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# Identification Of Gender And Face Recognition Using Adaboost And SVM Classifier

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## Abstract:

When the discussion starts about a computer based automatic facial feature extraction system which can identify face, gesture etc and estimate gender, age, expirations etc. The system asks for a dependable, fast, reliable classification process. This paper presents an approach to extract effective features for face detection and gender classification system. The proposed algorithm converts the RGB image into the YCbCr color space to detect the skin regions in the color image. Finally Gaussian fitted skin color model is used to obtain the likelihood of skin for any pixel of an image. For facial feature extraction we use Gabor filters at five scales and eight orientations. To solve the classification problem this system deploys Adaboost and SVM based classifier. Biometrics is an advanced way of person recognition as it establishes more direct and explicit link with humans than passwords, since biometrics use measurable physiological and behavioral features of a person. In various biometric applications, gender recognition from facial images plays an important role. In this paper gender recognition image sequence have been successfully investigated. Gender recognition plays an important role for a wide range of application in the field of Human Computer Interaction. In this paper, we propose a gender recognition system based on Neural Networks. The system comprises two modules: a face detector and a gender classifier. The human faces are first detected and localized in the input image. Each detected face is then passed to the gender classifier to determine whether it is a male or female. Both the face detection and gender classification modules employ the same neural network architecture; however, the two modules are trained separately to extract different features for face detection and gender classification.

KEYWORDS: Adaboost, SVM, Gender Classification, Feature extraction, Gaussian filter, Gabor filter.

## Introduction:

The most important and impressive biometric feature of human being is the face. It conveys various information including gender, ethnicity etc. Face information can be applied in many sectors like biometric authentication and intelligent human-computer interface. Many potential applications such as human identification, smart human computer interface, computer vision approaches for monitoring people, passive demographic data collection, and etc needs a successful and dependable classification method. It is really a very challenging job to detect male or female accurately separating two sets of data. So it is very urgent to have a reliable classifier to improve the classification performance.

The face can be recognized with the help of the following features such as the Pose correction, illumination normalization, periocular normalization, PCA and unsupervised discriminant projection and so on… The face is recognized with the 66 facial features such as nose, eyes, head, forehead, eyebrows, cheeks, mouth, skin tone and etc…

Gender recognition plays an important role for a wide range of applications in the field of Human Computer Interaction also for commercial purposes. Gender recognition may in fact find application in areas such as advertising. An example might be an advertising screen, which uses a camera for detecting the gender of a human who looks at it and displays the content accordingly. Gender recognition represents a very common task for humans. Since the first moment of life we learn to recognize our mother and father and during all existence we constantly perform gender recognition, often without being aware of it. By the way, notwithstanding this continuous training, gender recognition remains a difficult task due to the high variability of the characteristics that identify a male or a female. In several situations, the humans error rate in gender recognition can be surprisingly high.

## Existing System:

Majority of existing face detection techniques rely only on image gray values in spite of the fact that most images generated today are color. A small number of techniques use color information to detect faces in images . Methods that are based on image gray values detect predefined image features and use them either in a system that has a learning ability or in a model matching algorithm to detect the faces.

Gender recognition belongs to the category of pattern recognition. This implies that a large amount of methods exist. Usually, a pattern recognition system consists of three main blocks such as information source, feature extraction and classifier. In our case an RGB camera is the source of information, used for acquiring the face image. The image from camera is transformed to grayscale and continues to next block. Because the image contains a large amount of redundant information, system must include a block for the selection of relevant information that best describes the pattern. Features extraction is therefore a very important block of the pattern recognition system.

Due to different lighting conditions, the appearance of the skin-tone color can change. The existing system use a lighting compensation technique that uses “reference white” to normalize the color appearance. According to the lighting compensation (LC) algorithm is very efficient in enhancing and restoring the natural colors into the images which are taken in darker and varying lighting conditions.

