Face Detection Using Statistical and Multi-Resolution Texture Features

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Abstract— **We present a texture-based technique for detecting faces in static gray-scale images under diverse conditions. The proposed method uses a moving window to examine the texture of an image at multiple scales in order to detect facial patterns. The features considered in this work is a set of statistical and multi-resolution texture features including a 3-level wavelet transform that uses an orthonormal Daubechies filter of length 8. These features are augmented with the pixel values corresponding to an 8x8 rendition of the image resulting in a 73-dimensional vector. The algorithm first utilizes the feature vectors extracted from a set of training images containing facial patterns to compute a pair of thresholds (based on the Euclidean distance metric) which is later used to eliminate non-facial window patterns from an image. The training vectors are next subjected to a clustering procedure that emits a pre-determined number of clusters each characterized by a centroid, a radius and a covariance structure. When a test image is presented to the system, the non-face window patterns are eliminated by utilizing the threshold values computed during the training phase. The feature vectors associated with the remaining candidate face windows are then compared with the centroid of individual clusters via the Mahalanobis distance in order to determine facial patterns. The algorithm uses fewer training samples than current learning-based techniques; does not require non-facial training patterns; can detect multiple faces in a scene; and is observed to perform well on images containing frontal, side-profile and slightly tilted faces under diverse lighting and background conditions.**

Key words— **face detection; statistical features; multiresolution features; texture; one-class problem.**

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1. INTRODUCTION

Detection of faces in static or video images is an important but challenging problem in computer vision that has applications in image retrieval systems [1], biometrics [2], surveillance [3] and law enforcement [4]. It is an essential first-step in face recognition where the goal is to localize the spatial extent of a face in order to determine the identity of an individual in an image. Several methods have been proposed in the literature for detecting faces [5]. Most techniques perform well in constrained environments but perform poorly on noisy images having a cluttered background. Face detection task is challenging as faces could occur at different scales, orientations, positions and pose in an uncontrolled background. The illumination and camera conditions also drastically affect the way in which a face occurs in an image. In general, face detection methods can be classified into three broad categories [6]: intensity-based methods, rule-based methods and feature-based methods. *Intensity-based methods* use classifiers that operate directly on the pixel intensity of the image without attempting to extract any facial features. The input to these classifiers is a set of image pixel values or simple additive features computed on the pixel values. In this category, machine learning methods that employ Support Vector Machines (SVMs) [7] or Multi Layer Perceptrons (MLP) [8, 15] are used to distinguish face and non-face entities. Such methods require a large number of training samples, although bootstrap techniques can be used to select non-face samples. A boosting chain algorithm is adopted to detect faces in different poses in [9] while an adaptive boosting method has been used for learning face and non-face images in [10]. Principal Component Analysis [11], Linear Discriminant Analysis [12], Independent Component Analysis [13, 14], and kernel-based methods [17] have been used for face recognition, but these may be applied to the face detection problem as well. Other intensity-based methods include those employing Bayesian classifiers and Hidden Markov Models [16].

The second category comprises of *rule-based methods* which employ the knowledge of the components of the face such as the eyes, nose and mouth, and their relationships [18]. The difficulty with these methods is that the number of possible rules in real world face images is large all of which cannot be encoded. A good review of these methods can be found in [13].

The third category comprises of *feature-based methods* and a large number of algorithms developed for face detection fall in this category. These include the use of edge features, skin color thresholding, size, shape from shading, template matching methods, etc. to localize/recognize faces. Edge feature methods group edges using heuristics, and components are labeled and matched to pre-computed models [19]. In color-based face detection, the skin color pixels are detected by thresholding in a color space such as RGB, normalized RGB or YCrCb. Post-processing operations include the use of morphological operators to discard non-face pixels and locate facial regions. Shape from shading methods compute an illumination normalized face image which is then used as a model for face recognition [20]. Template matching schemes compute the correlation values of an input pattern with predefined templates of the frontal face, eyes, nose and ears [21]. Methods based on motion (video) employ frame differencing to locate facial regions [22], [23]. Methods based on optical flow are discussed in [24]. Statistical multiresolution Gaussian pyramid features have been used in [25] for face detection. Edge operators along with variance and gradient variance are used to locate face and eyes in [26].

