]	Yale (Single face of frontal and rotated up to 45°, from 640×480 to 54×40 pixels)	90	-
Hsu *et al*. [5]	Video (320×240 pixels)	65	-
Zhang and Zhang [19].	Georgia Tech (640×480 pixel, single face and frontal)	80	149
Marciniak *et al*. [13] Skin color model	Low-resolution images database	44.1	51
Marciniak *et al*. [13] Haar features	Low-resolution images database	80.3	95
Proposed method	Low-resolution images database	87.8	92

The first three studies made use of common databases to evaluate their works as shown in this table. The images of these databases are high resolution, frontal or semi profile, which cannot measure precisely the performance of the detectors in uncontrolled environments and low-resolution images. For this purpose, the algorithms of three different approaches of face detection were prepared. Then each of these works tested on low-resolution images database. As shown in Table 4, the proposed method achieved higher detection rate compared to other works. Furthermore, the number of false positives is much lower than others, significantly represented the effect of proposed framework on reduction of false alarms. Figure 6 shows some samples of low-resolution images. The proposed detector could detect significantly, human faces in these images.

a) Noisy and rotated low resolution image.

b) Rotated face with glass Image. c) Occluded face in low resolution image.

d) Noisy image with pose variantions. e) Low resolution image under noise and pose and illumination variations.

Figure 6. Sample detected human faces in low-resolution images taken from CCTV.

6. Conclusions and Future Directions

In this paper, a high performance face detection method based on a combination of the cascade Adaboost algorithm and a verification module, based on the histogram of oriented gradients and support vector machine, is proposed. The first module detects the existence of faces in the input image with a high detection rate. In order to improve the detection performance, the verification module further removes the majority of the false positives within the input image. The novelty of this work is based on acting of the proposed method on low resolution images which is like to natural images taken by CCTV. However many of the existence researches are applied on high quality images.

In all object detection framework, increasing detection rate effects on the growing in false alarms numbers. In low-resolution images the number of false positives increases because the quality of the images is not as clear as high quality images and as a result the performance of the detection decreases dramatically. Experimental results show that our proposed method achieves a high detection rate as well as a low false alarm rate compared to existing works when tested on low resolution images test dataset.

Our future work will aim at utilizing deep learning for the classification stage on the proposed method. We will also explore non-linear SVM classifiers to improve face detection performance. We also plan to extend the approach to other more complex face detection scenarios such as multi-view face detection or face detection under illumination and rotation variations.

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