The LC algorithm can be defined as followings:

$Sc=CstdCavg$
$Cavg= (Ci)>0mi=1\ (1)>0mi=1$
$Cstd= (Ri,i,Bi)+min(Ri,Gi,Bi)\ mi=12*n\ \ n=m=$ $(1)(Ri=Gi=Bi=0)$

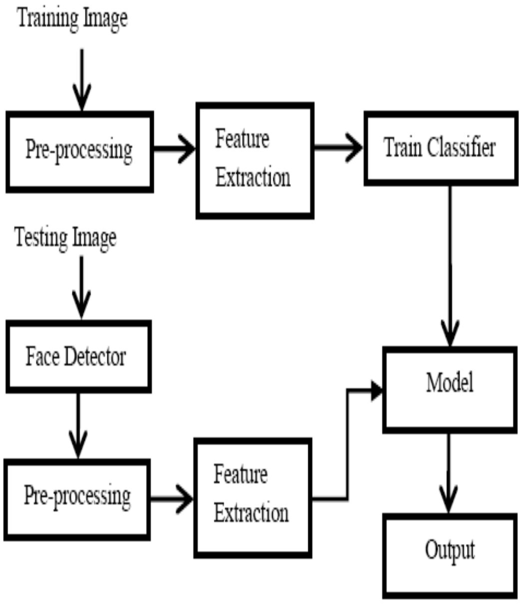


**Fig: 1 General approach for Gender identification system.**

## Problems related with existing system:

- There is no standard algorithm for face recognition in image processing.
- The co-ordinate points in the face may vary from one algorithm to another algorithm.

- Major characteristics of an image such as color, texture, and shape are not considered while producing the output.

## Proposed system:

An overview of our face detection system is depicted in Fig. 2, which contains the major module: face localization for finding face candidates.

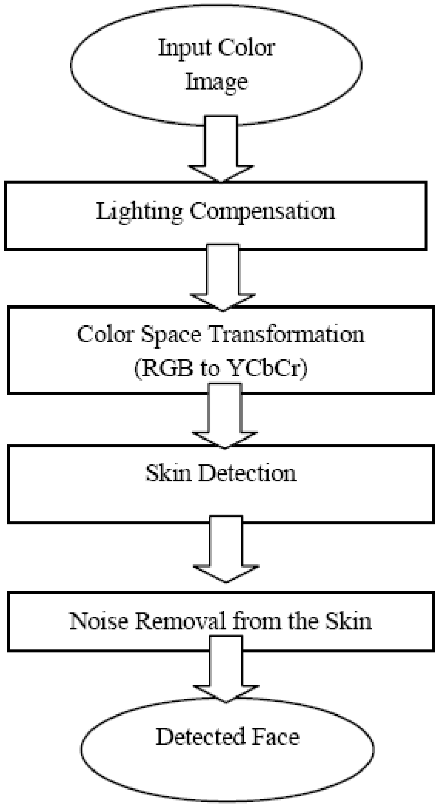


**Fig: 2 Face detection algorithms for localization of face candidate.**

## AdaBoost:

Boosting is a method to combine a collection of weak classification functions (weak learner) to form a stronger classifier. AdaBoost is an adaptive algorithm to boost a sequence of classifiers, in that the weights are updated dynamically according to the errors in previous learning. AdaBoost is a kind of large margin classifiers. Tieu and Viola adapted the AdaBoost algorithm for natural image retrieval. They made the weak learner work in a single feature each time. So after Trounds of boosting, Features are selected together with the weak classifiers. If Tieu and Viola's version can get comparable results with the original Freund and Schapire's AdaBoost, it will be a better choice for face recognition because of the reduced computation of Tcomparisons instead of T_Din the original AdaBoost.

## GENDER RECOGNITION USING ARTIFICIALNEURAL NETWORKS:

Gender classification is an important task which in turn can enhance the performance of a wide range of applications including identity authentication, human-computer interaction, access control, and surveillance, involving frontal facial images. A large majority of gender classification approaches are based on extracting features from face images and then giving these features to a binary classifier. The feature extraction phase has been carried out by using either (a) appearance based methods or (b) geometric methods. In appearance based methods, the whole image is considered rather than the local features corresponding to different parts of the face. While, in geometric based methods, the geometric features like distance between eyes, face length and width, etc., are considered. For classification purposes, mostly neural networks, nearest neighbor method, linear discreminant analysis, and other binary classifiers are used. Automatic acquisition of attributes characterizing the person interacting with a computer makes it possible to conduct the dialog in the way that is best suited to predicted needs of the user. One of key features of (initially anonymous) interacting user is her/his gender. Automatic gender recognition can be considered as a method from the domain of biometry. In medical applications it is the source of important information of the interacting patient, especially in voice-controlled network applications, where e.g. emotional state of the patient may be important feature necessary to more precisely diagnose the patient or provide necessary aid. As pointed out in , detection of emotional state can be in turn aided by the knowledge about patient gender.

