Image Quality Measures for Gender Classification

Anusree Bhaskar*, Aneesh R.P.**
*Sarabhai Institute of Science and Technology, CUSAT,Vellanad, Kerala, India
anusreebhaskar@yahoo.com
**Regional Centre IHRD, Thiruvananthapuram, India,
aneeshprakkulam@gmail.com

Abstract : - The major problem that we are facing in biometric systems is the use of fake biometric identifiers. 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 25 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.

Index Terms - *Biometric Systems, Image quality assessment, Liveness Detection, Gender Classification, Geometric features.*

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I. INTRODUCTION

Automatic authentication of people is a common technology that has become widespread in this era. This has led to the technology named Biometrics which is usually associated with the use of unique physiological or behavioral characteristics to identify an individual. Physiological characteristics are related to the shape of the body (DNA, palm print, iris recognition etc.) and behavioral characteristics are related to the pattern of behavior of a person (typing rhythm, voice, gait etc.). A number of biometric traits have been developed and are used to authenticate the person's identity. The idea is to use the special characteristics of a person to identify him. By using special characteristics we mean the using the features such as face, iris, fingerprint, signature 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.

(i) **(ii)**

Fig. 1.(i) Fraudulent attacks performed face (ii) 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

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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.

II. PROPOSED WORK

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 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 channelwill differ in some properties that are found in natural images.

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 is given in Section III. 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.

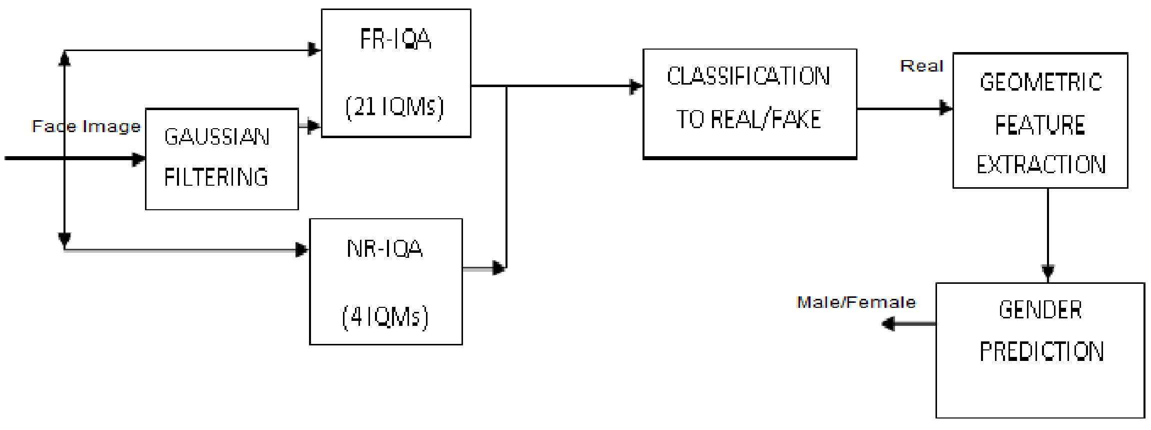

Fig 2. Block diagram of the proposed system

III. IMAGE QUALITY ASSESSMENT

Fig.2 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.

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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 ($\bar{I}$) is calculated.[5] The various FR-IQMs considered are MSE, PSNR, SC, SNR, MD, AD, RAMD, NAE, LMSE, NXC, MAS, MAMS, TED, TCD, SME, SPE, GME, GPE, SSIM, VIF and RRED.

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

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

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

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

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

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

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

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

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

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

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

$$NXC(I,\bar{I})=\frac{\sum_{i=1}^{N}.\sum_{j=1}^{M}(Ii,j.\bar{I}i,j)}{\sum_{i=1}^{N}.\sum_{j=1}^{M}(Ii,j)^2} \quad (10)$$

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

$$MAMS(I,\bar{I})=\frac{1}{NM}\sum_{i=1}^{N}.\sum_{j=1}^{M}\left(1-[1-(\alpha_{i,j})]\left[1-\frac{|Ii,j-\bar{I}i,j|}{255}\right]\right) \quad (11)$$

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

$$TED(I,\bar{I})=\frac{1}{NM}\sum_{i=1}^{N}.\sum_{j=1}^{M}|I_Ei,j-\bar{I}_Ei,j| \quad (12)$$

$$TCD(I,\bar{I})=\sum_{i=1}^{N}\sum_{j=1}^{M}\frac{|Ncr-\overline{Ncr}|}{\max(Ncr-\overline{Ncr})} \quad (13)$$

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.

$$SME(I,\bar{I})=\frac{1}{NM}\sum_{i=1}^{N}.\sum_{j=1}^{M}(|Fi,j|-|\bar{F}i,j|)^2 \quad (14)$$

$$SPE(I,\bar{I})=\frac{1}{NM}\sum_{i=1}^{N}.\sum_{j=1}^{M}|\arg(Fi,j)-\overline{\arg(F}i,j)|^2 \quad (15)$$

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

$$GME(I,\bar{I})=\frac{1}{NM}\sum_{i=1}^{N}.\sum_{j=1}^{M}(|Gi,j|-|\bar{G}i,j|)^2 \quad (16)$$

$$GPE(I,\bar{I})=\frac{1}{NM}\sum_{i=1}^{N}.\sum_{j=1}^{M}|\arg(Gi,j)-\overline{\arg(G}i,j)|^2 \quad (17)$$

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.

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].

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.

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

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.

