



FAKE BIOMETRIC DETECTION USING IMAGE QUALITY ASSESSMENT

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Abstract:

Image Quality Assessment (IQA) is one of the statistical techniques used in image processing to determine whether the biometric sample is real or fake. The objective of the system is to enrich the biometric recognition security. This paper deals with two distinct measures of IQA. The first measure is Full-Reference (FR) IQA consists of a 2D image extracting different image quality features using a reference image which is filtered by a technique called Gaussian filtering. The second measure is No-Reference (NR) IQA used to estimate the quality level of an image. Eventually, 26 image quality features are extracted to minimize the degree of complexity. Quality of test sample implies to results of the following process of classification based on IQA. Presented paper briefly introduces the IQA theory and its measures. Results are documented for the selected real and fake pictures.

Index Terms— Image Quality Assessment (IQA), biometrics, security.

INTRODUCTION :

Nowadays, estimation of biometric systems security is getting higher so we directed on this major line of work study. Image processing technology was developed to integrate not only with preprocessing steps but also used for feature selection[2], template matching[1] and other applications such as surveillance and security camera systems, underwater research. Various publications make enquiries on assessing biometric liabilities the proposal of Liveness detection (LIVDET) [3], the estimation of blur and noise[4], the detection of high correlation[5], the suggestion of multi-biometrics[6], the recognition of face datasets[14], the evaluation of face anti-spoofing technique[11], the discovery of different distortion specific experts[10], the exposure of spoofing technique[12], the information of local or global approximation[9], the recognition of iris[8], the exposure of manipulating images[7], the acquaintance of signal power to the noise power[15], the introduction of pattern recognition[13]. For instance, the Windows XP and Vista laptops of Lenovo and Toshiba come with built-in webcams and embedded biometric systems that authenticate users by scanning their faces.

The whole inventiveness visibly focused the significance of rising in the biometrics system security leads to use practically in

an environment. Among the various threats examined, the *spoofing* attacks have inspired biometric similarity to study the liabilities against various types of fraud access in modalities such as the iris, the fingerprint, the face etc. In these attacks, the impostor uses synthetically manufactured article (e.g., face mask). Usually the digital protection mechanisms such as encryption, watermarking are not operative.

Liveness detection (LIVDET) is a technique to detect antispoofing approaches in multi-biometrics or challenge-response methods. Thus, the liveness detection method presented has the added advantage over previously studied techniques of needing for different modalities to decide whether it comes from a real or fake image. The advantages i) non-intrusive, specifically not harmful to the contact user; ii) easy to access; iii) speed,

results have to be produced in a small interval; iv) minimize cost ; v)enactment.. It limits long period of time to access an image.

Liveness detection methods are differentiated into two techniques: i) *Hardware-based*, some special device is added to the sensor in order to estimate specific properties such as blood pressure, reflection of eye etc..ii) *Software-based*, in which the fake modalities are detected once the sample has been acquired with a standard sensor. The two types of methods have some advantages and dis-advantages. So, combination of both approaches is used to enrich the security in biometric recognition.

In the proposed system we present a novel software based multi-biometric and multi-attack protection method which overcome part of the limitations through the use of image quality assessment (IQA). It is capable of functioning with a very high enactment under different biometric systems (multi-biometric) and also provides a very good level of protection against certain non-spoofing attacks (multi-attack).

Computer vision is in parallel to the study of biological vision, as a major effort in the biometric study. By using biometric recognition we can solve the problem of user authentication in identity management systems.