## GENDER CLASSIFIER:

Once the face is located and segmented into a face image, the next process is to determine the gender of the face. To perform this task, we apply the same network structure, except that no local averaging operation is applied to the feature maps of the last hidden layer, i.e. all the neurons in the feature maps of the second layer are fully connected to the output neuron. To extract and learn the features that differentiate between a male and a female, the network is trained on segmented male and female face images; see Fig. 4 for some sample images. The training of the network is based on a set of 11,000 face patterns including the mirror image versions, and the aforementioned training algorithm is used to train the network. The desired responses for male and female face images are set to 1 and −1, respectively. A detected face is passed to the gender classifier where both the face image and its mirror version are processed by the trained gender classifier. The average of both network responses is taken as the gender score of the face image, which is compared to a threshold *Tgd*; if the score is greater than *Tgd*, the face is considered a male, otherwise it is a female. In certain cases, the face detector does not detect the exact size of the face. Therefore, the face image is evaluated at seven scales of its detected size, ranging from 0.7 to 1.3; a majority voting scheme is applied on the set of scores to verify the gender of the face image.

## Steps involved in the proposed system:

Let X = f($x_1$, $x_2$…….., $x_n$) be a random vector with observations $x_i$.

1. Compute the mean M

M =1/n SIGMA i=1 to n $x_i$ (1)

2. Compute the the Covariance Matrix S

S =1/n SIGMA i=1 to n ($x_i$ - M) ($x_i$ - M)^T (2)

3. Compute the eigenvalues $PIE_i$ and eigenvectors vi of S

$Sv_i$ = $PIE_i v_i$ , where i = 1, 2, ………, n (3)

4. Order the eigenvectors descending by their eigenvalue. The k principal components are the eigenvectors corresponding to the k largest eigenvalues. The k principal components of the observed vector x are then given by:

y = W^T (x - M) (4)

where W = ($v_1$,$v_2$, ……, $v_k$). The reconstruction from the PCA basis is given by:

x = Wy + M (5)

The Eigenfaces method then performs face recognition by:

1. Projecting all training samples into the PCA subspace.
2. Projecting the query image into the PCA subspace.
3. Finding the nearest neighbor between the projected training images and the projected query image.

Still there's one problem left to solve. Imagine we are given 400 images sized 100 * 100 pixel. The Principal Component Analysis solves the covariance matrix S = XX^T , where size(X) = 10000 * 400 in our example. You would end up with a 10000 * 10000 matrix, roughly 0.8GB. Solving this problem isn't feasible, so we'll need to apply a trick. From your linear algebra lessons you know that a M * N matrix with M > N can only have N - 1 non-zero eigen values. So it's possible to take the eigen value decomposition S = X^T X of size N x N instead:

X^T $Xv_i$ = PIEivi (6)

and get the original eigenvectors of S = XXT with a left multiplication of the data matrix:

XX^T ($Xv_i$) = $PIE_i$($Xv_i$) (7)

The resulting eigenvectors are orthogonal, to get orthonormal eigenvectors they need to be normalized to unit length.

## Feature Extraction:

In machine learning problem, feature selection also known as variable selection, is the technique of selecting a subset of relevant features for building strong learning models. For the selection of facial features for our gender classification problem, Gabor filters is well suited. A 2D form of Gabor wavelet consists of a planer sinusoid multiplied by a two dimensional Gaussian. 2D Gabor wavelet highlights and extracts local features from an image, and it has the tolerance of changes in location, shape, scale and light.

