# Detection of Multiple Faces in Color Images using Haar Wavelets

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## ABSTRACT
Face detection is a very challenging and interesting problem. In this paper, a new scheme for detection of multiple faces using Haar wavelet packet decomposition based on quantized skin color region merging under unconstrained scene conditions is presented. Color clustering and filtering using approximations of the YCbCr and HSV skin color subspaces are applied on the original image by providing quantized skin color regions. A merging stage is then iteratively performed on the set of homogeneous skin color regions in the color quantized image, to provide a set of potential face areas. Face intensity texture is analyzed by performing wavelet packet decomposition on each face candidate in order to detect human faces. The wavelet coefficients of the band filtered images characterize the face texture and a set of simple statistical deviations is extracted in order to form compact and meaningful feature vectors. Then, an efficient and reliable probabilistic metric derived from the Bhattacharyya distance is used to classify the extracted feature vectors into face or nonface areas, using some prototype face area vectors, acquired in a previous training stage.
The proposed system leading to a successful detection rate of 99% for single face, animal and nonfaced images. If the image consists of multiple faces, more complex background and extreme lighting conditions, the efficiency is reduced to 85% due to false acceptance and false rejection especially in scene with much partially occluded face or under extreme lighting conditions or with pose. If faces are oriented more than $15^0$ our system fails to detect such faces.

**General Terms:** Face Detection, Pattern Recognition.

**Keywords:** Face Detection, Wavelet Packet Decomposition, Bhattacharyya Distance.

## 1. INTRODUCTION
Face detection is a well-known pattern recognition problem. Such task is the first fundamental step for many applications such as face recognition and 3D face reconstruction. Although many approaches have been proposed over the last few years, it still remains a very challenging problem today [1] [2] due to significant face appearance variations, such as pose (front, nonfront), occlusion, image orientation, lighting conditions and facial expression

Although face detection is closely related to face recognition as a preliminary required step, face recognition algorithms have received most of the attention in the academic literature compared to face detection algorithms. In most of the face recognition approaches, existence and location of human faces in the processed images are known a priori, so there is little need to detect and locate faces. In image and video databases, there is generally no constraint on the number, location, size, and orientation of human faces and the background is generally complex. Moreover, color information is very useful for face detection, whereas this information is not used in face recognition approaches. Over the last ten years, increasing activity has been noticed in developing algorithms to either detect or locate faces in "mugshot" style images, or detect faces in uncontrolled images [3], [4]. Existing methods may be roughly divided into three broad categories: local facial features detection, template matching and image invariants. In the first case, low-level computer vision algorithms are applied in order to detect facial features such as eyes, mouth, nose and chin. Then, statistical models of human face are used like in [5], [6], [7], [8], [9]. In the second case, several correlation templates are used to detect local subfeatures which can be considered as rigid in appearance (viewbased eigenspaces [10]) or deformable templates [11]. In the third case, image-invariants schemes assume that there are certain spatial image relationships common and possibly unique to all face patterns, even under different imaging conditions. Instead of detecting faces by following a set of human-designed rules, alternative approaches are based on neural networks [12], [13], [14] which have the advantage of learning the underlying rules from a given collection of representative examples of face images, but have the major drawback of being computationally expensive and challenging to train because of the difficulty in characterizing "nonface" representative images.

In this paper, we propose a new algorithm for automatically detecting human faces in digital still color images, under unconstrained scene conditions, such as presence of a complex background and uncontrolled illumination, where most of the local facial features based method are not stable. First it performs color clustering of the original image, in order to extract a set of dominant colors and quantize the image according to this reduced set of colors. Then, a chrominance-based segmentation is performed. A merging stage is iteratively applied on the set of homogeneous skin color regions in the color quantized image, in order to provide a set of candidate face areas, without scanning all the different possible aspects ratios and the possible positions into binary segment areas. This improvement leads to a better precision in locating the faces and helps in segmenting the faces from the background, especially when parts of the surrounding background have a color that may be classified as skin color. Constraints related to shape and size of faces is applied, and face intensity texture is analyzed by performing wavelet packet decomposition by using Haar wavelets on each face area candidate in order to detect human faces. Each face area candidate is described by band filtered images containing wavelet coefficients. A set of simple statistical data is extracted from these coefficients, in order to form vectors of face descriptors, and a well-suited probabilistic metric derived from the Bhattacharyya distance is used to classify the feature vectors into face or nonface areas, using some prototype face area vectors, which have been built in a training stage.

