ADVANCED ALGORITHM FOR GENDER PREDICTION WITH IMAGE QUALITY ASSESSMENT

*ANUSREE BHASKAR
*Sarabhai Institute of Science and Technology, CUSAT, Vellanad, Kerala, India
anusreebhaskar@yahoo.com

***Abstract*-----Forged biometric systems are a crucial obstacle in the field of biometrics. Fake biometric identifiers can be of the form where one person imitates as another by falsifying data and thereby gaining an illegitimate advantage. This can be achieved either by using fake self manufactured synthetic or reconstructed samples. Gender classification has become an essential part in most human computer interactions especially in high security areas where gender restrictions are provided. In this paper, software based multi-biometric system that is used to classify real and fake face samples and a gender classification are presented. The main objective of the paper is to improve biometric detection in a fast, non intrusive way which maintains the generality that is lacking in other anti-spoofing methods. The proposed method incorporates liveness detection, extracts 30 general image quality measures from the input image and then classifies the input into real or fake sample. Algorithm for Gender classification is developed in accordance with the facial features. There features are classified into two i) appearance based ii) Geometric based. The image quality assessment algorithm is developed and tested with ATVS database. The gender classification with image quality assessment is developed and tested with medical students database.**

***KeyWords*---Image Quality measures, Liveness Detection, QDA, Gender classification, Geometric features.**

I.INTRODUCTION

The field of biometrics is evolving with new and advanced secured technologies day by day. This is the main reason for many fraudulent activities in biometric systems. The term biometrics is connected to the physiological and behavioral traits of human being. Physiological characteristics are mainly related to the shape of the body (fingerprint, face, iris etc.). The behavioral traits are related to the behavior of a person (gait, typing rhythm, handwriting etc).

In the past few decades many researches and experiments have been performed to analyze the exposure of biometric systems to various spoofing attacks. Though biometric identifiers are unique to individuals and reliable, nowadays identifiers are copied and used to create some artifacts that are deceiving the biometric devices. Among the different types of attacks the most important one is where the invader uses some type of synthetically produced artifact (e.g. gummy finger, printed iris image or face mask) or tries to mimic the behavior of the real user (e.g. gait, signature, voice) to fraudulently access the biometric system.[1]

Various researches have now been focused to detect the fake samples and reject them, thus increasing the efficiency and reliability of systems [2]. The most important thing to be noticed at the time of identification is to know whether the person to be identified is actually present at the time of acquisition. This has led to the special attention in the study of liveness detection. Liveness detection techniques use the different physiological properties such as skin perspiration, heartbeat, skin elasticity properties etc. Liveness detection has to satisfy certain important conditions which present a lot challenging difficulties [3].The main principle behind liveness detection is that supplementary information can be earned above and beyond the data acquired by a standard verification system, and this supplementary data can be used to verify if a biometric measure is genuine.

Liveness detection is of two types: 1) Hardware Based:- This technique affix a particular device to the sensor to detect the traits of a live person such as heartbeat, fingerprint sweat, reflection of eye etc. 2) Software Based:- This technique does not provide any specific device, it just tracks the fake biometric identifier which is injected into the communication channel by extracting the features from the input sample.

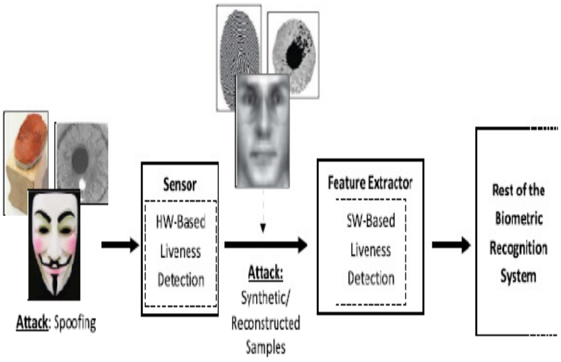

Fig 1. Different categories of liveness detection methods.