IMAGE QUALITY ASSESSMENT FOR LIVENESS DETECTION

Image Quality Assessment (IQA) is a technique used to extract image quality features and compare whether an image is real or fake. During the fraudulent attempts the fake image has various quality compared to real image. Image Quality Measures depends on several criteria i) Performance, ii) Complexity,

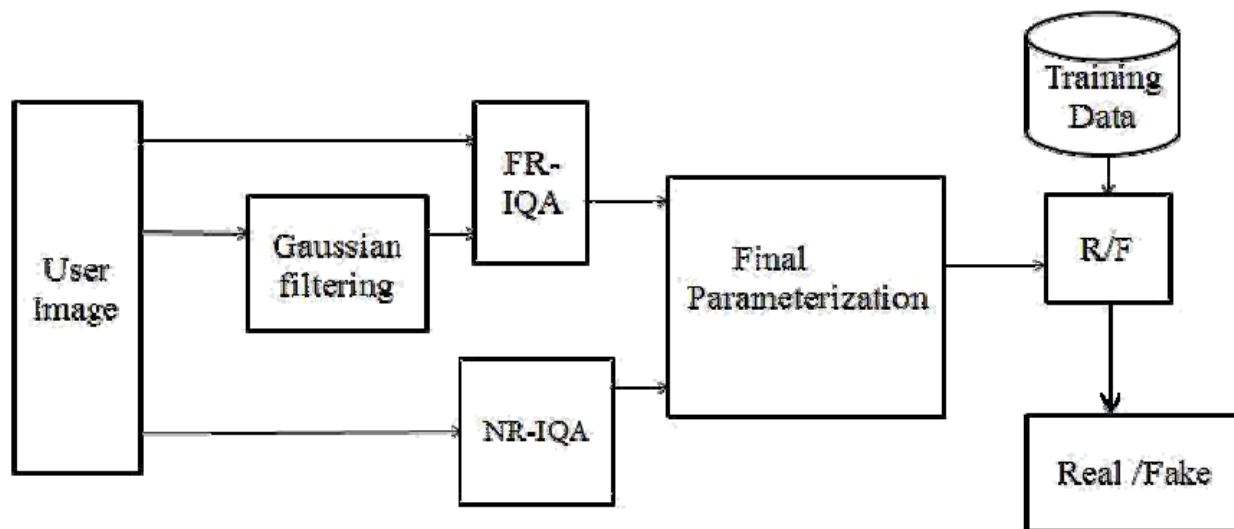


Fig 1. An architecture diagram of Image Quality Assessment to protect the biometric security system using a 2D image.

iii) Speed. Predictable quality feature differences degree of sharpness, level of luminance, blur, noise, gradient, covariance, high correlation, content of information extracted from both type of images will be different. For instance, when comparing real fingerprint image with printed fingerprint image, printed image gives a high blur density. Spoofing attacks will be determined based on estimating different image quality features.

FULL REFERENCE IQ MEASURES:

Full-reference (FR) IQA methods are used to estimate the quality of the test sample using a reference image. If reference image is unknown then the image quality will be different compared to a known image. Reference image implies that an image is filtered using Gaussian filtering technique. The input of an image is in grey scale with low pass Gaussian, size of a matrix is $N \times M$. To generate a soft version \hat{I} . Then both qualities are computed according to full-reference IQA measures.

Error Sensitivity Measures:

It is used to detect differences of signal between an original and reference image. Advantages are minimizing complexity, easy calculation.

Pixel Difference Measures:

2. Peak Signal to Noise Ratio (PSNR):

Peak signal-to-noise ratio short form is PSNR, is a business term for the ratio between the maximum power of a signal and the power of distorting noise that distress the fidelity of its demonstration. Because many signals have a very wide dynamic range, PSNR is normally articulated in lexes of the logarithmic

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

decibel scale. The equation is given by,

PSNR is most commonly used to measure the quality of reconstruction of lossy compression codecs . The signal in this case is the real data, and the noise is the fault introduced by compression.

Signal to Noise Ratio (SNR):

Signal-to-noise ratio (is expressed as SNR or S/N) is a measure used in science and business that contrast the desired signal level to the background noise level. It is stated as the ratio of signal power to the noise power, articulated in decibels. A ratio higher than 1:1 (greater than 0 dB) indicates more signal than noise. Electrical signal is a form of signal applied to SNR.