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 $\Sigma_{y=0}$. ,$\Sigma_{y=1}$. Then the likelihood ratio will be given by

$$\textbf{Ratio}=\left(\frac{\sqrt{2\pi\,|\Sigma_{y=1}\cdot|)}^{-1}\exp(-\frac{1}{2}(x-\mu_{y=1})^{T}(\Sigma_{y=1}\cdot)^{-1}(x-\mu_{y=1}}{\sqrt{2\pi\,|\Sigma_{y=0}\cdot|)}^{-1}\exp(-\frac{1}{2}(x-\mu_{y=0})^{T}(\Sigma_{y=1}\cdot)^{-1}(x-\mu_{y=0}}\right)) < t \quad (19)$$

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.

Σ_k 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) Appearance based features*:** It uses the low level data of areas of the face images which depends on pixel values [9]. Various texture features, histogram of gradients, brightness and contrast are some of the appearance based features that are considered.

ii) Geometric based features:

- 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 geometric based features of face such as eyes, nose, mouth etc have to be segmented. For feature extraction, first divide the face image into four equal parts [10]. At each part, the centroid is calculated using the region properties. After finding centroids, calculate the distances between the centroids by using the distance formula. Then locate the eyes at upper right and left parts and then locate lips. For locating the chin and nose, add +45 and -30 to the centroid value of lips so that it can locate chin and nose respectively.

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 and for maleratio1<=1.09,ratio2<=0.7440,ratio3>=1.3714,ratio4<=0.6400.

IV. 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.

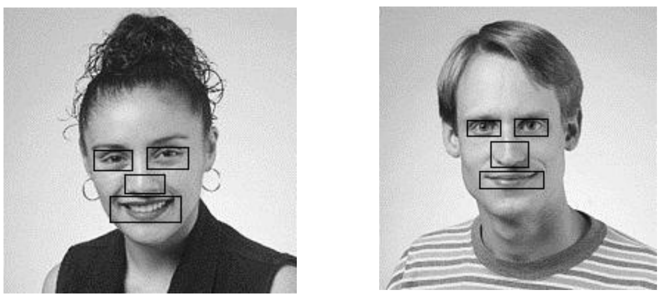

Fig. 3: Face segmentation

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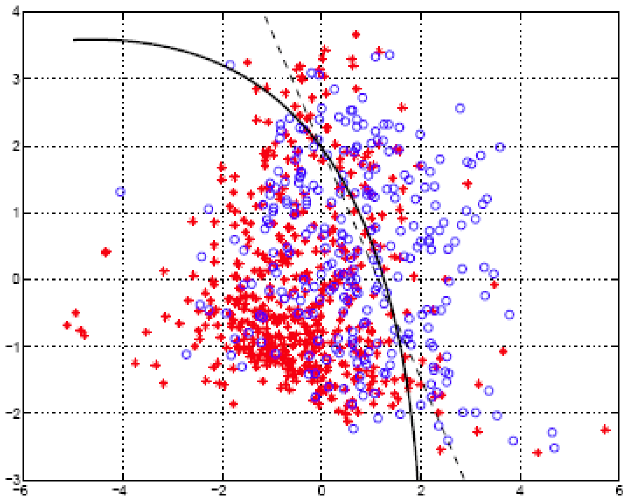

Fig. 4: Graph of QDA classifier

V. CONCLUSION& FUTURE SCOPE

The method uses 25 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.

REFERENCES

[1] Javier Galbally, SébastienMarcel,Member,IEEE, and Julian Fierrez, , "Image quality assessment for fake biometric detection" IEEE Trans. Image Process vol 23, Feb 2014
[2] J. Galbally, F. Alonso-Fernandez, J. Fierrez, and J. Ortega-Garcia,"A high performance fingerprint liveness detection method based onquality related features,"FutureGenerat. Comput. Syst., vol. 28, no. 1,pp. 311–321, 2012.
[3] G. L. Marcialis, A. Lewicke, B. Tan, P. Coli, D. Grimberg, A. Congiu, et al., "First international fingerprint liveness detection competition—LivDet 2009," in Proc. IAPR ICIAP, Springer LNCS-5716. 2009, pp. 12–23.
[4] SwathiKalam, GeethaGuttikonda,International Journal of Computer Applications (0975 – 8887) Volume 85–No 7, January 2014 "Gender Classification using Geometric Facial Features"
[5] Ahmet M. Eskicioglu and Paul S .Fisher, "Image Quality Measures and Their Performance", IEEE TRANSACTIONS ON COMMUNICATIONS, VOL. 43, NO. 12, DECEMBER 1995.
[6] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: From error visibility to structural similarity," IEEETrans. Image Process. vol. 13, no. 4, pp. 600–612, Apr. 2004.
[7] A. K. Moorthy and A. C. Bovik, "A two-step framework for constructing blind image quality indices," IEEE Signal Process. Lett., vol. 17, no. 5, pp. 513–516, May 2010.
[8] D. Maltoni, D. Maio, A. Jain, S. Prabhakar, Handbook of Fingerprint Recognition,Springer, 2003
[9] Zehang Sun, George Bebis, Xiaoping Yuan, and Sushi J. Louis, "Genetic Feature Subset Selection for Gender Classification": A Comparison Study, IEEE Workshop on Applications of Computer Vision, pp.165-170, 2002.
[10] B. Moghaddam and M.H. Yang, "Gender Classification with Support Vector Machines", Proc. Int'l Conf. Automatic Face and Gesture Recognition, pp. 306-311, Mar.2000.