ISSN: 0974-2115
www.jchps.com Journal of Chemical and Pharmaceutical Sciences

Fake biometric detection using image quality assessment: application to iris, fingerprint recognition

J.Anitha Gnana Selvi*, N.Krishnaveni, M.Bharathi, R.Ashlin Balareena
Department of Computer science and Engineering, Jeppiaar Engineering College
***Corresponding Author: anithagnanaselvi@gmail.com**

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 exacted 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.

KEY WORDS: Image Quality Assessment (IQA), biometrics, security.

1. 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 (Jain, 1997), template matching (Jain, 2008) 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) (Marcialis, 2009), the estimation of blur and noise (Zhu, 2009), the detection of high correlation (Anjos, 2011), the suggestion of multi-biometrics the recognition of face datasets (Galbally, 2010), the evaluation of face anti-spoofing technique (Chingovska, 2012), the discovery of different distortion specific experts (Abhyankar, 2006), the exposure of spoofing technique (Maatta, 2011), the information of local or global approximation (Soundararajan, 2012), the recognition of iris (Galbally, 2012), the exposure of manipulating images (Bayram, 2006), the acquaintance of signal power to the noise power (Yao , 2005), the introduction of pattern recognition (Pudil, 1994). 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 is not operative.

Liveness detection (LIVDET) is a technique to detect anti-spoofing 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 qualities compared to real image. Image Quality Measures depends on several criteria i) Performance, ii) Complexity,

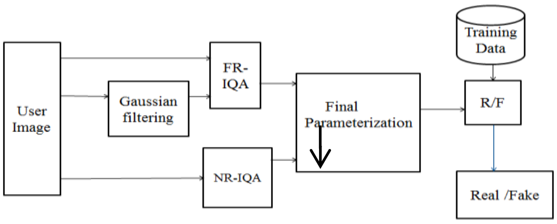

Figure.1. An architecture diagram of Image quality assessment to protect the biometric security system using a 2D image

iii) Speed. Predictable quality feature differences degree of sharpness, level of luminance, blur, noise, gradient, covariance, high correlation, content of information extracted from both types 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 x M. To generate a soft version 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: 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.

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,

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

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 decibel scale. The equation is given by,

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

PSNR is most commonly used to measure the quality of reconstruction of loss 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 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.

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

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,

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

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

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

Average Difference (AD): Absolute difference image average value is estimated for every pixel (original image is detracted to the reference image). The equation is given by,

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

Normalized Absolute Error (NAE): It is defined as the ratio between sum of absolute of difference image andabsolute of original image. The equation is given by,

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

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, $R = 10$.

Laplacian MSE (LMSE): Using this h(image) = **I**i+1, j +**I**i−1, j +**I**i, j+1 + **I**i, j−1 − 4**I**i, j equation .the h(**I**i, j) and h(**I**^i, j) will be estimated .The ratio between the square of differences of two values to the sum of real image h(**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:

Normalized Cross Correlation (NCC): Images are normalized to vary the image brightness and template because of exposure and lightning conditions. Iris 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,

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

Mean angle Similarity (MAS): It is the similarity measureof mean angle among the real image and reference image. The equation is given by,

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

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,

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

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

$\alpha i, j = 2\pi$ arccos((**I***i, j* ,ˆ**I***i, j*)/ (||**I***i, j* ||·||ˆ**I***i, j* ||), where**I***i, j* ,ˆ**I***i, j* indicates the scalar product.