The SNR, the capacity of a channel communication and bandwidth channel are linked by the Shannon-Hartley theorem. Signal-to-noise ratio is rarely used to refer to the ratio of Mean Squared Error , Peak Signal to Noise Ratio, Signal to Noise Ratio , Structural Content, Maximum Difference , Average Difference, Normalized Absolute Error , R-Averaged Maximum Difference and Laplacian Mean Squared Error.

1. Mean Squared Error (MSE):

The mean squared error (MSE) of a measure is the average of the squares of the "errors", that is, the difference between the estimator and estimated value. The equation is given by,

$$MSE(I, \hat{I}) = \frac{1}{NM} \sum_{i=1}^N \sum_{j=1}^M (I_{i,j} - \hat{I}_{i,j})^2$$

useful information to false or unrelated data in a discussion or exchange. For instance, in online conversation councils and other online societies, junk are regarded as "noise" that inhibits with the "signal" of proper conversation.

$$SNR(I, \hat{I}) = 10 \log\left(\frac{\sum_{i=1}^N \sum_{j=1}^M (I_{i,j})^2}{N \cdot M \cdot MSE(I, \hat{I})}\right)$$

4. Structural Content (SC):

It is defined as the ratio between the square of sum of original image and reference image. The equation is given by,

$$SC(\mathbf{I}, \hat{\mathbf{I}}) = \frac{\sum_{i=1}^N \sum_{j=1}^M (\mathbf{I}_{i,j})^2}{\sum_{i=1}^N \sum_{j=1}^M (\hat{\mathbf{I}}_{i,j})^2}$$

5. Maximum Difference (MD):

Absolute difference image maximum value is estimated (original image is detracted to the reference image). The equation is given by,

$$MD(\mathbf{I}, \hat{\mathbf{I}}) = \max |\mathbf{I}_{i,j} - \hat{\mathbf{I}}_{i,j}|$$

6. Average Difference (AD):

Absolute difference image average value is estimated for every pixel (original image is detracted to the reference image). The

$$AD(\mathbf{I}, \hat{\mathbf{I}}) = \frac{1}{NM} \sum_{i=1}^N \sum_{j=1}^M (\mathbf{I}_{i,j} - \hat{\mathbf{I}}_{i,j}) \quad \text{equation is given by,}$$

7. Normalized Absolute Error (NAE):

It is defined as the ratio between sum of absolute of difference image and absolute of original image. The equation is given by,

$$NAE(\mathbf{I}, \hat{\mathbf{I}}) = \frac{\sum_{i=1}^N \sum_{j=1}^M |\mathbf{I}_{i,j} - \hat{\mathbf{I}}_{i,j}|}{\sum_{i=1}^N \sum_{j=1}^M |\mathbf{I}_{i,j}|}$$

8. R-Averaged MD (RAMD):

Average maximum difference is calculated to the sum of maximum of R number value and divided by R . The equation is given by,

$$RAMD(\mathbf{I}, \hat{\mathbf{I}}, R) = \frac{1}{R} \sum_{r=1}^R \max_r |\mathbf{I}_{i,j} - \hat{\mathbf{I}}_{i,j}|$$

In RAMD, \max_r is r -greatest pixel difference of two images. For the proposed system, $R = 10$.

9. Laplacian MSE (LMSE):

Using this $h(\text{image}) = \mathbf{I}_{i+1,j} + \mathbf{I}_{i-1,j} + \mathbf{I}_{i,j+1} + \mathbf{I}_{i,j-1} - 4\mathbf{I}_{i,j}$ equation, the $h(\mathbf{I}_{i,j})$ and $h(\hat{\mathbf{I}}_{i,j})$ will be estimated. The ratio between the square of differences of two values to the sum of real image $h(\mathbf{I}_{i,j})$ value. The equation is given by,

$$LMSE(\mathbf{I}, \hat{\mathbf{I}}) = \frac{\sum_{i=1}^{N-1} \sum_{j=2}^{M-1} (h(\mathbf{I}_{i,j}) - h(\hat{\mathbf{I}}_{i,j}))^2}{\sum_{i=1}^{N-1} \sum_{j=2}^{M-1} h(\mathbf{I}_{i,j})^2}$$