The remainder of this paper is organized as follows. The System Architecture is presented in Section 2.The skin detection algorithm is described in Section 3. In Section 4, we present the algorithm for face detection. In Section 5, we are describing the extraction of face texture descriptors vectors using Haar wavelet packet analysis and their classification using a distance derived from the Bhattacharya dissimilarity measure. Results are discussed in Section 6. Finally in Section 7 conclusion is given.

# 2. THE SYSTEM ARCHITECTURE

The architectural design process is concerned with establishing a basic structural framework for a system. It involves identifying the major components of the system and communications between these components. Figure 2.1depicts the proposed system architecture.

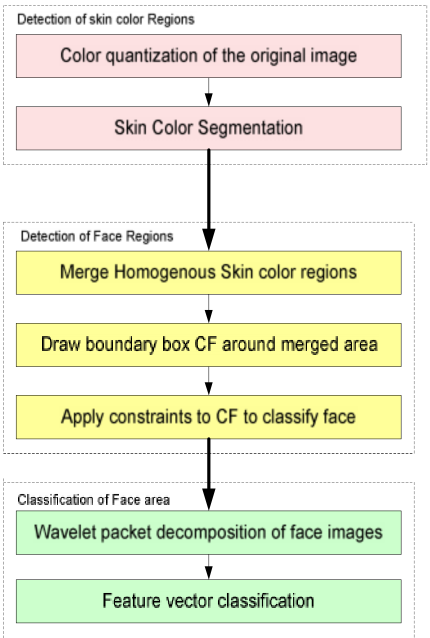



**Figure 2.1 Proposed System Architecture**

The proposed system is mainly divided into 3 different phases, it involves

1. Detection of skin color region.
2. Detection of candidate face regions.
3. Classification of candidate facial area.

# 3 DETECTION OF SKIN COLOR REGION

Human skin color has been used and proven to be an effective feature for face detection, localization and tracking. Although different people have different skin color, several studies have shown that the major difference lies largely between their intensity rather than their chrominance [15] [16]. In the proposed system, to reduce the search space skin chrominance information is used to locate the potential face areas in the image and then a color quantization of the original image is performed, in order to improve skin color segmentation.

## 3.1 Color Quantization of the Original Image

Color quantization is applied to quantize the image colors to a reduced set of dominant colors. In this implementation, a fixed number of 16 color clusters are considered. The final set of codebook vectors is obtained using an iterative algorithm, the Kmeans algorithm, also known as the Linde–Buzo–Gray algorithm (LBG) [17].At each iteration, each color vector (pixel) is assigned to the closest color cluster according to its Euclidian distance *Dc* to the mean color vector of the cluster, and the mean color vector of the set of pixels which have been associated to one color cluster is updated. The algorithm stops after a given number of iterations. Then, color clusters are merged according to a predefined maximum distance. Finally, each pixel in the image receives the value of the mean color vector of the cluster it has been assigned to. The resulting image is therefore quantized according to the set of dominant colors.

## 3.2 Skin Color Segmentation

Next stage is to segment the quantized color image according to skin color characteristics. Two color models have been used. The YCbCr model is naturally related to MPEG and JPEG coding. The HSV (Hue, Saturation, Value) model is used mainly in computer graphics and is considered by many to be more intuitive to use. Skin color patches have been used in order to approximate the skin color subspaces, in both models. Experiments have shown that segmentation results are quite equivalent using both color models. In the below figure four examples of skin color based image segmentation are shown. Figure 3.1 displays the original images. Figure 3.2 shows the color quantized image obtained after dominant colors detection and Figure 3.3 displays the skin color areas of the quantized color image, using the skin color subspaces approximation.