A face image can be viewed as a texture pattern exhibiting symmetry and regularity. It has been theorized that the human visual system (HVS) exploits the textural nature of the human face as well as the relationship between its component features to detect and recognize faces spontaneously [23]. Since a human face has a distinct texture compared to other objects, this property is expected to work well for face detection. Dai and Nakano [27] use the inverse difference moments computed from the Spatial Grey Level Dependence (SGLD) matrix to represent the texture of human faces in color images. Duta and Jain [28] use the grey-level histogram of an image along with a set of local second-order spatial averages (proposed by Gagalowicz [29]) to characterize texture and detect faces. Richert et al. [30] apply a multi-resolution wavelet transform to the facial patterns in order to generate a set of "parent" feature vectors; the estimated distribution of these vectors, which captures the joint occurrence of local texture features at multiple resolutions, is then used to detect face-like patterns in test images.

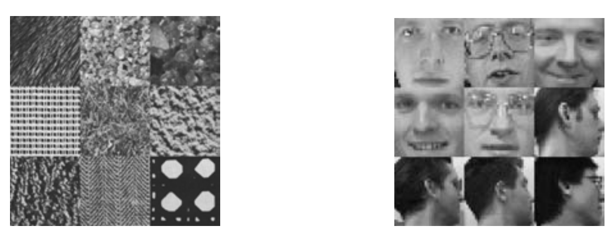
In this paper, we introduce a set of features that succinctly capture the textural properties of a face. These features are a judicious combination of statistical and wavelet features that are used in conjunction with the pixel intensities in order to detect faces at multiple resolutions, various poses and different backgrounds in grey-scale images. The proposed method does not require negative training examples (i.e., non-facial patterns) and, therefore, uses a set of thresholds to identify candidate facial patterns in an image. Experimental results highlight the significance of the proposed technique.

2. TEXTURE FEATURES FOR FACE DETECTION

Texture features have been used widely in image processing for classification, segmentation and object recognition. While no strict definition exists for texture, it can be described as the structural pattern of surfaces which exhibit homogeneity in spite of fluctuations in brightness and color. Statistical texture features, multiresolution wavelet features, random field models, etc. have been widely used for image classification [31]. In this work we consider a set of statistical and multiresolution wavelet features for face detection.

2.1 Texture features

A texture surface is formed by the placement of primitive patterns called texels in a grid with various rules that govern different properties of the region such as regularity, randomness, directionality and coarseness. A texture-based classification system computes features based on spatial or structural relationships inherent in the pattern. Several statistical measures (known as texture measures [32]) such as variance, entropy, correlation, homogeneity and contrast, attempt to capture these relationships. A face may be viewed as a fairly homogeneous symmetric texture region composed of an intricate network of eyes, nose and mouth. Fig. 1 compares non-facial texture patterns [33] against facial patterns.



(a) (b)

Fig. 1. A mosaic illustrating non-facial and facial texture objects.

2.2 Face Texture Measurement

Let $\{X(i,j)\}, i,j \in I,\ 1 \le i \le N_1,\ 1 \le j \le N_2$, represent a face pattern where N_1 and N_2 are the height and width of the pattern, respectively. The goal is to compute robust measures of the face pattern that can be used to distinguish facial objects from other textures. Texture features initially considered for this work were Haralick features computed from the co-occurrence matrices (entropy, contrast, correlation, homogeneity, sum of squares, sum average, sum variance, inverse difference moment, sum entropy, difference variance, difference entropy and information measures of correlation), run length features computed from the run length histograms (long run emphasis, short run emphasis, run length nonuniformity, grey level nonuniformity and run percentage), Fourier power spectrum features (maximum magnitude, average magnitude and energy of magnitude), statistical features, and features computed from wavelet transforms [35]. A feature selection process that combines the distance between the means of each feature and the measure of standard deviation of the feature vector was used to quantify the separation between face and non-face classes [36], [37]. The "best" set of 9 features isolated by the feature selection process is described below.

