IMAGE QUALITY ASSESSMENT USING BIOMETRIC LIVINESS DETECTION FOR FAKE FINGER PRINT

R.SOWMIYA[1], C.DHIVYA[2],B.NANDHINI[3],T.ANAND[4]

[1]*M.E., Applied Electronics, Vivekanandha College of Engineering for Women, Tamilnadu.*

[2 3]*M.E.,VLSI Design, Vivekanandha College of Engineering for Women, Tamilnadu.*

[4]*Assistant Professor, Department of ECE, Vivekanandha College of Engineering for Women, Tamilnadu.*

Abstract

A biometric system is a computer based system and is used to identify the person on their behavioural and logical characteristics such as (for example fingerprint, face, iris, keystroke, signature, voice, etc.).A typical biometric system consists of feature extraction and matching patterns. But nowadays biometric systems are attacked by using fake biometric samples. This paper described the fingerprint biometric techniques and also introduces the attack on that system and by using Image Quality Assessment for Liveness Detection to know how to protect the system from fake biometrics and also how the multi biometric system is more secure than uni-biometric system. The proposed approach presents a very low degree of complexity, which makes it suitable for real-time applications, using 25 general image quality features extracted from one image to distinguish between authentic and fake samples. The experimental results, obtained on publicly available data sets of fingerprint. The general image quality of real biometric samples reveals highly valuable information that may be very efficiently used to discriminate them from fake qualities.

Keywords: Image quality, biometrics security, countermeasures, liveness detection.

I.INTRODUCTION

In Recent years, the increasing interest in the evaluation of biometric systems security has led to the creation of numerous and very diverse initiatives focused on this major field of research: the publication of many researches works disclosing and evaluating different biometric vulnerabilities the proposal of new protection methods related book chapters the publication of several standards in the area the dedication of specific tracks, sessions and workshops in biometric-specific and general signal processing conferences, the organization of competitions focused on vulnerability assessment the acquisition of specific datasets, the creation of groups and laboratories specialized in the evaluation of biometric security or the existence of several European Projects with the biometric security topic as main research interest. All these initiatives clearly highlight the importance given by all parties involved in the development of biometrics (i.e., researchers, developers and industry) [1] to the improvement of the systems security to bring this rapidly emerging technology into practical use.

Among the different threats analyzed, the so-called *direct* or *spoofing* attacks have motivated the biometric community to study the vulnerabilities against this type of fraudulent actions in modalities such as the iris , the fingerprint the face , the signature , or even the gait and multimodal approaches. In these attacks, the intruder 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 genuine user (e.g., gait, signature), to fraudulently access the biometricsystem. As this type of attacks are performed in analogy domain and the interaction. With the device is done following the regular protocol, the usual digital protection mechanisms (e.g., encryption, digital signature or watermarking) is not effective. The aforementioned works and other analogue studies have clearly shown the necessity to propose and develop specific protection methods against this threat

[6]. This way, researchers have focused on the design of specific countermeasures that enable biometric systems to detect fake samples and reject them, improving this way the robustness and security level of the systems.

II. RELATED WORK

2.1 LIVENESS DETECTION METHODS

Liveness detection methods are generally classified onto two types (see Fig. 1): **(I) Software-based techniques**, on this type the fake trait is Detected once the sample has been acquired with a normal sensor (i.e., features used to differentiate between real and fake traits are extracted from the biometric sample, and not from the characteristic itself); **(II) Hardware-based techniques**, which add some particular device to the sensor on order to detect Exacting properties of a living feature. Liveness detection techniques use different physiological properties to differentiate between real and fake sample. Liveness detection methods represent a difficult engineering problem as they have to satisfy certain challenging requirements (i) user friendly, people should be averse to use it; (ii) fast, results have to be generate on a very less time interval as the user cannot be asked to interact with the sensor for a long period of time; (iii) low cost, a large use cannot be expected if the cost is very high. The two types of methods have certain advantages and disadvantages over the other and, on general, a combination of both would be the most advantageous protection approach to increase the security of biometric systems. As a common comparison, hardware-based schemes generally present a higher fake detection rate, at the same time software-based techniques are on general less expensive (like no extra device is needed), and less intrusive since their implementation is clear to the user. Moreover, as they run directly on the acquired sample, software techniques may be embedded on the feature extractor module which makes them potentially accomplished of detecting other types of illegal break-on attempts not necessarily classified as spoofing attack. For instance, software- based methods can protect the system against the addition of reconstructed or synthetic samples onto the communication channel between the sensor and the feature extractor [11].