Here is the formula of Gabor wavelet in space domain:

$g(x)= 12\pi\sigma x\sigma y\ exp\ -12\ x2\sigma x2+y2\sigma y2\ +j2\pi\omega x$ (8)

The formula in frequency domain is defined as follows:

$(u,v)=exp\ -12\ u-\omega\ 2\sigma u2+v2\sigma u2$ (9)

The Gabor wavelet transform adopted in our system is:

$F\ x, =ascale-scaleindexg\ x',' $ (10)

$x'= x\ cos\theta+y\ sin\theta$ (11)

$y'= -x\ sin\theta+y\ cos\theta$ (12)

Where $(x)$represents a pixel in the image, *scale* is a parameter of spatial frequency, $\theta$ is an orientation angle.

$\theta=n\pi k$ where k=(0,1……,$k$−1) (13)

Where, k is the number of orientations. This wavelet can be used at 8 orientations ( n=0,… ... 7 ) and 5 spatial frequencies ( scale=1,… …,5 ).

After applying Gabor filter, an image is converted into 40 images with different scales and orientations. The operation is very complex and slow in spatial domain, so we use FFT in frequency domain and then IFFT to obtain the output in spatial domain.

## AdaBoost and SVM with PCA:

In this paper, we employ RBFSVM as component classifier in AdaBoost . RBF is one of the popular kernels used in SVM classification problem, which has a parameter known as Gaussian width, $\sigma$. Here, RBFSVM is used as component classifier in AdaBoost with relatively large value of $\sigma$, which corresponds to a RBFSVM with relatively weak learning ability. To update the weights of training samples, re-weighting technique is used.

Consider a set of training samples $x_1$ ,1 ……, $x_n,y_n$

Initial value of $\sigma$ is set to $\sigma ini$, minimal value of $\sigma$ is set to $\sigma min$ and each step is set to $\sigma stp$.

The weights of training samples are initialized as:

$wi1=1n$, for all $i$=1,…,n (14)

Initially, a large value is set to $\sigma$. Then we train a RBFSVM component classifier, h$t$, on the weighted training set.

Training error of h$t$,

h$t$= $wit$,≠ht $xi$ $ni$=1 (15)

RBFSVM with this $\sigma$ is trained as many cycles until error becomes less than 50%. Otherwise decrease the value of $\sigma$, by $\sigma stp$, to increase the learning ability.

For $t$=1 …n

Set the weight of component classifier h$t$,

$\alpha t=12\ ln\ 1-\varepsilon t\varepsilon t$ (16)

To, update the weights of training samples,

$wit+1=witexp\ -\alpha tyi$ht $xi$ $Ct$ (17)

Where, $Ct$ is normalization constant.

This process continues until $\sigma$ is decreased to the given minimal value. Final classifier is the linear combination of a series of weak classifiers.

$(x)=sign\ \alpha t$ht $x\ Tt$=1 (18)

## Applications:

The proposed system has several applications. some of them are:

- **Crime prevention:** Image recognition systems are used by police forces to find the criminals involved in a particular case.
- **Foreseenic Department:** It is used to recognize a person who has been missed several years before.
- **Intellectual Property:** Trademark image registration, where a new candidate mark is compared with existing marks to ensure no risk of confusing property ownership.