Gender is a range of characteristics related to and distinguishing between muscularity and femininity. The basic meaning of gender classification is the hereditary technique that is used to identify a person as male or female. Gender recognition is definitely a difficult process for computers. The present work mainly focuses on fraudulent attacks on face and then a gender classification on the input that is identified as real is done. [4]. Face extraction is considered to be a key requirement in many applications such as biometrics, Facial recognition systems, video surveillance, Human computer interface etc. Therefore, reliable face detection is required for success of these applications.

The task of human facial extraction is not an easy task. Human face varies from person to person. The race, gender, age and other physical characteristics of individual have to be considered thereby creating a challenge in computer vision. Facial feature detection aims to detect and extract specific features such as eyes, nose and mouth. It is hard to compare male to female faces simply because each face is unique, but there are some features in the face that can make a male portrait look more masculine or a female portrait look more feminine.

II.PROPOSED WORK

The work mainly focuses on i) the security of the face recognition biometric system ii) a gender recognition system as an extension to biometric system. Precisely saying, the proposed work mainly concentrates on finding out the fraudulent access of face images by calculating the image quality measures and identifying the real sample as male or female by considering the geometric and appearance features from the facial images.

The degree of sharpness, color and luminance levels, local artifacts, entropy, structural distortions or natural appearance are the various expected quality differences between real and fake samples [1]. To quote an example, images of face taken from a mobile phone will be under or over exposed. In addition to this, a synthetically produced image that is directly given to the communication channel will differ in some properties that are found in natural images.

Fig 2. The left face appears male, while the right face appears female, yet both images were produced by making slight alterations of the same original image

An additional advantage is its speed and very low complexity that makes it suitable to work on real scenarios. The proposed work consists of mainly two parts: First part consists of calculating image quality features from the input face image and then classifying the input sample to real or fake using a simple classifier. Second part consists of classifying the real face sample to male or female using the geometric features of face.

Detailed explanation on image quality assessment is given in Section III. Detailed explanation on Gender classification is given in Section IV. Section V deals with the Results and discussions. Section VI deals with conclusion. The various quality measures used present different sensitivity to image distortions and noise. For example, mean squared error is more sensitive to additive noise, spectral phase error respond more to blur; whereas gradient based features respond to noise around the edges and textures. Hence exploiting a vivid range of measures allows finding the quality differences between real and fake samples found in many attack attempts.

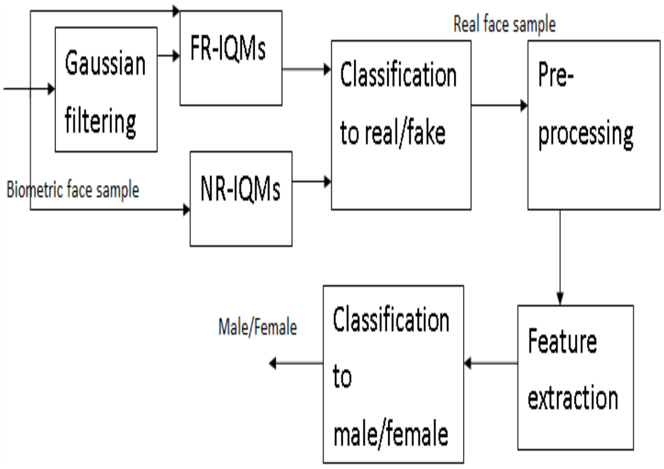

Fig 3. Block Diagram of the work

III. IMAGE QUALITY ASSESSMENT

Fig.3 shows the proposed system which enhances the protection of biometric systems [5]. Here, the protection is initiated by adding a software based liveness detection and finally classifying into male or female.

A. *Gaussian Filtering*

The input face image is first Gaussian filtered to get a smoothed version of the input. A Gaussian low pass filter of size 3x3 and $\sigma = 0.5$ is used.