The average (f_1), the standard deviation (f_2), the average deviation of gradient magnitude (f_3), and the average residual energy (f_4) of the pixel intensities are given by,

$$f_1 = \frac{1}{N_1 N_2}\sum_{i=1}^{N_1}\sum_{j=1}^{N_2} X(i,j), \tag{1}$$

$$f_2 = \sqrt{\sum_{i,j}\left(X(i,j) - f_1\right)^2}, \tag{2}$$

$$f_3 = \frac{1}{N_1 N_2}\sum_{i=1}^{N_1}\sum_{j=1}^{N_2} \left|X(i,j) - X(i+1,j)\right| + \left|X(i,j) - X(i,j+1)\right|, \tag{3}$$

and

$$f_4 = \frac{1}{N_1 N_2}\sum_{i=1}^{N_1}\sum_{j=1}^{N_2} \left|X(i,j) - \bar{X}\right|. \tag{4}$$

Here, $\bar{X}$ is the mean value of the face texture. The average deviation of the horizontal directional residual (f_5) and the vertical directional residual (f_6) are computed as below,

$$f_5 = \frac{1}{N_1 N_2}\sum_{i=2}^{N_1-1}\sum_{j=1}^{N_2} \left|X(i,j) - \left(X(i-1,j) + X(i+1,j)/2\right)\right| \tag{5}$$

$$f_6 = \frac{1}{N_1 N_2}\sum_{i=1}^{N_1}\sum_{j=2}^{N_2-1} \left|X(i,j) - \left(X(i,j-1) + X(i,j+1)/2\right)\right|. \tag{6}$$

Features f_1 to f_6 capture the edge information of the texture pattern. Most of the texture discrimination information is contained in high spatial frequencies such as edges. These features are useful in characterizing the coarseness and randomness of the texture.

Apart from these features, a 3-level wavelet transform of the face image is constructed by convolving the face pattern with the orthonormal Daubechies filter [38] of length 8. This produces 4 subimages: the approximate, vertical, diagonal and horizontal detail images. The approximate subimages are further decomposed in a similar manner. After convolution the subimages are subsampled by 2. Hence, the subimages at level r are half the size of the subimages at level $r-1$. Wavelet features are computed from horizontal, vertical and diagonal subimages at each level of decomposition. The subimages are represented by the wavelet coefficients which capture the texture context information denoting the horizontal, vertical and diagonal variations in the texture [36]. The energy (f_7), standard deviation (f_8) and residual energy features (f_9) are computed as:

$$f_7 = \frac{1}{N_1 N_2}\sum_{i=1}^{N1}\sum_{j=1}^{N2} |C_{ij}|, \tag{7}$$

$$f_8 = \left[\frac{1}{N_1 N_2}\sum_{i=1}^{N_1}\sum_{j=1}^{N_2} |C_{ij} - M|^2\right]^{1/2}, \tag{8}$$

and

$$f_9 = \frac{1}{N_1 N_2}\sum_{i=1}^{N_1}\sum_{j=1}^{N_2} \left|C_{ij} - M\right|. \tag{9}$$

Here, the C_{ij}'s are the coefficient values of the subimage and M is the mean of the subimage. The wavelet energy (f_7) and residual energy (f_9) features measure the regularity of the texture while the variance feature (f_8) measures the homogeneity of the pattern. Earlier methods for face detection have used only the average value from wavelet filtering which has been found to be inadequate in characterizing the face texture [30], [39]. Only upright frontal and profile faces are considered here, so the orthonormal wavelet filters are sufficient for these textures. They have already been shown to give good results in classifying upright textures [34], [36]. In case of detecting faces exhibiting large variations in pose and tilt, the features have to be suitably transformed [39].

