Gabor wavelet and neural network face detection

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Abstract One of the most difficult tasks in image processing is facial area detection. This study introduces a new face detection method. To improve detection rates, the system incorporates two facial detection algorithms. Gabor wavelets and neural networks are the two algorithms. Convolutional face images undergo initial transformation using Gabor wavelets, with 8 orientations and 5 scales chosen to extract the grey characteristics of the facial region. When added to the original photos, these 40 Gabor wavelets reveal the full extent of the response. We use a second feedforward neural network specifically designed for facial detection. The neural network is trained by backpropagation using the training set of faces and non-faces. Our experiments show that the suggested Gabor wavelet faces, when combined with the neural network feature space classifier, provide very respectable results. Comparing our proposed system to other face detection systems reveals that it performs better in terms of detection and false negative rates.

1.Introduction

Face detection has piqued the interest of numerous academics due to its broad range of applications. Given a picture, face identification involves pinpointing the exact location of any and all face inside the image. To begin solving problems like face recognition, face tracking, and facial expression recognition, all automated systems must first identify faces. Multiple face recognition technologies are now available. [1].

Face detection techniques are divided into two categories: feature-based and image-based. [2]. Face detection methods necessitate prior information of the face. To get the necessary knowledge about faces, feature-based approaches rely on feature generation and analysis. Physical characteristics include skin tone, the contours of one's face, the position of one's ears, etc... For real-time systems, when the multi-resolution window scanning of image-based techniques is impractical, feature-based approaches are preferred. On the other hand, image-based methods treat face identification as a more broad pattern recognition issue. Using training methods, it separates areas into those with faces and those without. Face recognition using image-based methods is more accurate than using feature-based algorithms, but it is also more time-consuming. [3].

Pentland and Turk [4] proved that It is possible to build a very effective and efficient facial recognition system using a Principal Component Analysis (PCA) model. Linear Discriminate Analysis (FLD) by Fisher [5] is employed as a categorizer in [5] with a good result. In [6] The Gabor-Fisher Classifier (GFC) was created by C. Liu and Wechsler, and it is a hybrid of Gabor Wavelets, principal component analysis (PCA), and the Enhanced Fisher Discriminate Model (EFM). The Gabor feature in face recognition was greatly enhanced by the GFC method. The basic neural network classifier is often used for facial recognition. Stan Li and colleagues. [7] suggested a Nearest Feature Line (NFL) classifier that outperformed the NN classifier in terms of classification error. Jen-Tzung Chien and colleagues. [8] have proposed an alternative to the NFL classifier based on Nearest Feature Space (NFS) for use in situations when there are significant variances in the appearance of the subjects.

In this paper, a new method for face detection has been proposed based on combining the powerful of Gabor filter as a features extractor and a conventional NN as a classifier. Experiments are conducted on a dataset consists of 400 faces and non_faces. The test on data sets shows that the proposed method outperforms the NFS classifier in term of the detection rate as well as positive errors in a sample.

The remainder of this essay is structured as follows. Part two shows the background and methodologies. The proposed face detection system algorithm is described in Section 3. Section 4 describes the system and the experimental setup. Section 5 offers the findings and discussion, while Section 6 wraps up the paper.

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The remainder of this essay is structured as follows:

2. Backgrounds and Methodologies

2.1. Gabor Wavelet

Gabor wavelets is applied to the image to extract features. A Gabor wavelet $\psi_{u,v}(z)$ is defined as :

$$\psi_{u,v}(z) = \frac{\|k_{u,v}\|^2}{\sigma^2} e^{-\frac{\|k_{u,v}\|^2 \|z\|^2}{2\sigma^2}} \left[e^{ik_{u,v}z} - e^{-\frac{\sigma^2}{2}} \right] \ldots\ldots\ldots\ldots(1)$$

where z = (x, y) represents the coordinates of the intersection of both the vertical and horizontal axes. The specifics μ and v determine the Gabor kernel's scale and orientation, $\|.\|$ stands for the norm operator, and σ determines the ratio of the Gaussian window width to the wavelength and is connected to traditional kernel-based Gaussian window derivation. The wave vector $k_{u,v}$ consists of the following:

$$k_{u,v} = k_v \, e^{i\phi u} \ldots\ldots\ldots\ldots\ldots(2)$$

where $k_v = \frac{k_{\max}}{f^v}$ and $\phi_u = \frac{\pi u}{8}$ if eight distinct orientations have been selected. $k_{\max}$ is the maximum frequency, and f^v is the spatial frequency in the frequency domain between kernels.