B. *FR-IQA*

FR-IQA stands for Full Reference Image Quality Assessment. As the name implies it needs a reference image for calculating the image qualities. The quality between the input (I) and the smoothed image (Ī) is calculated.[5] The various FR-IQMs considered are MSE, PSNR, SC, SNR, MD, AD, RAMD, NAE, LMSE, PRNSD, NXC, MAS, MAMS, RM, TED, TCD, SME, SPE, GME, GPE, SSIM, MS-SSIM, VIF, VSNR and RRED.

$$\mathrm{MSE}(\mathrm{I},\bar{\mathrm{I}})=\frac{1}{NM}\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}(Ii,j-\bar{I}i,j)^2 \quad (1)$$

$$\mathrm{PSNR}(\mathrm{I},\bar{\mathrm{I}})=10\log\left(\frac{\max(\mathrm{I}^2)}{\mathrm{MSE}(\mathrm{I},\bar{\mathrm{I}})}\right) \quad (2)$$

$$\mathrm{SC}\ (\mathrm{I},\bar{\mathrm{I}})=\frac{\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}(\mathrm{Ii,j})^2}{\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}(\bar{I}i,j)^2} \quad (3)$$

$$\mathrm{SNR}(\mathrm{I},\bar{\mathrm{I}})=10\log\left(\frac{\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}(\mathrm{Ii,j})^2}{\mathrm{N.M.MSE}(\mathrm{I},\bar{\mathrm{I}})}\right) \quad (4)$$

$$\mathrm{MD}(\mathrm{I},\bar{\mathrm{I}})=\max\ |Ii,j-\bar{I}i,j| \quad (5)$$

$$\mathrm{AD}(\mathrm{I},\bar{\mathrm{I}})=\frac{1}{NM}\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}(Ii,j-\hat{I}i,j) \quad (6)$$

$$\mathrm{RAMD}(\mathrm{I},\bar{\mathrm{I}},\mathrm{R})=\frac{1}{R}\sum_{r=1}^{R}\max_{\mathrm{r}}\ |Ii,j-\bar{I}i,j| \quad (7)$$

$$\mathrm{NAE}(\mathrm{I},\bar{\mathrm{I}})=\frac{\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}|\mathrm{Ii,j}-\bar{\mathrm{I}}i,j|}{\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}|\bar{I}i,j|} \quad (8)$$

$$\mathrm{LMSE}((\mathrm{I},\bar{\mathrm{I}})=\frac{\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}(\mathrm{h(Ii,j)}-\mathrm{h}(\hat{\bar{\mathrm{I}}}i,j))^2}{\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}\mathrm{h(Ii,j)}^2} \quad (9)$$

$$\mathrm{PRNSD}((\mathrm{I},\bar{\mathrm{I}})=\frac{\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}\mathrm{sd(Ii,j)}-\mathrm{sd}(\bar{\mathrm{I}}i,j)}{\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}sd\mathrm{(Ii,j)}} \quad (10)$$

In RAMD, R=10 and $\max_r$ represents the highest pixel difference between the two images I and Ī.

In LMSE, h(I)= $I_{i+1,j}+I_{i-1,j}+I_{i,j+1}+I_{i,j-1}-4I_{i,j}$

In PRNSD, sd represents standard deviation.

$$\mathrm{NXC}(\mathrm{I},\bar{\mathrm{I}})=\frac{\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}(\mathrm{Ii,j}\ .\ \bar{\mathrm{I}}i,j)}{\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}(\mathrm{Ii,j})^2} \quad (11)$$

$$\mathrm{MAS}(\mathrm{I},\bar{\mathrm{I}})=1-\frac{1}{NM}\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}(\alpha_{i,j}) \quad (12)$$

$$\mathrm{MAMS}(\mathrm{I},\bar{\mathrm{I}})=\frac{1}{NM}\sum_{1=1}^{N}\cdot\sum_{j=1}^{M}\left(1-[1-\alpha_{i,j}][1-\frac{\mathrm{Ii,j}-\bar{\mathrm{I}}\mathrm{i,j}}{255}]\right) \quad (13)$$