Correlation Based Measures:

10. Normalized Cross Correlation (NCC):

Images are normalized to vary the image brightness and template because of exposure and lightning conditions. It is used in image processing applications. It is estimated at each step by detracting the mean and dividing the standard deviation. The equation is given by,

$$NXC(\mathbf{I}, \hat{\mathbf{I}}) = \frac{\sum_{i=1}^N \sum_{j=1}^M (\mathbf{I}_{i,j} \cdot \hat{\mathbf{I}}_{i,j})}{\sum_{i=1}^N \sum_{j=1}^M (\mathbf{I}_{i,j})^2}$$

11. Mean angle Similarity(MAS):

It is the similarity measure of mean angle among the real image and reference image. The equation is given by,

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

12. Mean angle Magnitude Similarity (MAMS):

It is the magnitude similarity measure of mean angle magnitude between the real image and reference image. The equation is given by,

$$MAMS(\mathbf{I}, \hat{\mathbf{I}}) = \frac{1}{NM} \sum_{i=1}^N \sum_{j=1}^M (1 - [1 - \alpha_{i,j}] [1 - \frac{|\mathbf{I}_{i,j} - \hat{\mathbf{I}}_{i,j}|}{255}])$$

In MAS and MAMS records, $\alpha_{i,j}$ depicts the angle among two vectors,

$\alpha_{i,j} = 2\pi \arccos((\mathbf{I}_{i,j}, \hat{\mathbf{I}}_{i,j}) / (|\mathbf{I}_{i,j}| \cdot |\hat{\mathbf{I}}_{i,j}|))$, where $\mathbf{I}_{i,j}, \hat{\mathbf{I}}_{i,j}$ indicates the scalar product.

Using positive matrices such as \mathbf{I} and $\hat{\mathbf{I}}$, we are restrained to the Cartesian space of the first quadrant so maximum difference is obtained will be $\pi/2$, thus the coefficient $2/\pi$ is added for normalization.

Edge Based Measures:

13. Total Edge Difference (TED):

It is denoted as the relation between the total number of edge differences of the two images to the total number of pixels. The equation is given by,

$$TED(\mathbf{I}, \hat{\mathbf{I}}) = \frac{1}{NM} \sum_{i=1}^N \sum_{j=1}^M |\mathbf{E}_{i,j} - \hat{\mathbf{E}}_{i,j}|$$

14. Total Corner Difference (TCD):

It is defined as the ratio between the total number of corner differences between the two images to the total number of pixels. The equation is given by,

$$TCD(\mathbf{I}, \hat{\mathbf{I}}) = \frac{|N_{cr} - \hat{N}_{cr}|}{\max(N_{cr}, \hat{N}_{cr})}$$

Spectral Distance Measures:

15. Spectral Magnitude Error (SME):

The variance between the Fourier transform of real image to the Fourier transform of reference image is averaged using total number of pixel. The equation is given by,

$$SME(\mathbf{I}, \hat{\mathbf{I}}) = \frac{1}{NM} \sum_{i=1}^N \sum_{j=1}^M (|\mathbf{F}_{i,j}| - |\hat{\mathbf{F}}_{i,j}|)^2$$

16. Spectral Phase Error (SPE):

The variance between the Fourier angle transformed real image to the Fourier angle transformed reference image is

averaged using total number of pixel. The equation is given by,

$$SPE(\mathbf{I}, \hat{\mathbf{I}}) = \frac{1}{NM} \sum_{i=1}^N \sum_{j=1}^M |\arg(\mathbf{F}_{i,j}) - \arg(\hat{\mathbf{F}}_{i,j})|^2$$

Gradient Based Measures:*17.Gradient Magnitude Error (GME):*

The variance between the gradient of real image to the gradient of reference image is averaged using total number of pixel.