Using positive matrices such as **I**and ˆ**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:

Total Edge Difference (TED): It is denoted as the relation between the total numbers of edge differences ofthe two images to the total number of pixels. The equation is given by,

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

Total Corner Difference (TCD): It is defined as the ratio between the total numbers of corner differences between the two images to the total number of pixels. The equation is given by,

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

Spectral Distance Measures:

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,

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

Spectral Phase Error (SPE): The variance between the Fourierangle transformed real images to the Fourier angletransformed reference image is averaged using totalnumber 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

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,

$$GME(I,\hat{I}) = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}(|G_{i.j}| - |\ddot{G_{i,J}}|)^2$$

Gradient Phase Error (GPE): The variance between the gradient angles of real image to the gradient angleof reference image is averaged using totalnumber of pixel. The equation is given by,

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

Structural Similarity Measures

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:

Visual Information Fidelity (VIF): The measure of VIF is on the basis of hypothesis that human visual images are natural scenario and thus they have the statistical properties of same kind. Reduced 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:

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.

High-Low Frequency Index (HLFI): The HLFI 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 HLFI, *il* , *ih*, *jl* , *jh* are the indices corresponding to the lower and upper frequency thresholds. In the current implementation, *il*= *ih* = 0.15*N* and *jl*= *jh*= 0.15*M*.

Training Based Measures

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 withinan assured subspace of all images possible. If computed properly, deviancies from the regularity of natural statistics can help to estimate the perceptual quality of an image.

Methods and Materials Used in NIQE:

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.

Spatial Spectral Entropy Quality (SSEQ): The normal image is converted to spatial and spectral format to estimate entropy value using Fourier transform. Then, comparing 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 multi-biometric dimension. Then to detect non spoofing attacks estimate the multi-attack dimension of protection method.

Discriminant Analysis: The discriminant analysis procedure makes 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 ($\boldsymbol{\mu}$, $\boldsymbol{\Sigma}$) where $\boldsymbol{\mu}$ is amean vector and $\boldsymbol{\Sigma}$ is a covariance matrix there are *D*-dimensional data, vectors noted, are column-oriented. The multivariate density is calculated as

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

where j$\boldsymbol{\Sigma}$j = 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 $P\ (k\mathrm{j}\boldsymbol{x})$ is estimated by at point x observing an instance of class k.
Bayes rule gives,

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

Real

Fake

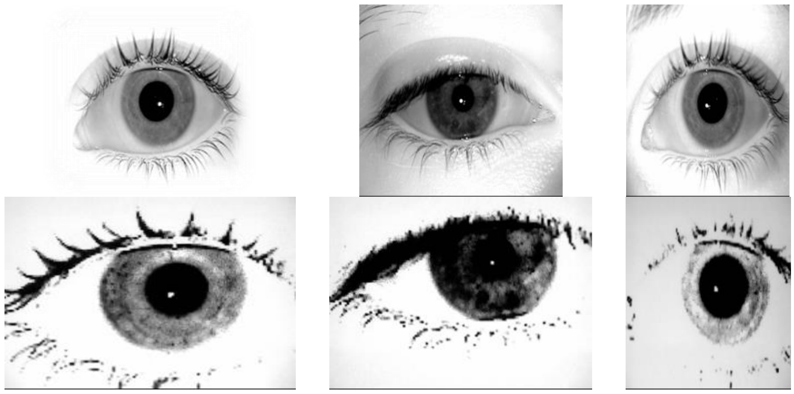

Figure.2. IRIS

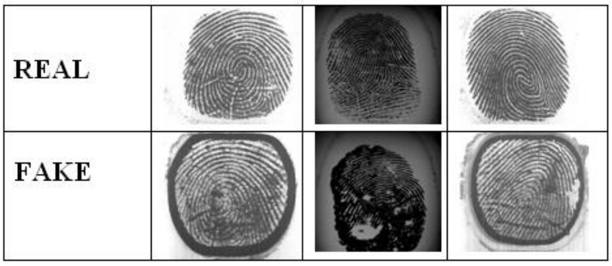

Figure.3. Fingerprint

Results and Discussion of LDA and QDA:

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.