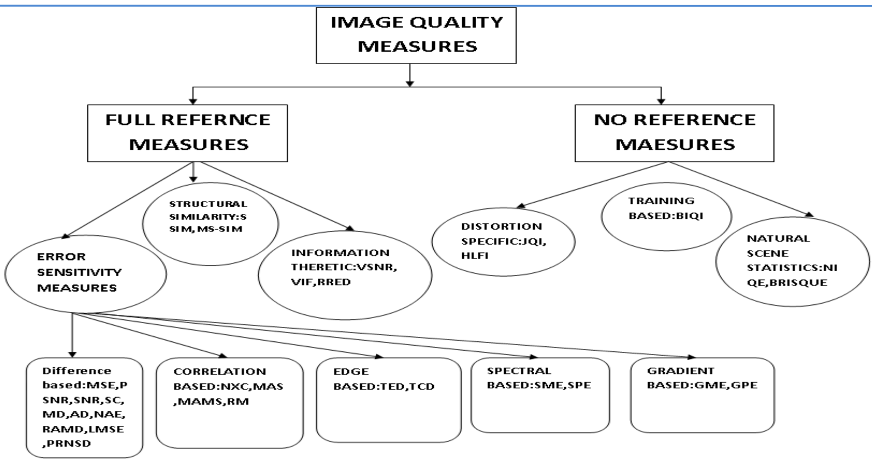

Fig 4. Classification of 30 Image Quality Measures.

In MAS and MAMS, α represents the angle between vectors.

$$RM(I,\bar{I})=\frac{\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}\mu 2}{\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}\mu 1} \qquad (14)$$

Where $\mu 1$ and $\mu 2$ are the mean of original and distorted image

$$TED(I,\bar{I})=\frac{1}{NM}\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}|I_E i,j-\bar{I}_E i,j| \qquad (15)$$

$$TCD(I,\bar{I})=\sum^{N}_{i=1}\sum^{M}_{j=1}\frac{|Ncr-\overline{Ncr}\ |}{\max\,(Ncr-\overline{Ncr}\ )} \qquad (16)$$

In TED, I_E represents the edge maps of input image which is calculated using sobel operator. In TCD, Ncr represents the number of corners which is calculated using harris-corner detector.

$$SME(I,\bar{I})=\frac{1}{NM}\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}(|Fi,j|-|\bar{F}\,i,j|)^2 \qquad (17)$$

$$SPE(I,\bar{I})=\frac{1}{NM}\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}|\arg\,(Fi,j)-\overline{\arg(\bar{F}}\,i,j)|^2 \qquad (18)$$

In SME and SPE, F(I) represents the fourier transform of the input image.

$$GME(I,\bar{I})=\frac{1}{NM}\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}(|Gi,j|-|\bar{G}\,i,j|)^2 \qquad (19)$$

$$GPE(I,\bar{I})=\frac{1}{NM}\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}|\arg\,(Gi,j)-\overline{\arg(\bar{G}}\,i,j)|^2 \qquad (20)$$

In GME and GPE, G(I) represents the gradient maps of input image.

SSIM represents Structural Similarity Index Measure. Images in the natural scenario are highly structural and therefore their pixels have strong dependencies with the adjacent pixels [6]. These dependencies contain significant informations about the structure of images in the natural scene. A measure in change of structural information provide a good approximation to perceived image distortions.

MS-SSIM represents Multi Scale SSIM. The perceivability of image details depends the sampling density of the image signal, the distance from the image plane to the observer, and the perceptual capability of the observer's visual system. In practice, the subjective evaluation of a given image varies when these factors vary. Multi-scale method is a convenient way to incorporate image details at different resolutions.

VIF refers to Visual Information Fidelity. It is the ratio of the mutual information between the input and the output of the HVS channel when no distortion channel is present (i.e., reference image information) and the mutual information between the input of the distortion channel and the output of the HVS channel for the test image [1].