Gabor wavelets were used in five different sizes and eight different orientations in our method, i.e., $v \in$ {0, . . . , 4}, and $u \in$ {0, . . . , 7}. Gabor wavelets were selected with regard to $\sigma = 2\pi, k_{\max} = \frac{\pi}{2}$ *and* $f = \sqrt{2}$.

Gabor wavelet illustration $o_{u,v}(z)$ is the image's convolution I(z) with a Gabor kernel family $\psi_{u,v(z)}$. The reaction $o_{u,v}(z)$ A complicated function is applied to each Gabor kernel, resulting in a magnitude response. $\|o_{u,v}(z)\|$ is used to represent the characteristics. As a result, a Gabor wavelet feature j is configured by the three important parameters:

location z, direction μ, and scale v, which are specified

$$j(z,u,v) = \|o_{u,v}(z)\| \ldots\ldots\ldots\ldots\ldots(3).$$

we call it Gabor wavelet faces [9].

2.2 Artificial Neural Networks

Many pattern recognition problems, such as optical character recognition and object recognition, have been solved using neural networks. In neural network-based face identification systems, the neural network learns the underlying rules from provided samples rather than following a set of predetermined human-designed rules. Rowley et al. presented the most successful image-based face detection algorithm that uses neural networks [10].

A glance of neural networks will be presented and more in particular about the backpropagation networks and their learning rules which are most used in pattern-object detection tasks.

Neurocomputing is concerned with information processing, it basically involves twos steps, a learning step where an artificial neural network learns from the input and adapts according to a learning rule, after the learning process is complete the neural network becomes ready to function in its environment and perform the task that it was designed for. Their adaptable capability is what makes them fascinating resembling their biological counterparts.

Neurocomputing evolved since it first emerged in 1943 with McCulloch and Pitts neurons which then were just a simple logical units with no learning involved yet it lead the foundation to developing the field as its known today, now neural networks are successfully used in several fields, pattern classification where an input pattern represented by feature vectors is assigned to a predefined class, like speech, character recognition, also in clustering where no training is involved and no classes are predefined, the similar objects with similar attributes are categorized and clustered together, neural networks have been used also for function approximation, prediction and forecasting, optimization and many other interesting application. Different neural network architectures with different learning rules and learning algorithms are used to perform more specific tasks, for instance, Data compression tasks uses vector quantization learning algorithm with competitive architecture and learning rule, associative memory uses associative memory learning rule algorithm with Hopfield network. Pattern classification can use different types of architectures including RBF (radial basis function activation network), a multilayer feed forward, or a recurrent architecture. The learning process can be supervised or unsupervised or sometimes hybrid depending on the task and architecture used [11].

The network architecture is the first design decision made in neural network-based face identification systems. The structure details the number of layers, layer sizes, inputs to the network, and output values for faces and non-faces. After that, face and non-facial samples are used to teach the network. Most image-based techniques use a window scanning technique to recognize faces in an input image. The window has a set pre-determined size and travels in steps until it has scanned all of the input image. Each time, the output is calculated, and if it's higher than some threshold, the window is labelled as the face [3].

2.3 ALGORITHM FOR BACK PROPAGATION

To efficiently learn from a training set of input-output data, a feed-forward network with differentiable activation function units can benefit from a back propagation neural network, which is a multi-layer forward, supervised learning network based on the delta learning rule. The goal of training this network is to achieve a compromise between a satisfactory response to input with comparable features and a proper response to the input patterns utilized for training. To decrease the network's prediction errors, it modifies the weights and thresholds of the neurons using training data. A back-propagation network is shown in the following basic block diagram in the fig (1) [12].