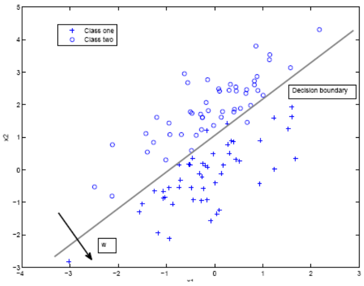

Figure.4.Linear Discriminant Analysis Strategy

A continuous dependent variable is used by ANOVA and continuous independent variable is used by a discriminant analysis. Like to LDA Logistic regression and profit regression, by using continuous independent variable values they describe 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. In order to use feature combination of similarities the PCA and factor analysis use the combinations based on differences.

Discriminant analysis is varying from factor analysis. Differences 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 class 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=1and the covariance are defined to be y=0; y=1.

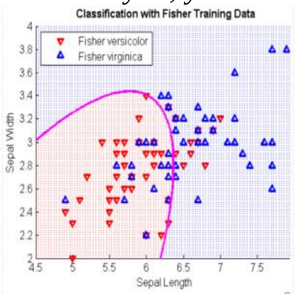

Figure.5.QDA Comparison Chart

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.

2. 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 disparity provided by their own optical qualities (absorption, reflection, scattering, refraction), which other materials such as paper, gelatin are 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 extorted 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 provide 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, palm print, hand geometry and vein; c) prevention of video attacks by using the video quality measures.

REFERENCES

Abhyankar A and Schuckers S, Fingerprint liveness detection using local ridge frequencies and multi resolution texture analysis techniques, in Proc. IEEE ICIP, 2006, 321–324.

Anjos A and Marcel S, Counter-measures to photo attacks in face recognition, A public database and a baseline, in Proc. IEEE IJCB, 2011, 1–7.

Bayram S, Avcibas I, Sankur B and Memon N, Image manipulation detection, J. Electron. Image. 15(4), 2006, 041102-1–041102-17.

Chingovska I, Anjos A, and Marcel S, On the effectiveness of local binary patterns in face anti-spoofing, in Proc. IEEE Int. Conf. Biometr, Special Interest Group, 2012, 1–7.

Galbally J, McCool C, Fierrez J, Marcel S and Ortega-Garcia J, On the vulnerability of face verification systems to hill-climbing attacks, PatternRecognition, 43(3), 2010, 1027–1038.

Galbally J, Ortiz-Lopez J, Fierrez J and Ortega-Garcia J, Iris livenessdetection based on quality related features, 2012, 271–276.

Jain A.K and Zongker D, Feature selection, Evaluation, application, and small sample performance, IEEE Trans. Pattern Anal. Mach. Intell, 19(2), 1997, 153–158.

Jain A.K, Nandakumar K and Nagar A, Biometric template security, EURASIP J. Adv. Signal Process, 2008, 113–129.

Maatta J, Hadid A and Pietikainen M, Face spoofing detection from single images uses micro-texture analysis, in Proc. IEEE IJCB, 2011, 1–7.

Marcialis G.L, Lewicke A, Tan B, Coli P, Grimberg D, A. Congiu, First international fingerprint liveness detection competition—LivDet, in Proc. IAPR ICIAP, Springer LNCS-5716. 2009, 12–23.

Nixon K.A, Aimale V and Rowe R.K, Survey based on fingerprint, face and iris biometric recognition system, 13(4), 11-34.

Pudil P, Novovicova J and Kittler J, Floating search methods in feature selection, Pattern Recognit, Lett, 15(11), 1994, 1119–1125.

Soundararajan R and Bovik A.C, RRED indices, Reduced reference entropic differencing for image quality assessment, IEEE Trans, Image Process, 21(2), 2012, 517–526.

Yao S, Lin W, Ong E and Lu Z, Contrast signal-to-noise ratio for image quality assessment, in Proc. IEEE ICIP, 2005, 397–400.

Zhu X and Milanfar P, A no-reference sharpness metric sensitive to blur and noise, in Proc. Int. Workshop Qual, Multimedia Exper, 2009, 64–69.