VSNR refers to visual signal to noise ratio. It is used for quantifying the visual fidelity of distorted images based on recent psychophysical findings reported by the authors involving both near-threshold and supra-threshold distortions. The proposed metric operates by using both low-level and mid-level properties of human vision. Low-level HVS properties of contrast sensitivity and visual masking are first used to determine if the distortions are below the threshold of visual detection. If the distortions are supra-threshold, the low-level HVS property of perceived contrast and the mid-level HVS property of global precedence (i.e.,the visual system's preference for integrating edges in a fine-to-coarse-scale fashion.

RRED refers to Reduced Reference Entropic Difference.It computes the average difference between scaled local entropies of wavelet coefficients of reference and projected distorted images in a distributed fashion.

C. NR-IQA

No Reference Image Quality Assessment does not require a reference image for quality computations [7]. The various NR measure considered are JQI, HLFI, BIQI, NIQE.

$$\mathrm{HLFI(I)}=\frac{\sum_{i=1}^{il}\cdot\sum_{j=1}^{jl}|Fi,j|-\sum_{i=ih+1}^{N}\cdot\sum_{j=jh+1}^{M}|Fi,j|}{\sum_{i=1}^{N}\cdot\sum_{j=1}^{M}|Fi,j|} \quad (18)$$

Here , i_l=i_h=0.15N and j_l=j_h=0.15M

JQI represents JPEG Quality Index.It computes the quality in images affected by the usual block artifacts found in many compression algorithms running at low bit rates such as the JPEG.

In Blind Image Quality Index (BIQI), the model is trained according to images affected by different types of distortions and then one final quality score is evaluated.

NIQE represents Natural Image Quality Evaluator which is a completely blind image quality analyzer based on the construction of a quality aware collection of statistical features (derived from a corpus of natural undistorted images) related to a multivariate Gaussian natural scene statistical model.

BRISQUE refers to blind/ referenceless image spatial quality evaluator. It does not compute distortion-specific features, such as ringing, blur, or blocking, but instead uses scene statistics of locally normalized luminance coefficients to quantify possible losses of "naturalness" in the image due to the presence of distortions, thereby leading to a holistic measure of quality. The underlying features used derive from the empirical distribution of locally normalized luminances and products of locally normalized luminances under a spatial natural scene statistic model. No transformation to another coordinate frame (DCT, wavelet, etc.) is required, distinguishing it from prior NR IQA approaches [13].

D. Classification to real/fake

The classifier that is used for classification is Quadratic Discriminant Analyzer. Suppose there are only two groups, y ε {0,1}, and the means of each class are defined to be $\mu_{y=0}$,$\mu_{y=1}$ and the covariances are defined as $\sum_{y=0}$. ,$\sum_{y=1}$. Then the likelihood ratio will be given by

$$\textbf{Ratio}=\left(\frac{\sqrt{2\pi\,|\sum_{y=1}\cdot|)}^{-1}\exp(-\frac{1}{2}(x-\mu_{y=1})^{T}(\sum_{y=1}\cdot)^{-1}(x-\mu_{y=1}}{\sqrt{2\pi\,|\sum_{y=0}\cdot|)}^{-1}\exp(-\frac{1}{2}(x-\mu_{y=0})^{T}(\sum_{y=1}\cdot)^{-1}(x-\mu_{y=0}}\right)) \quad (21)$$

for some threshold t. After some rearrangement, it can be shown that the resulting separating surface between the classes is a quadratic [8]. The sample estimates of the mean vector and variance-covariance matrices will substitute the population quantities in this formula. ∑ is the covariance matrix

IV. GENDER CLASSIFICATION

A. Pre-Processing

The real face image classified in the previous step is then subjected to pre-processing. The main steps in pre-processing are noise reduction and edge detection. Noise removal is done using processes like adaptive filtering, nonlinear, linear filters etc. [4]. Here, median filters are used since they are good at preserving image details. Edge detection is primarily used for finding the boundary features in an image. Canny edge detector is used for extracting the edges.