The equation is given by,

$$GME(I, \hat{I}) = \frac{1}{NM} \sum_{i=1}^N \sum_{j=1}^M (|\mathbf{G}_{i,j}| - |\hat{\mathbf{G}}_{i,j}|)^2$$

18.Gradient Phase Error (GPE):

The variance between the gradient angle of real image to the gradient angle of reference image is averaged using total number of pixel. The equation is given by,

$$GPE(I, \hat{I}) = \frac{1}{NM} \sum_{i=1}^N \sum_{j=1}^M |\arg(\mathbf{G}_{i,j}) - \arg(\hat{\mathbf{G}}_{i,j})|^2$$

Structural Similarity Measures:*19.Structural Similarity Index Measurement (SSIM):*

The Structural SIMilarity index is a way to measure the similarity of two images. The SSIM index can be observed as a measure of quality of one of the Images being contrasted, providing the other image is deemed as of flawless quality. It is a revised version of the widespread index of image quality.

Information Theoretic Measures:*20.Visual Information Fidelity (VIF):*

The measure of VIF is on the basis of hypothesis that human visual images are natural scenery and thus they have the statistical properties of same kind.

21Reduced Reference Entropy Difference (RRED):

The RRED measure gives the problem of QA from the perception of measuring the local information content difference between the reference image and the prognostication of the unclear image for natural images, given to a sub band of the domain which is wavelet. The RRED algorithm estimates the average variance between calculated local entropies of wavelet coefficients of reference and prognosticated unclear images in a scattered fashion. The VIF feature, for the RRED is unnecessary to access the reference image entirely. But used to reduce a part of its data. This essential data can even be decreased to only one scalar to all calculated entropy lexes in the preferred sub band of wavelet are contemplated in a single block.

NO REFERENCE IQ MEASURES**Distortion Specific Measures:***22.JPEG Quality Index (JQI):*

The JPEG Quality Index, which estimates the quality in images exaggerated by the usual block artificial found in many compression algorithms series at low bit rates such as the JPEG.

23.High-Low Frequency Index (HLFI):

The HLF1 feature is responsive to the sharpness of the image by evaluating the difference between the power in the lower and upper frequencies of the Fourier Spectrum.

$$HLFI = \frac{\sum_{i=1}^{i_l} \sum_{j=1}^{j_l} |\mathbf{F}_{i,j}| - \sum_{i=i_h+1}^N \sum_{j=j_h+1}^M |\mathbf{F}_{i,j}|}{\sum_{i=1}^N \sum_{j=1}^M |\mathbf{F}_{i,j}|}$$

In the HLF1, i_l , i_h , j_l , j_h are the indices corresponding to the lower and upper frequency thresholds. In the current implementation, $i_l = i_h = 0.15N$ and $j_l = j_h = 0.15M$.

Training Based Measures:

24. Blind Image Quality Index Measurement (BIQI):

Blind IQA techniques use *an earlier* knowledge taken from natural scene alteration-free images to train the initial model. The rationale behind this tendency counts on the hypothesis that clear images of the world naturally present certain *regular* properties which drop within a assured subspace of all images possible. If computed properly, deviances from the regularity of natural statistics can help to estimate the perceptual quality of an image.

Natural Scene Statistic Approaches:

25. Natural Image Quality Evaluator (NIQE):

The NIQE is used to analyze blind image quality on the basis of creating quality awareness in collecting features of statistics allied to many variations.

26. Spatial Spectral Entropy Quality (SSEQ):

The normal image is converted to spatial and spectral format to estimate entropy value using fourier transform. Then, compare both entropy values the difference between them is calculated and considered.

CLASSIFICATION :

To achieve a high performance when compared with other approaches first estimate the protection method of multibiometric dimension. Then to detect non spoofing attacks estimate the multi-attack dimension of protection method.

Discriminant Analysis:

The discriminant analysis procedure make a start with a set of observations. The purpose of discriminant analysis is considerate the data set, examination of the data which is extract from the input image with the information of the original image.