**Figure 3.1 Original Input Images**

**Figure 3.2 Color Quantized Images**

**Figure 3.3 Skin Color Filtered Images**

## 4. DETECTION OF CANDIDATE FACE REGIONS

This section describes how to locate candidate face areas in the skin color filtered image, denoted as SCF image. Skin color areas have to be segmented in order to form potential face areas which will be classified in the later stage of the proposed scheme, by performing wavelet packet analysis. A merging stage is iteratively applied on the set of homogeneous skin color regions in the color quantized image, in order to provide a set of candidate face areas, without scanning all the possible aspects ratios and the possible positions into binary segment areas. This improvement leads to a better precision in locating the faces and helps to segment the faces from the background, especially when parts of the surrounding background have a color close to skin color. The SCF image is composed of a relatively small set of homogeneous regions, denoted as $R_i$ due to color quantization. We aim at building potential candidate face areas by iteratively merging adjacent homogeneous skin color regions. By merging adjacent similar and homogeneous skin color regions, we are able to iteratively construct candidate face areas while distinguishing between the different skin tones in the skin color areas. This approach allows to segment faces from a surrounding skin color background.

The skin color regions merging algorithm starts by computing a region adjacency graph, where each node represents a homogeneous skin color region of the quantized image. The criterion of connectivity is based on a minimum distance computed between the associated bounding boxes of each homogeneous region. Evaluating connectivity using a distance between the vertices of the bounding boxes is much faster than estimating the connectivity in the pixel domain.

Let $C_0$ be the set of homogeneous skin color regions $\mathbf{R_i}$, i € [1….N]. First, the criterion of connectivity is applied to build the region adjacency graph. Since we are dealing with bounding boxes, a fast algorithm has been implemented, which considers the normal distance between the vertices of the disconnected bounding boxes or determines if the bounding boxes are overlapping. Therefore, adjacent regions are defined. The merging criterion among the bounding boxes of adjacent regions $R_i$ and $R_j$ is based on a maximum allowed distance, which encodes color dissimilarity in the bounding boxes.

The set of potential face areas is built iteratively, starting from the $C_0$ set and its adjacency graph. The set $C_1$ is obtained by merging the compatible adjacent regions of $C_0$. Then, each new set of merged region $C_k$, (k € [1….K]) is obtained by merging iteratively the set of merged region $C_{k-1}$ with the original set $C_0$ by using equation (1).

$$\forall k \in [1...K], \quad \forall R_i \in C_0, \quad \forall R_j \in C_{k-1}$$

$$C_k = \bigcup R_i \cup R_j \tag{1}$$

In the current implementation, iterative merging is performed with a maximum number of iterations K=3. Finally, the candidate face area set CF contains the original regions set $C_0$ and the iteratively built sets of merged region $C_k$, (k € [1….K]).

In Figure 4.1, the merging process of the skin color areas is presented with real example. The first four images contain the homogeneous regions corresponding to four dominant skin colors. The regions corresponding to the considered skin color are displayed in white. For reasons of readability, the bounding boxes have not been drawn around each skin color (white) area. In the fifth image, the bounding boxes of the candidate face areas built by the merging process and contained in the CF (Candidate Face area) are drawn. The final detected face is shown in the last image. As one can notice in the fifth image, some bounding boxes in CF are small or have an aspect ratio which is not compatible with the one of a human face. Therefore, constraints related to shape, acceptable size, range, color homogeneity and texture are then applied to the candidate face areas CF.

In order to classify these regions into face or nonfaces, first constraints relative to shape and size are applied in order to remove most of the non potential candidate face areas. The shape of human faces can be approximated and can be considered as discriminant information. In order to perform fast computation, analyze the face shape by considering the aspect ratio of its bounding box. Moreover, constraints related to allowed sizes are applied. By applying these two constraints, an important number of regions are removed from the set of candidate face areas.