The BP Neural Network Algorithm is as follow:

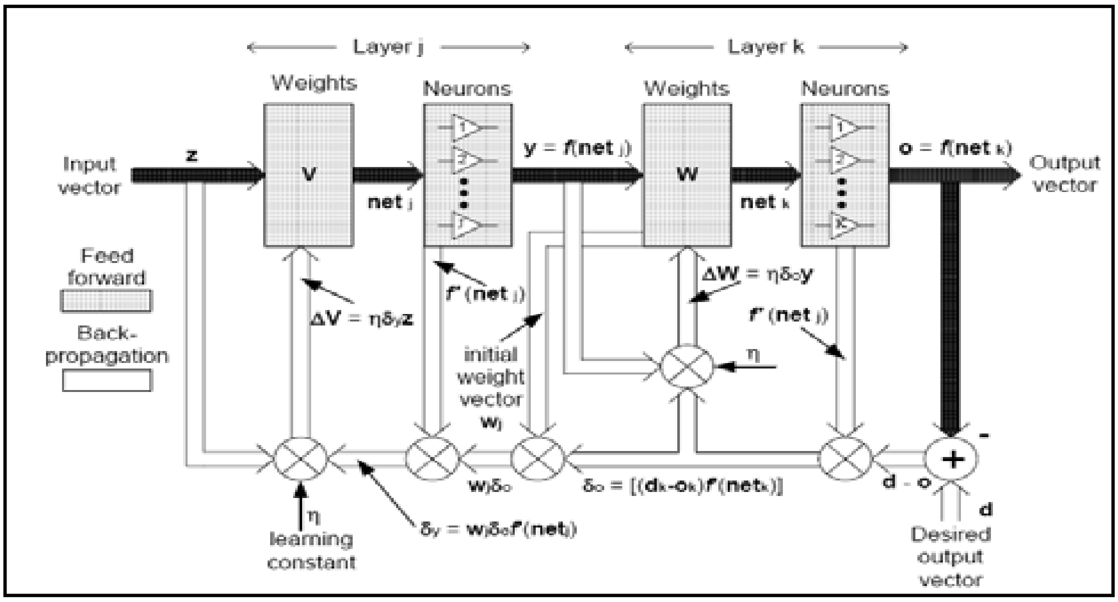


Fig (1) . Basic Block of Back propagation neural network

Step 1: At first, set the weightings of reasonable arbitrary integers
Step 2: Give the network the practice case,
then compute the result

$$\delta_0 = [(d_k - o_k)\, f'(net_k|)|]$$

dk– Desired output , ok– Actual results
Step 3: Determine the each layer's weight adjustment phrase, including the layer's weight correction term k is:

$$\Delta W = \eta \delta_0 y$$

□□- A tiny signal with a steady input, y- signal from the covert layer.
Step 4: Delta terms (errors) should be propagated backward,
The delta terms (errors) are sent back into the network through the hidden unit weights in the following way, with the delta input for the j^{th} hidden layer being:

$$\delta_y = wj\delta 0 f'(net_j)$$

Step 5: Determine a covert layer's phrase for weight correction:

$$\Delta V = \eta \delta_{yz}$$

Step 6: Weights should be updated:
In the outcome layer $w(new) = w(old) + \Delta w$
For a covert layer v(new) = v(old) + Δv
Step 7: Small modifications are used to test for halting. As a result, the input image is acknowledged by the neural-back propagation network.

3. The proposed system Algorithm

The proposed face detection system's operation can be divided into five major steps:

1. Create the 40 gabor wavelet as shown in fig(2).
2. Load the dataset (face and non_face).
3. The first step in using a neural network is called "initialization".
4. Methods for training (including data and parameter selection)
5. Detection (scanning an image to find all faces).

The all operation of the system found in the interface of the system as shown in fig(3)