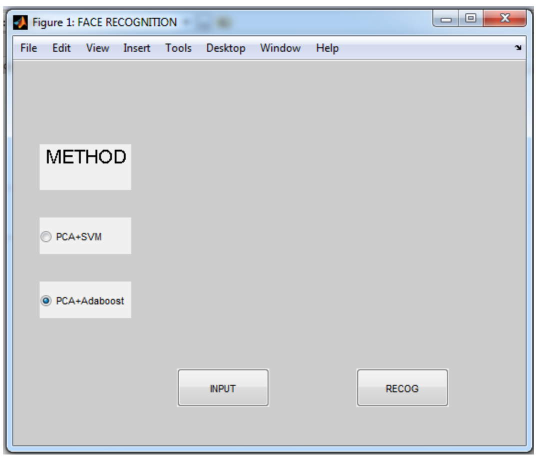


Fig:3 The dialog box shows the face recognition with Adaboost and SVM

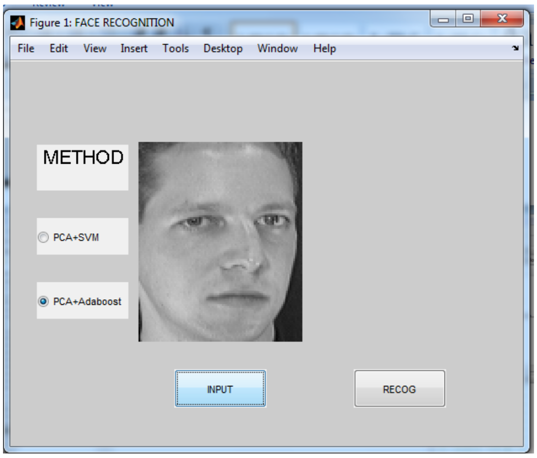


Fig 4: The input will be given with any angle of a face

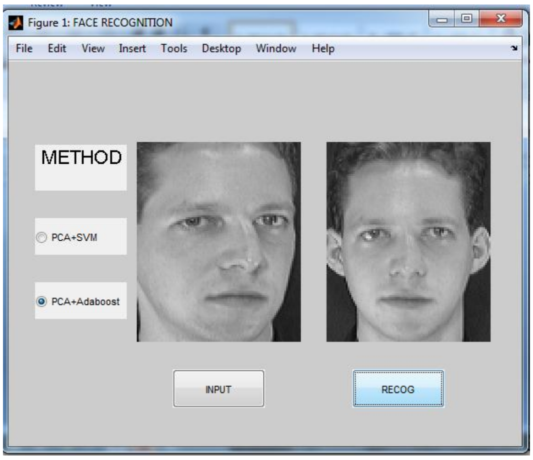


Fig 5:The output of a recognized face

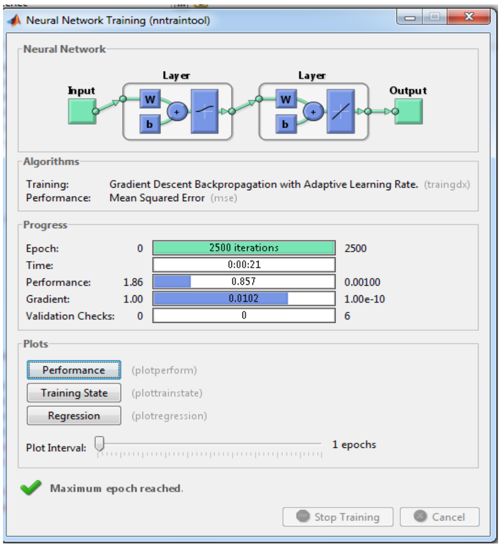


Fig 6: Neural Network schema for training set

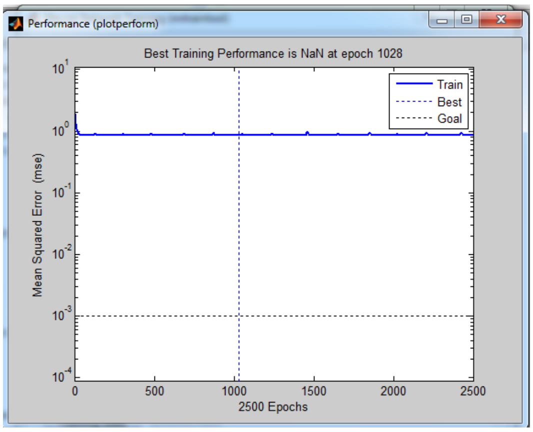


Fig 7: Performance chart of a training Set

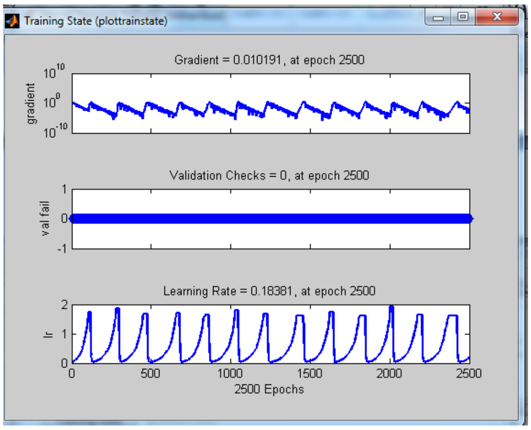


Fig 8: Color and Gradient of images

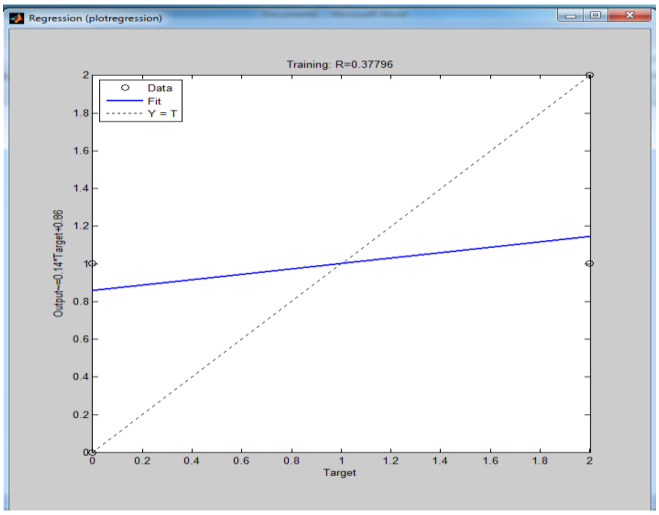


Fig 9: Excepted result and the output

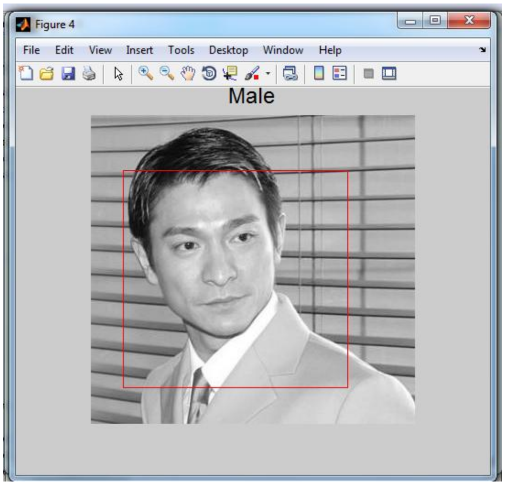


Fig 10: Output of Gender Identification

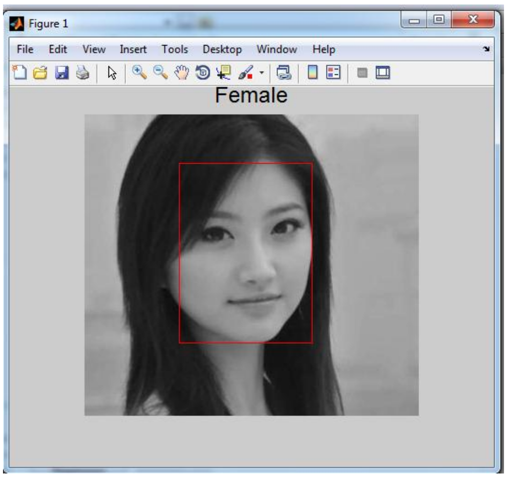


Fig 10: Output of Gender Identification

## Performance of the Gender Recognition System:

In this experiment, the gender recognition system is tested on digital images collected from the Web and BioID database. Here, the ability of the system to automatically detect and recognize the gender of the face is tested. A set of 502 images collected from the Web, the gender recognition system detects 485 faces (115 males and 370 females) and achieves recognition rates of 80.9% for male and 84.6% for female. On the BioID database with 968 male and 543 female faces detected, the recognition rates for male and female are 89.2% and 81.4%, respectively. These experiments demonstrate that the proposed gender classification system, based on a unified framework of convolution neural networks, can perform face detection and gender recognition.

## Conclusion:

In this paper, an attempt has been made to identify face and gender from the color image. Experimental results indicate the superiority of this work than other related works in terms of the numbers of face parts, databases and classifiers employed. We have evaluated the relevance of face parts in gender recognition, and considered its potential usefulness in classification under partial occlusions. Detection of human faces is the first step in our proposed system. It is also the initial step in other applications such as video surveillance, design of human computer interface, face recognition, and face database management. We have proposed a face detection method for color images in the presence of various lighting conditions as well as complex backgrounds. We also presented AdaBoost with properly designed SVM-based component classifiers which is achieved by adaptively adjusting the kernel parameter to get a set of effective RBFSVM component classifiers. Experimental results show that proposed AdaBoost, SVM performs better than other approaches of using component classifiers such as Neural Networks.

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