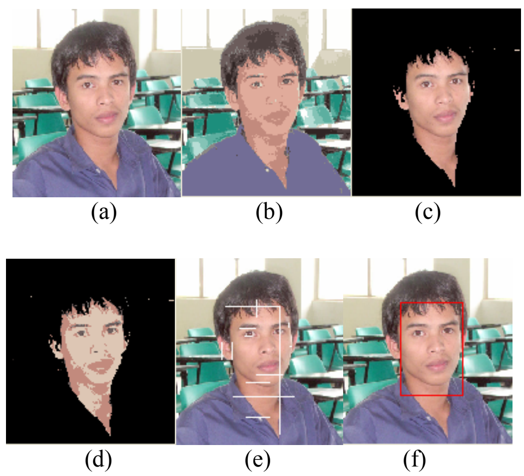



**Figure 4.1 Skin Color Merging and Face Detection (a) - (d): Homogeneous Skin Color Regions, (e): Candidate Face Bounding Boxes and (f): Detected Face.**

Then, a constraint of color homogeneity is applied by computing the density of skin color pixels in each candidate face area $R_i$ bounded by the outer and the inner areas. The outer area corresponding to the border area of $R_i$ (whose width is a percentage of the bounding box width, typically 15%) and the inner area corresponding to the remaining central part of $R_i$. A $R_i$ area is accepted as a potential face area, if the density of skin color pixels in the whole $R_i$ area, denoted as P is below a threshold value. Finally inner area is the central part of the face with no background, whereas in the whole $R_i$ area, hair and part of background have to be taken into consideration.

# 5. CLASSIFICATION OF CANDIDATE FACIAL AREAS

The purpose of this section is to classify the areas, which are compatible with the constraints of shape, size and color homogeneity, into faces or nonfaces. The classification aims at removing false regions caused by objects with color similar to skin color and similar aspect ratios, such as other exposed parts of the body or part of background. For this purpose a wavelet packet analysis scheme is applied using Haar Wavelets. Wavelet packet decomposition is performed on the intensity plane of the image and feature vectors are extracted from a set of wavelet packet coefficients in each area.

Wavelet packet decomposition for analyzing the face texture has been found suitable because this scheme provides a multiscale analysis of the image in the form of coefficient matrices with a spatial and a frequential decomposition of the image at the same time.

## 5.1 Wavelet Packet Decomposition of Faces

The discrete wavelet series for a continuous signal S(t) is defined by equation (2).

$$c_{n,k} = \frac{1}{2^{n/2}} \int s(t)\psi^*(2^{-n}t - k)dt \quad (2)$$

The series use a dyadic scale factor, n being the scale level and k being the localization parameter. The function ψ (t) is the mother wavelet, which satisfies some admissibility criteria and ensures a complete, nonredundant, and orthogonal representation of the signal. The discrete wavelet transform (DWT) results from the above series, and is equivalent to the successive decomposition of the signal by a pair of filters h (.) and g (.). The low-pass filter h(.) provides the approximation of the signal at coarser resolutions, while the high-pass filter g(.) provides the details of the signal at coarser resolutions. The extension to the 2-D case is usually performed by applying these two filters separately in the two directions. The convolution with the low-pass filter results in an approximation image and the convolutions with the high-pass filter in specific directions result in detail images.

In classical wavelet decomposition, the image is split into an approximation and details. The approximation is then split into a second-level of approximation and details. For n-level decomposition, the signal is decomposed by using equation (3).

$$\begin{aligned} A_n &= \left[h_x * \left[h_y * A_{n-1}\right]\downarrow 2,1\right]\downarrow 1,2 \\ D_{n1} &= \left[h_x * \left[g_y * A_{n-1}\right]\downarrow 2,1\right]\downarrow 1,2 \\ D_{n2} &= \left[g_x * \left[h_y * A_{n-1}\right]\downarrow 2,1\right]\downarrow 1,2 \\ D_{n3} &= \left[g_x * \left[g_y * A_{n-1}\right]\downarrow 2,1\right]\downarrow 1,2 \end{aligned} \quad (3)$$

Where * denotes the convolution operator, ↓ 2, 1 (↓ 1, 2) subsampling along the rows (columns), and $A_0$=I(x,y) is the original image. $A_n$ is obtained by low-pass filtering and is the approximation image at scale n. The detail images $D_{ni}$ are obtained by bandpass filtering in a specific direction (i= 1, 2, 3 for vertical, horizontal and diagonal directions respectively) and thus contain directional details at scale n. The original image I is thus represented by a set of subimages at several scales: $\{A_n, D_{ni}\}$.