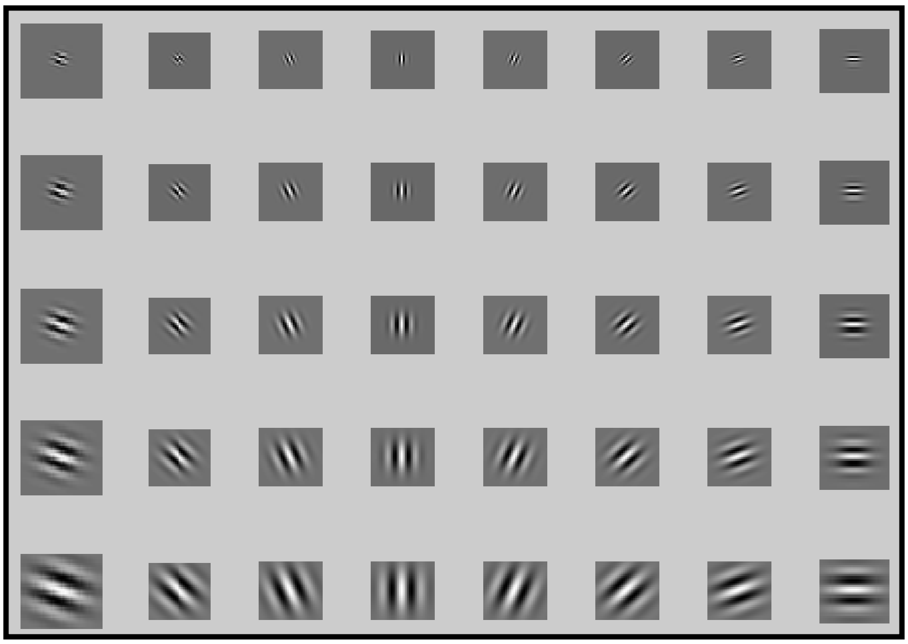
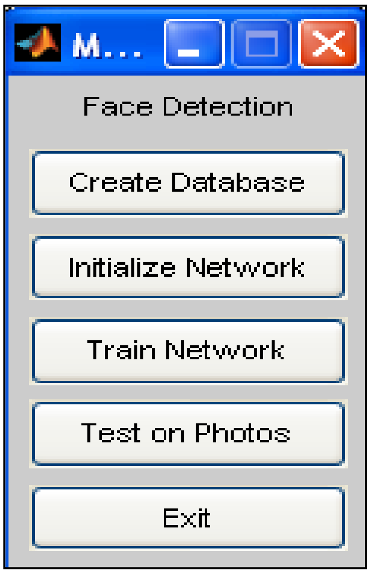


Fig (2). Gabor functions

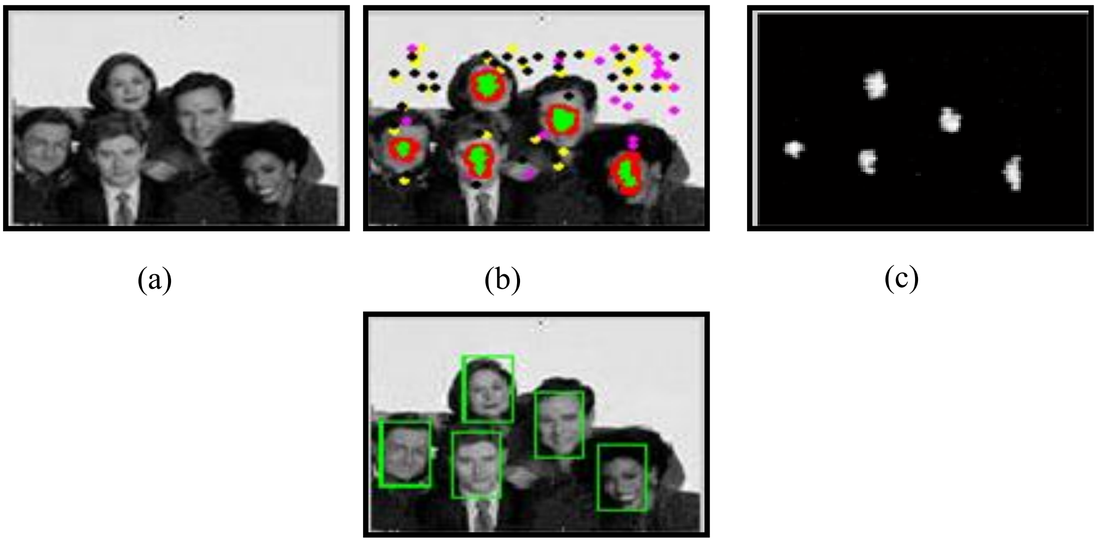


Fig(3) .interface of the system

4.System Description and Experimental Setups

This section investigates the implementation of face identification techniques based on Gabor wavelet and neural network. Experiments are carried out on a dataset of 400 faces and non_faces. Each image is 27 × 18 pixels in size, with 256 grey levels per pixel. Each image is convolved with the 40 Gabor wavelets depicted in fig (2) according to Equation (1) with $\nu \in \{0, . . . , 4\}$, and $\mu \in \{0, . . . , 7\}$. As a result, the total number of imagined features is reduced 27 × 18 × 40 = 19440 A feedforward neural network is created and trained corresponding to each feature from all 19440 features by using back propagation.