These 9 features are augmented with the pixel values of an 8x8 rendition of the textural pattern resulting in a 73-dimensional feature vector. It is this 73-dimensional vector that is used for detecting faces in an image. In Section 4.1, the sufficiency of the 9 statistical and multiresolution features is described in the context of the Hughes phenomenon. Fig. 2 depicts these features computed for the face mosaic shown in Fig. 1(b). Each row of this image represents the feature values (depicted as intensity values) of a face pattern.

Fig. 2. Feature image for the faces in Fig. 1(b). Each row depicts the feature values pertaining to a face pattern.

3. FACE DETECTION ALGORITHM

A face detector determines whether one or more faces are present in an image, while face localization determines their location and spatial extent. The proposed algorithm operates in two phases: (i) the training phase, when certain thresholds are computed, and (ii) the detection phase, when the performance of the algorithm is tested on various images.

Let T=$\{\Gamma_1, \Gamma_2, ..., \Gamma_{m_1}\}$ be a *training* set of m_1 face images and E=$\{E_1, E_2, ..., E_{m_2}\}$ be an *evaluation* set of m_2 face images. The intensity distribution of images in both the sets is normalized to zero-mean-unit-variance in order to reduce the effect of changes in lighting conditions.

Let $\{\Phi_i\}$, $i=1,2,...m_1$ and $\{\Psi_j\}$, $j=1,2,...m_2$ represent the feature vectors pertaining to the normalized images in both these sets. We compute two thresholds, T_1 and T_2, as follows:

$$T_1 = max_{i,j}\ \{\ \|\Phi_i - \Psi_j\|^2\ \}\ \text{and}$$

$$T_2 = min_{i,j}\ \{\|\Phi_i - \Psi_j\|^2\}, \tag{10}$$

$1\leq i\leq m_1$, $1\leq j\leq m_2$. Here ||.|| is the L_2-norm.

During the detection stage (described below), this threshold pair is used to eliminate non-facial patterns and retain face candidate windows. Since the within-class variability of the face class is high, a single threshold is not sufficient; employing two thresholds not only accounts for the intra-class variability but also aids in reducing the number of false positives.

Next, the feature vectors in the training set, $\{\Phi_i\}$, i=1,2,…m_1, are partitioned into *K* clusters via the *K*-means algorithm of unsupervised learning. The j^{th} cluster in this partition is characterized by its centroid $\boldsymbol{C_j}$, its covariance structure $\boldsymbol{\Sigma_j}$ and a radius D_j that indicates the maximum distance between the centroid and any element of the cluster. During the detection phase, the feature vectors associated with the candidate face windows are compared only against the centroid of each cluster and not the entire training set. This reduces the total number of comparisons that have to be performed by a factor of m_1/K.

Given an arbitrary image, **I**, the face detection process is executed as follows. A windowing process first extracts a sequence of windows from the image with 50% overlap and resizes each to a 8x8 array of pixel values. Let $\{\omega_k\}$, $k=1,2,...p$, be the texture feature vectors corresponding to each of the *p* extracted windows. ω_k is deemed to be a *candidate* face pattern if,

$$\begin{aligned} &max_i\ \{\|\Phi_i - \omega_k\|^2\} < T_1, \text{ and} \\ &max_i\ \{\|\Phi_i - \omega_k\|^2\} > T_2, \\ &1\leq i \leq m_1. \end{aligned} \tag{11}$$