The wavelet packet decomposition, which is performed in the proposed approach, is a generalization of the classical wavelet decomposition that offers a richer signal analysis. In our approach we used Haar wavelets for packet decomposition, here the details as well as the approximations can be split. In this approach good results are obtained by extracting statistical information from the coefficients in some different specific areas of the approximation image of the face, and statistical information from the wavelet coefficients of each detail image. Like in [18], we considered each $R_i$ area as a bounding box, and by dividing it into four parts: a left top part (top1), a right top part (top2), a left bottom part (bottom1) and a right bottom part (bottom2), all of equal size, where the wavelet packet analysis is performed. By extracting moments from the wavelet coefficients in these areas, obtain the information about the face texture, related to different facial parts, like the eyes, the nose, and the mouth, including facial hair. Standard deviations have been chosen as face texture descriptor coefficients from the top and bottom areas. Then extract corresponding standard deviations **σtop1, σtop2, σbottom1, and σbottom2** of the wavelet coefficients contained in the approximation image of the selected level of decomposition. From the m detailed images (m € 15), the corresponding standard deviations are extracted from the whole $R_i$ area. Thus, extracted feature vectors contain a maximum of 4+m components (four standard deviations for the approximation image and m standard deviations for the detail images).

## 5.2 Feature Classification

This phase decides how a $R_i$ feature vector is classified into the two possible classes: face or nonface. From the database of manually extracted face areas, feature vectors are extracted and an average prototype feature vector has been retained. An important issue here is the choice of the probabilistic distance between the density functions. This choice may be done according to the model of the density functions. Concerning our classification problem, statistical analysis of experimental results has shown that the probability distribution of the wavelet images could be the generalized Gaussian function and is given by equation (4).

$$P(x) = \frac{c}{2\sigma\Gamma\left(\frac{1}{c}\right)} e^{-(|x|/\sigma)^c} \quad (4)$$

Where the parameter $\sigma$ is the standard deviation and reflects the sharpness of the probability density function. For Gaussian function the standard value for c is 2, and for Laplacian function the standard value for C is 1.

One of the most popular probabilistic distances in the field of pattern recognition is the Bhattacharya distance. It is related to the well known chernoff bound and therefore, has an explicit expression for a generalized Gaussion distribution. Bhattacharyya distance B is used as a probabilistic distance and is given by equation (5).

$$B_c = \frac{1}{C}\ln\left(\frac{\sigma_1^c + \sigma_2^c}{2\sqrt{\sigma_1^c \sigma_2^c}}\right) \quad \textbf{(5)}$$

with C described above.
Here interband values are decorrelated and therefore the distance between two feature vector $V_k$ (a candidate feature vector) and $V_l$ (a prototype feature vector) may be computed on a component pair basis, that distance is considered as a sum of distances relative to each of these component pairs. According to Bhattacharyya distance, the resulting distance D between two feature vectors $\mathbf{V_k}$ and $\mathbf{V_l}$ is given by equation (6).

$$D(V_k, V_l) = \frac{1}{2}\sum_{i=0}^{3}\ln\left(\frac{\sigma_{ik}^2 + \sigma_{il}^2}{2\sigma_{ik}\sigma_{il}}\right) + \sum_{i=4}^{m+3}\ln\left(\frac{\sigma_{ik} + \sigma_{il}}{2\sqrt{\sigma_{ik}\sigma_{il}}}\right) \quad (6)$$

Therefore, classification is performed by evaluating the distance D from each $R_i$ feature vector $\mathbf{V_k}$ to the prototype feature vector $\mathbf{V_l}$ of the corresponding size category. Each $R_i$ feature vector has to be classified as face or nonface according to distance D to the average prototype vector of the corresponding size category. $R_i$ is classified as a face area if D is below threshold $T_{HD}$, and rejected otherwise. Threshold value is taken as 1, so the values that appear below 1 are taken as face and above 1 are taken as nonface. Finally, problem of overlapping of selected $R_i$ areas are solved as follows; the set of face areas that overlap by more than 25% in both dimensions is sorted in ascending order according to normalized distances D/hw, (height and width) related to the size $R_i$. Then, the first ranked face area is selected and the other ones are rejected.