the detector is trained to output a value between 1 and -1 (1 indicates the presence of a face, -1 indicates the lack of a face). Depending on the 40 Gabor wavelet above, a new picture is resized and cut up into windows before being sent to the network for feature recognition. This is seen in fig. (4b). Then convert the image to binary corresponding to the threshold value, Multiple threshold values were tried and the best equal to 0.5 as shown in fig.(4c), Once the process is complete, a copy of the picture is shown, labeling the positions of facial regions to any faces that were detected, as illustrated in fig.(4d).



(a) (b) (c)

(d)

Fig.(4). (a) original image . (b) facial area detection in the original image. (c)binary image under threshold value equal 0.5. (d) detection result of proposed system

5.Result and Discussion

When we apply the proposed system " Facial Area Detection by Using Gabor Wavelet and Neural network " on new example and compare it with the another proposed system " Face Detection using Gabor Wavelets and Neural Networks" by Hossein ahoolizadeh[13] we find that the result from our system was better than other system as shown in fig.(5d) and fig.(5e) . Face detection systems are evaluated based on their detection rate and the quantity of false positives.

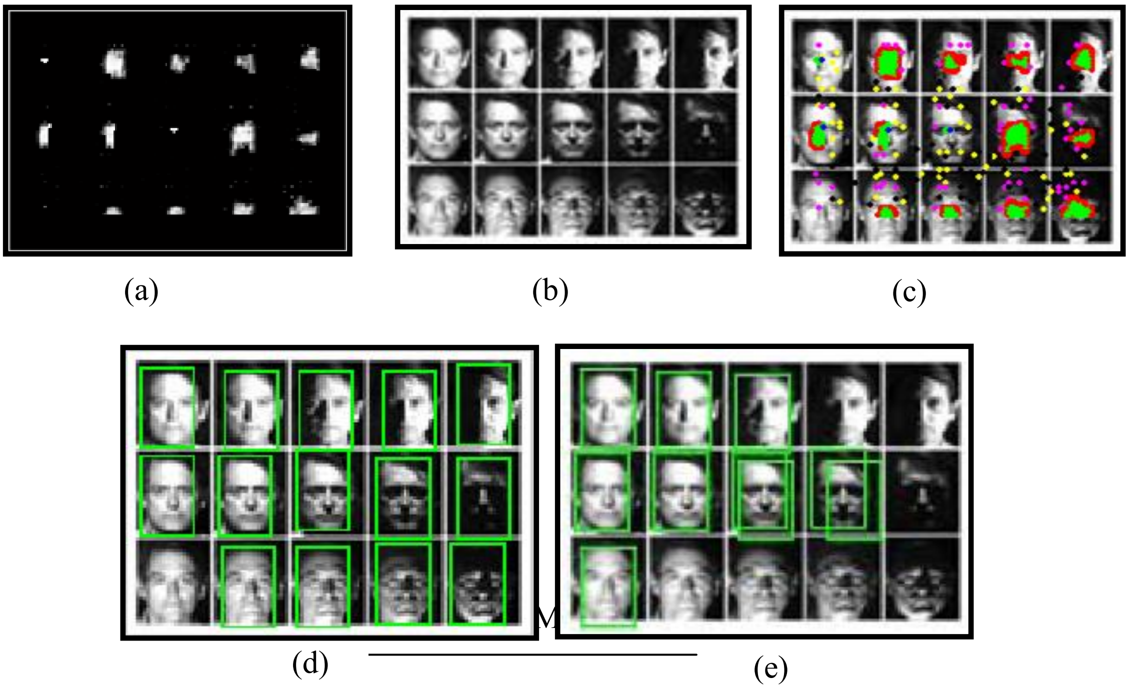


Fig.(5). (a) original image . (b) facial area detection in the original image. (c)binary image under threshold value equal 0.5. (d) detection result of our proposed system.(e) detection result of other proposed system