Let $\{\omega_1, \omega_2, ..., \omega_r\}$ represent the *r* vectors satisfying (11). Each of these vectors is then compared with the centroids of the *K* clusters using the Mahalanobis distance metric. ω_i is labeled as a face pattern if, $(C_j - \omega_i)^T \Sigma_j (C_j - \omega_i) < \lambda D_j$ for any $j=1,2,...K$ where λ is a constant. This condition ensures that the window pattern is sufficiently close to the centroid of one of the *K* clusters. Fig. 3 depicts the sequence of operations necessary to detect facial patterns in an image. In the case of multiple detections, near the vicinity of a face, a post-processing step is done. The distance of the feature vectors of the detected windows from each of the cluster centroids is sorted in ascending order. The window whose feature vector has the shortest distance from a majority of the clusters is selected as the detected window. This is shown in Fig. 4. In order to test the performance of this algorithm, 3 distinct experiments were conducted as explained in the next section.

4. FACE DETECTION RESULTS

4.1 *Mugshot Faces*

In this experiment, mugshot images consisting of only a single frontal or profile face image each were considered. As each window is a face image, eqn. (11) is not necessary for setting up thresholds and eliminating non-face windows. Hence, the Mahalanobis distance metric alone is used for detection. For all these experiments the ROC curves are generated by varying the λ in the Mahalanobis criterion from 0.65 to 1.25. The purpose of this experiment was to observe the performance of the algorithm in the presence of both facial and non-facial patterns. 400 facial images from the CMU database were used as training images [40]. The remaining 1000 face images were used for testing. 1000 non-face images (19x19-sized images) extracted from the non-face image databases of Brodatz textures [33] and background images [41] were used to test the performance of the algorithm. All images were resized to 8x8. The feature set consisted of the 8x8 image space; the 6 statistical texture features; and the 3 wavelet texture features resulting in a feature vector of dimension 73. The images were appropriately resized by bicubic interpolation for computing multiresolution wavelet features. The ROC (Receiver Operating Characteristic) curve in Fig. 5 shows the detection rate and false alarm rates at various λ values. At 0.1% false positive rate the correct detection rate is about 93%.

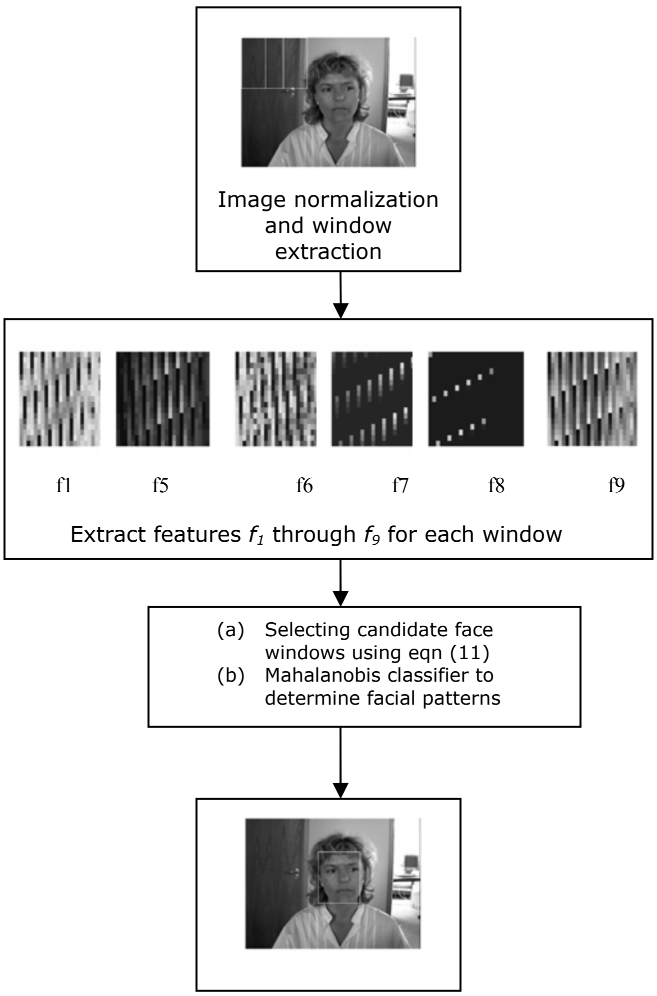


Fig. 3. Sequence of operations in the proposed algorithm.