For example, we obtain a sample from a multivariate normal distribution $N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ where $\boldsymbol{\mu}$ is a mean vector and $\boldsymbol{\Sigma}$ is a covariance matrix. There are D -dimensional data vectors noted, are column oriented. The multivariate density is calculated as

$$P(\mathbf{x}) = \frac{1}{\sqrt{(2\pi)^D |\boldsymbol{\Sigma}|}} \exp \left[-\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu}) \right],$$

where $|\boldsymbol{\Sigma}|$ = determinant of $\boldsymbol{\Sigma}$. If we obtain a sample of data from two classes, then multivariate normal density

$$P(x|k) = \frac{1}{\sqrt{(2\pi)^D |\Sigma_k|}} \exp \left[-\frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k) \right]$$

posterior probability $P(k|x)$ is estimated by at point x observing an instance of class k . Bayes rule gives,

$$P(k|x) = \frac{\pi_k P(x|k)}{P(x)}$$

Linear Discriminant Analysis (LDA):

Linear combination of features is known as characterize or detach more than two classes by objects or events. It will be find by pattern recognition and machine learning. The linear discriminant analysis is related to machine learning and pattern recognition. The combination of result will be used as a linear classifier. This will be used in dimensionality reduction. Regression analysis and Analysis of variance (ANOVA) is more important to LDA to dependent variables as a combination of other measurements. A continuous dependent variable is used by ANOVA and continuous independent variable is used by a discriminant analysis. Like to LDA Logistic regression and probit regression, by using continuous independent variable values they describe a categorical variables. These methods are used in applications where the independent variables are normally not distributed.

The principle component analysis and factor analysis are best method to explain the data similar to LDA they both seek for linear combinations. Inorder to use feature combination of similarities the PCA and factor analysis use the combinations based on differences.

Discriminant analysis is vary from factor analysis. A difference between independent variables and dependent variables (called criterion variables) have to be declared.

LDA work on independent variables for each observation. The equivalent technique known as discriminant correspondence analysis works on dependent variables.

Quadratic discriminant analysis (QDA):

Quadratic discriminant analysis (QDA) is nearly similar to linear discriminant analysis (LDA). It is assumed that in each class the measurements are normally distributed. Unlike LDA, in QDA the covariance of every classes is not identical. There will be better possible test for the hypothesis that the measurement is from a given class is the probability ratio test if normally assumption is true. If there are only two groups, and the means of those class are defined as $y=0$; $y=1$ and the covariances are defined to be $\Sigma_{y=0}$; $\Sigma_{y=1}$. So the likelihood ratio will be

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

for some threshold t . After some rearrangement, it will be given as the resulting separating surface among the classes is a quadratic. The substitution of the population quantities in this formula is made by the variance-covariance matrices.

CONCLUSION:

In last few years the research on biometric systems against various types of attacks experienced an important growth. In general visual inspection of an image of a real image and a fake sample of the same image shows that they can be very similar.

But, when the images are converted into proper features, some differences between the real and fake images may become evident. These disparities provided by their own optical qualities (absorption, reflection, scattering, refraction), which other materials such as paper, gelatin or artificially manufactured samples do not possess.

To design an algorithm which can assess the images or videos by their quality in a perceptually consistent manner is the main goal of image quality assessment. Several decisions may be extracted from the results presented in the experimental article:

a) The proposed method has the ability to perform consistently at different biometric traits (—multi biometric);
b) The proposed method provides a high level of protection from different types of attacks (—multi attack);
c) The error rates are very low when compared to other anti-spoofing attacks;
d) Due to the multi biometrics and multi attack characteristics, the proposed method is very fast, user-friendly and cost effective.

FUTURE ENHANCEMENT:

The overall performance of the present research may be further improved by including: a) adding new image quality features; b) estimation on various image-based modalities such as ear, palmprint, hand geometry and vein; c) prevention of video attacks by using the video quality measures.

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