False negative =

Total Amount of Real Faces

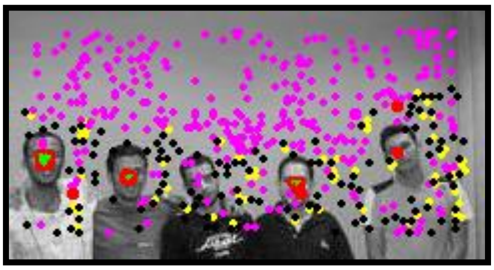
$$\text{False positive} = \frac{\text{Number of Faces Wrongly Detected}}{\text{Total Amount of Real Faces}}$$

The best detection ratio was 93%, and threshold equals 0.5 was used to achieve it. Generally speaking, there are two types of errors that detectors can make: erroneous positives, where a picture is incorrectly identified as a face, and false negatives, when faces are missed and cause low detection rates as shown in fig.(7) in the proposed system the false positive equal seven.

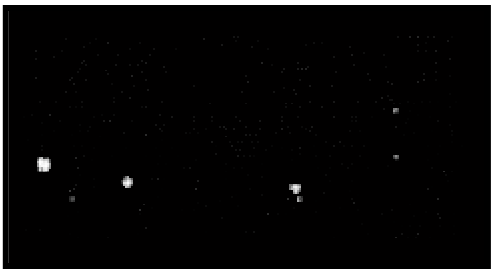
6. Conclusions

A brand-new face detection algorithm is introduced in this research. Features are extracted from original facial photos by Gabor wavelets. A feed-forward neural network chooses the key characteristics that set a particular face (or facial area) apart from other participants in the face database. On a database of 400 faces and non-faces, the experiment was run. The method based on all Gabor wavelet faces is superior to the baseline method when compared to other methods. In a subspace method, Gabor wavelets translate down-sampled face images into features for face detection, and the Gabor wavelet transform reflects prominent changes between pixels. The neural net feature space classifier combined with the proposed Gabor wavelet faces exhibits excellent performance in our testing and can obtain 93%. the current system detects upright faces looking at the camera only as shown in fig(6).

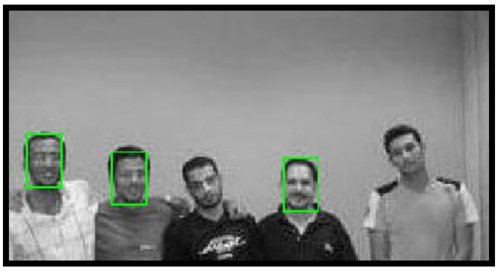
(a)



(b)

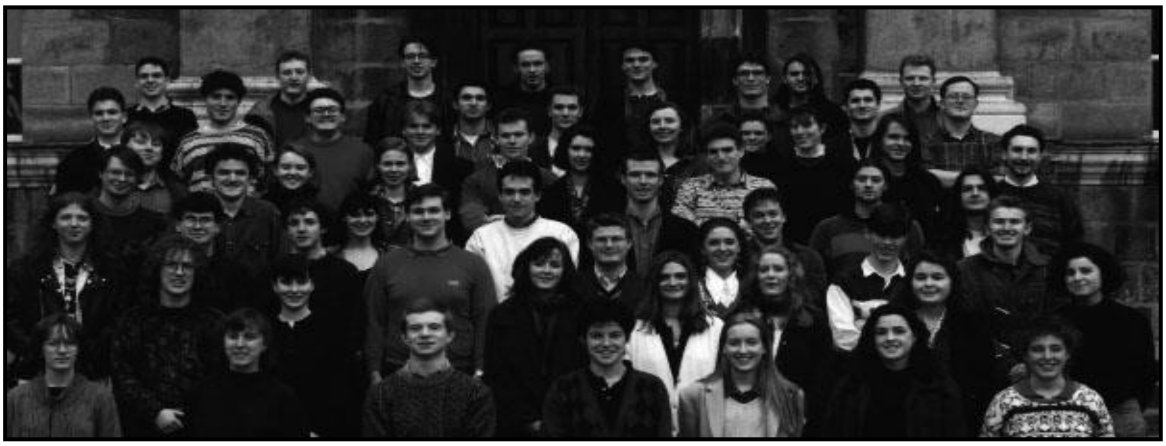


(c)



(d)

Fig.(6). (a) original image (b) facial area detection in the original image. (c) binary image under threshold value equal 0.5. (d) detection result of our proposed system (the system detect the upright faces only)



(a)

(b)

Fig.(7). another example (a)original image. (b) detection result of our proposed system(show the false positive)

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