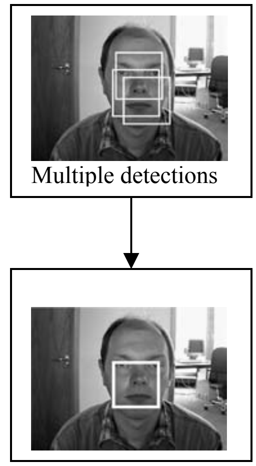


Fig. 4. The post-processing operation to avoid multiple detections in the vicinity of a face.

In order to demonstrate that the feature set selected is not affected by the curse of dimensionality or Hughes phenomena [42] an experiment was conducted to indicate the sufficiency of the 73 features. The λ value was fixed at 0.77. Fig. 6 shows the effect of increasing the number of features by adding the other features described in section 2.2 (Haralick, Fourier, etc.). The best detection rate was observed with the 73 features discussed above; with the addition of other features, the performance initially remains the same and then deteriorates as seen in Fig. 6.

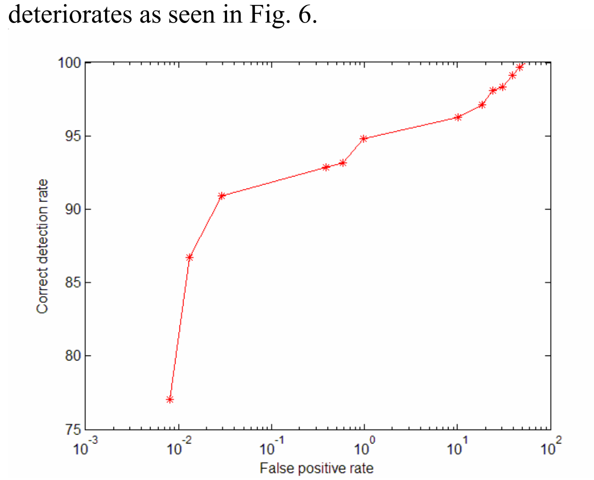


Fig. 5. The ROC curve for detecting faces in mugshot images.

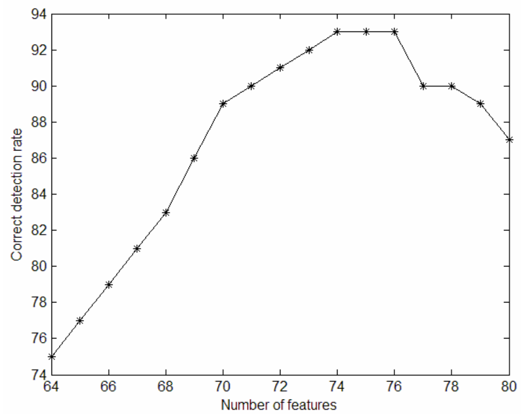


Fig. 6. Effect of the number of features on detection rate.

4.2 Varying Background

In the second set of experiments, the training and testing procedures were performed on different databases. Moreover, the test dataset had mugshots of human faces in a varying background.

The training images were selected from the ATT database [43]. 40 images constitute the training set and 20 images constitute the evaluation set. Some of the training images are shown in Fig. 7.

Fig. 7. Examples of frontal face images used for training [43].

The feature vector consists of the 6 statistical and 3 wavelet texture features, and the 8x8 image space (resized). Threshold values T_1 and T_2 were set using eqns. (10) and (11) to eliminate non-facial windows. The test dataset consisted of 400 images taken from the BioID database [44].