B. Feature Extraction

i) Geometric based feature:- In this mainly the eyes, nose, mouth and the face is identified first. This is mainly done by distinguishing each by their shapes. The main differences in geometric structures of male and female are given below. Generally, men have longer and larger faces than women. The female portrait has rounded curves wherever appropriate, to soften her features. The cranium is rounded, as are the cheeks and the neck line is curved rather than straightened [11].

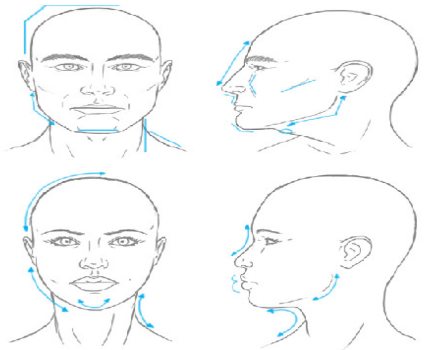

Fig 5.Differences in shape of face for male and female

Female eyes have long lashes that curl outwards and are oval in shape which makes the eyes bigger. Males have shorter eyelashes and have rectangular shape. For females, the depth of the bridge and ridge of the nose is minimum.

- Inter-ocular distance: The distance between the midpoint of right eye and midpoint of left eye in the face image.
- Lips to Nose: The distance between nose tip and the midpoint of the lips pixel in the facial image.
- Nose to Eyes: The distance between Nose tips to inter-ocular distance in the facial image.
- Lips to Eyes: The distance between lips midpoint to inter-ocular in the facial image.

The ratios that are considered are:

$$\text{Ratio1}=\frac{\text{left to right eye distance}}{\text{eye to nose distance}} \qquad (22)$$

$$\text{Ratio2}=\frac{\text{eye to nose distance}}{\text{eye to chin distance}} \qquad (23)$$

$$\text{Ratio3}=\frac{\text{left to right eye distance}}{\text{eye to chin distance}} \qquad (24)$$

$$\text{Ratio4}=\frac{\text{eye to nose distance}}{\text{eye to lip distance}} \qquad (25)$$

$$\text{Ratio5}=\frac{\text{verical face distance}}{\text{horizontal face distance}} \qquad (26)$$

ii) Appearance Based feature:- Female skin is generally lighter than male skin [12]. But, female eyes and lips are not lighter than male eyes and lips, there should be greater luminance contrast surrounding female eyes and lips than male eyes and lips. The brightness and contrast near the eyes, nose, mouth and whole face is found out. It is proved that brightness and contrast levels vary for females and males [13].

C. Gender Prediction

The final aim after extracting all the facial features is to find whether the features represent male or female. The ratios are calculated and threshold is found [4]. The ratios considered are shown below. Based on those four ratios threshold values final classification to male or female is done. The threshold values for female are ratio1>= 1.1000 && ratio2>=0.7450, ratio3<=1.3714 && ratio4>= 0.6404, for male, ratio1<=1.09 && ratio2<=0.7440 ratio3>=1.3714 && ratio4<=0.6400.

Based on the threshold values male and female are classified using quadratic discriminant analyzer.

V. RESULTS AND DISCUSSIONS

The databases considered are from ATVS and medical students face databases. The image quality measures are calculated on these images and threshold is calculated based on the ratios. The figure shows the face image segmented into eyes, nose and lip regions. Based on this segmentation, threshold value is calculated. For improving the accuracy of the classification to real or fake images, test has been conducted on iris and fingerprint images also. The iris and fingerprint databases are also taken from ATVS.