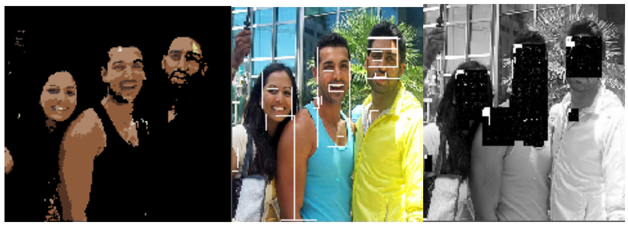
## 6. RESULTS AND DISCUSSION

In order to test the efficiency of the algorithm presented in the previous sections, a series of experiments have been performed using test data set. The test data set contains 100 images, most of them being extracted from face databases, advertisements, news, and external shots. These examples include color images with multiple faces of different sizes, different colors, different positions and images which do not contain any faces.

Detection of multiple faces in the given image is shown in Figure 6.1, 6.2 and 6.3 respectively. False acceptance and False rejection examples are also presented.

(a) (b) (c)

**Figure 6.1 Detection of Skin Color Regions**
**(a):Input Image, (b): Color Quantization and (c): Segmented Skin Regions**



(a) (b) (c)

**Figure 6.2 Detection of Face Regions**
**(a): Skin Color Filtering, (b): Candidate Face Bounding boxes and (c): Haar Wavelet Packet Decomposition**

**(a) (b) (c)**

**Figure 6.3 Classification of Face areas**
**(a): Bhattacharyya Distance Calculation, (b): Classifications of Faces and Nonfaces and (c): Detection of Multiple Faces**

Figure 6.4 shows the sample experimental results for false rejections.

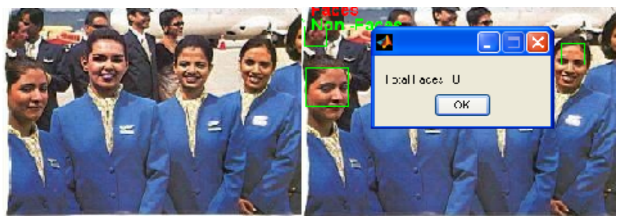



**Figure 6.4 (a): Input Image and (b): False Rejections**

Figure 6.5 and 6.6 shows the sample experimental results for non face images.

**Figure 6.5 (a): Input Image and (b): Final Result**

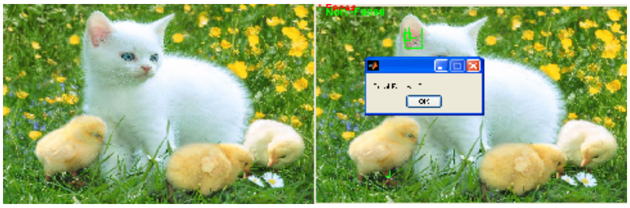


**Figure 6.6 (a): Input Image and (b): Final Result**

The proposed system leading to a successful detection rate of 99% for single face, animal and nonfaced images. If the image consists of multiple faces, more complex background and extreme lighting conditions then efficiency is reduced to 85 % due to false acceptance and false rejection, especially in scene with much partially occluded face or under extreme lighting conditions or poses. If faces are oriented more than $15^0$ our system fails to detect such faces.

## 7. CONCLUSIONS

Face detection is a very challenging and interesting problem. Here we presented a new method for detection of multiple faces using quantized skin color regions and Haar wavelet packet analysis. The use of the Bhattacharyya distance proved to be very suitable for classifying these feature vectors into faces or nonfaces classes. This method is very efficient especially for large size faces detection and skin color segmentation helps to improve the speed of face detection process by pre-selecting candidate face areas. Thus, the wavelet packet analysis provides a robust scheme for face detection; even if no constraint is imposed on the faces to be detected and achieves an efficiency of 85%.

In the future work, feature extraction process that extracts statistical information from the wavelet images, which convey most information about faces texture especially when faces are oriented more than $15^0$ is to be considered.

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