The BioID database consists of images of individuals in varying background under varying lighting conditions with different face sizes. A moving window of size 92x92 pixels with 50% overlap was used to scan the images. Some results of faces detected are shown in Fig. 8. In certain images the detected window encloses approximately 3/4th of the face (and not the entire face) and hence the notion of "correct detection" is based on two cases. The first case accounts for window masks that fully cover the face and the second accounts for masks that cover about 3/4th of the face. Experiments indicate that the face was fully detected in 70% of the images; partially detected in 21.5% of the images; and completely missed in 8.5% of images. The algorithm has performed well given the variations in the test images and the limited number of training images that were used from an entirely different database.

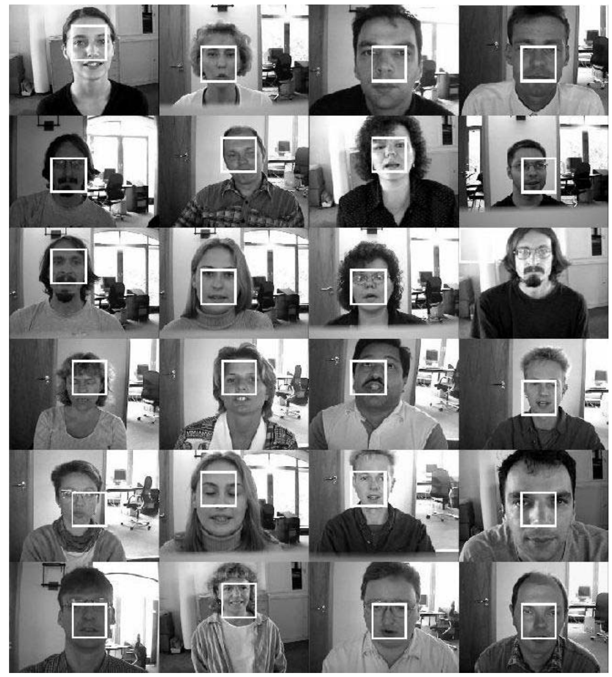
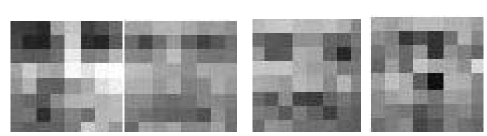


Fig. 8. Face detection in BioID database [44].

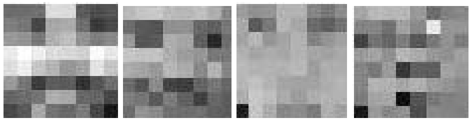
4.3 Detection of Frontal and Profile Faces

In the third set of experiments, the ability of the algorithm to detect both frontal and side profile of faces was evaluated. Also, some of the test images contained multiple faces at different resolutions (i.e., size). The training set was constructed using the 40 training images and the 20 evaluation images used in the previous experiment. Apart from this, 60 profile face images (Fig. 9) from the UMIST database [45] were also used (40 for training and 20 for evaluation). Hence, a total of 80 training images and 40 evaluation images were made available.

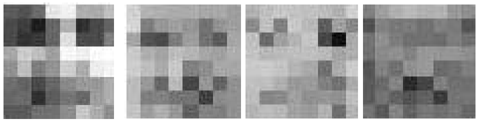
Fig. 9. Profile face images used for training [45].