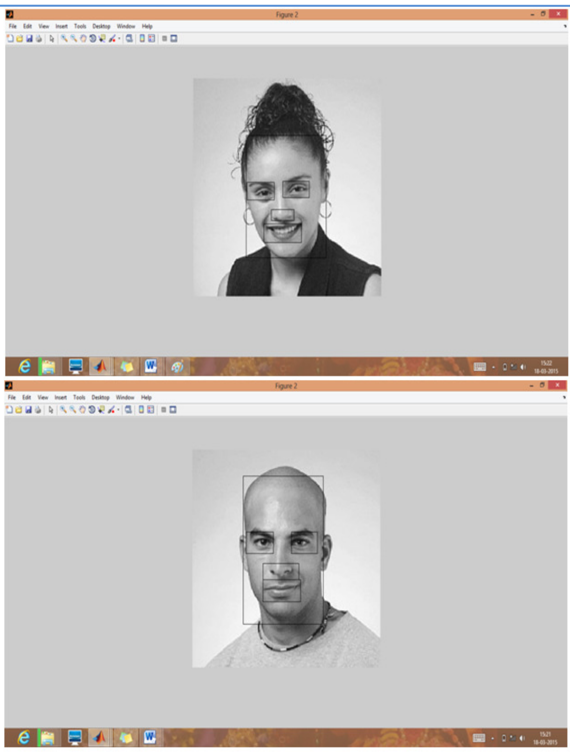

Fig 6.Face segmented for female and male

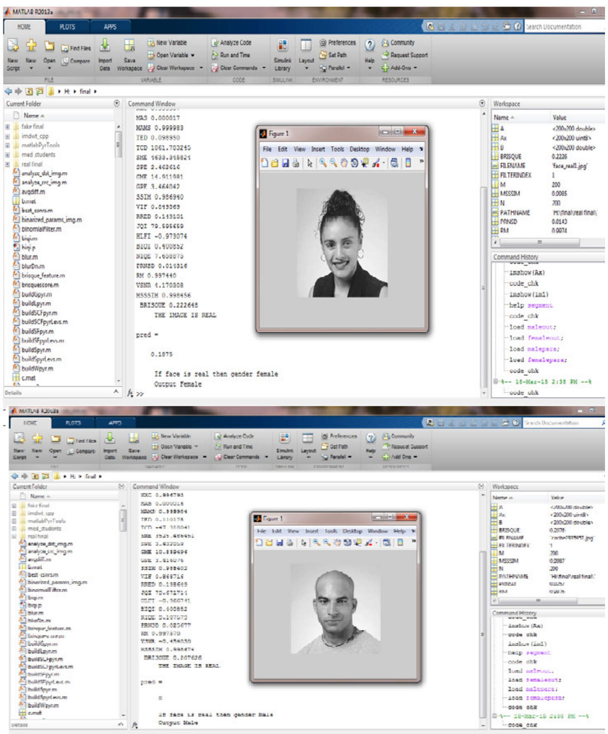

Fig 7.Final output

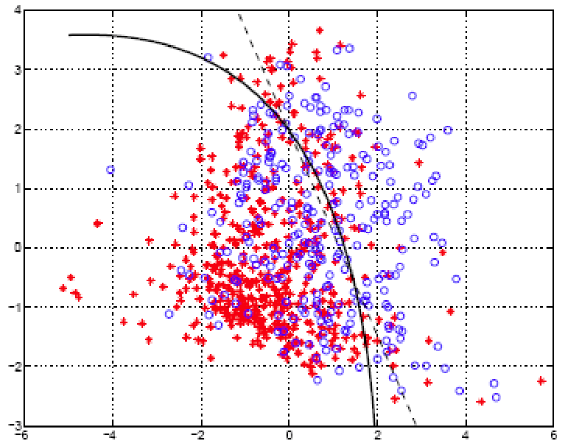

Fig. 8: Graph of QDA classifier

VI. CONCLUSION

The method uses 30 image quality measures to classify the face image to real and fake. Then an improved detection of gender has been carried out. Gender classification has been carried out by extracting the geometric based and appearance based features of facial images and effectively classifying into female or male images. The proposed method is able to consistently perform at a high level for different biometric traits ("multi-biometric"). The system is able to adapt to different types of attacks providing for all of them a high level of protection ("multi-attack"). The proposed method is able to generalize well to different databases, acquisition conditions and attack scenarios. Moreover an improved biometric detection is also provided by adding a gender classification to the system.

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