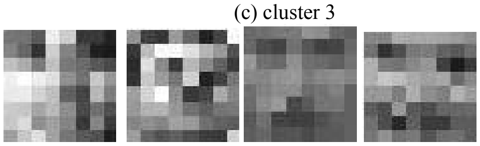
(a) cluster 1



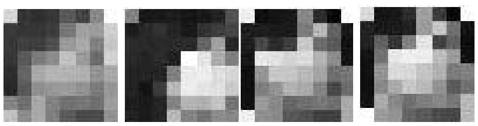
(b) cluster 2



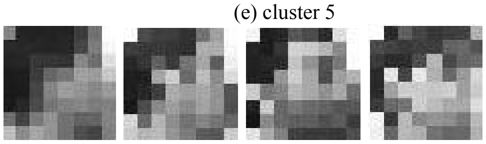
(c) cluster 3



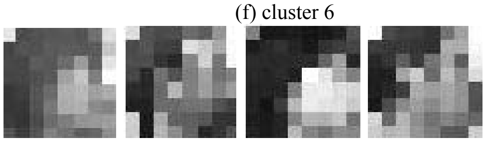
(d) cluster 4



(e) cluster 5



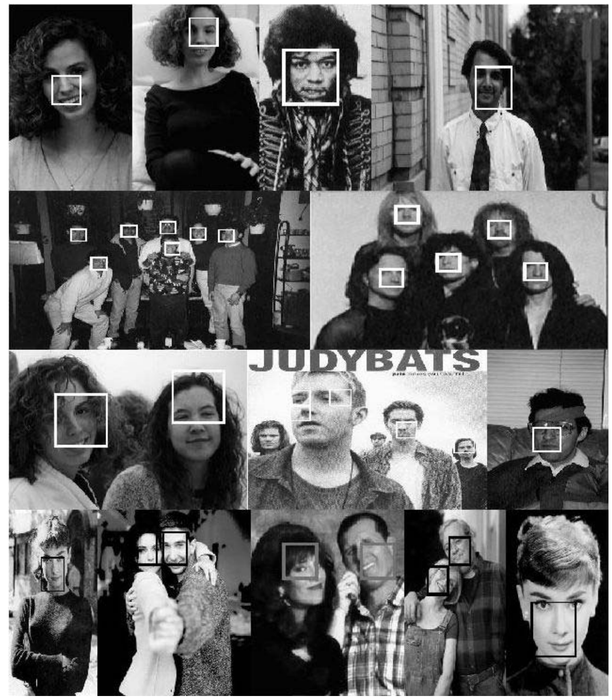
(f) cluster 6



(g) cluster 7

Fig. 10. Cluster images

The thresholds T_1 and T_2 were computed using eqns. (10) and (11) to eliminate non-facial windows. The feature space was then partitioned into 7 clusters using the K-means technique. Some images from each of the 7 clusters are shown in Fig. 10. The value of λ was set to 0.9 for this experiment. Each test image was scanned by windows (50% - 80% overlap) at three different scales (92x92, 64x64, and 32x32). A lower scale was used only if no faces were detected in the previous scale. Figures 11 (a) and 11 (b) present the results on a few test images from the CMU frontal [46] and profile databases [47], respectively. In several cases, multiple windows were detected as facial candidates in the vicinity of a face. In order to resolve this, the post-processing step described in section 3 was performed. Hence, the final detected window contains the eyes and nose or eyes and forehead, as well. The detection rate is calculated as the ratio of the number of faces detected to the total number of faces in the images (rather than as a function of the number of windows scanned) [47]. The total number of faces considered in the above experiment was 1309. The detection accuracy was ~90.6%. Note that only a few training samples were used in this experiment.



(a)

(b)

Fig. 11. Face detection on the CMU-MIT (a) frontal [46] and (b) profile database [47]. The faces are inaccurately localized

in some images. This is a consequence of using partially overlapping windows exhibiting limited number of scales (only 3). Further, the preprocessing step (Fig. 4) also introduces some errors.

5. CONCLUSION

We have successfully combined statistical and multi-resolution texture features to design an automatic face detection algorithm. The algorithm has been shown to perform well under different lighting and background conditions. It is shown that adding texture features, as defined here, results in improved performance. The thresholds T_1 and T_2 computed using the evaluation set of face images help in eliminating non-face windows thereby reducing the number of windows that have to be compared using the Mahalanobis criterion. By varying the threshold, λ, the number of false positives can be effectively reduced. Furthermore, the algorithm is feasible for implementation in real-time face detection systems.

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