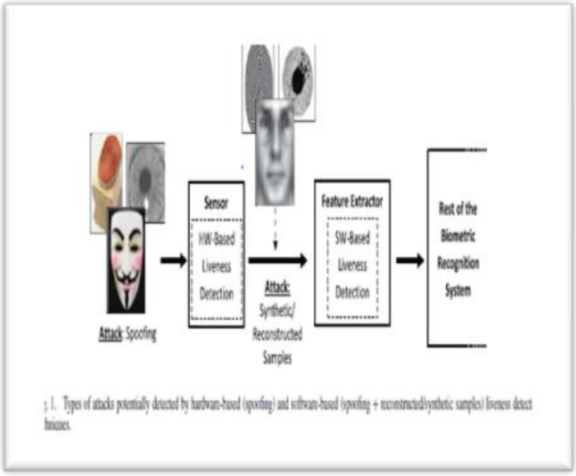

Fig 1: Types of attacks potentially detected by hardware-based (spoofing) and software-based (spoofing + reconstructed/synthetic samples) liveness detection techniques.

2.2 IMAGE QUALITY ASSESSMENT FOR LIVENESS DETECTION

The image quality assessment is used for the liveness detection is motivated by the fingerprint images acquired from a gummy finger present local gaining artifacts such as spots and patches. The potential of general image quality assessment as a protection method against different biometric attack (with special attention to spoofing). Different quality measures present diverse sensitivity to image artifacts and distortions [4]. For example, measures like the mean squared error respond additional to additive noise, although others such as the spectral phase error are extra sensitive to blur; while gradient-related features respond to distortions concentrated around edges and textures Therefore, using a large range of IQMs exploiting complementary image quality properties should allow detecting the aforementioned quality differences between real and fake samples expected to be found on many attack attempts. A novel parameterization using 25 general image quality measures. On order to keep its generality and simplicity, the system requires one input: the biometric sample to be classified as real or fake (i.e., the same image acquired for biometric recognition purposes).Once the feature vector has been generated the sample is classified as real or fake using SVM classifier. The parameterization proposed on the present work comprises 25 image quality measures for both reference and blond image quality has been successfully used on previous works for image manipulation detection and steganalysis on the forensic field [7]. To a certain extent many spoofing attack, especially those which involve taking a picture of a facial image displayed on a 2D device (e.g., spoofing attack with printed iris or face images), may be regarded as a type of image manipulation which can be effectively detected.

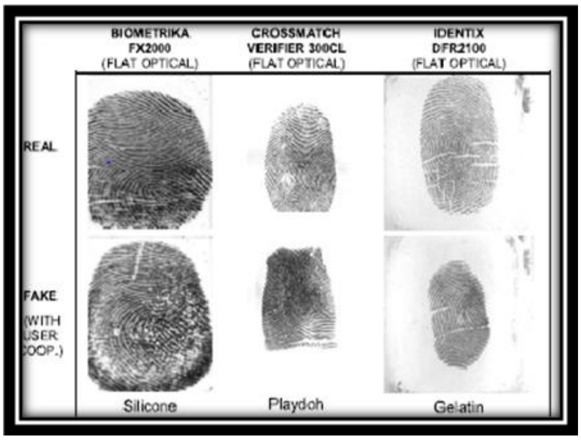

Fig 2: Typical examples of real and fake fingerprint images that can befound in the public

In figure2 the fingerprint images captured from a gummy finger present local acquisition artifacts such as spots and patches.

2.2.1 Block Diagram Description

Input Image: The input image captured from the sensor should be 2D image. Fingerprint is captured from the flat optical sensor for the real and fake classification shown in figure4. Biometric images like face, iris and palm print also are used for the input image for image quality assessment technique.

2.2.2 Wiener Filtering

The input gray-scale image **I** (of size N × M) is filtered with wiener filtering on order to generate a smoothed version ˆ**I** .The noise reduced by wiener filtered input fingerprint image is well capable for IQA technique. Because wiener filter are adaptive on nature. So wiener filtering technique is used for reducing noise on input fingerprint image [13].

2.2.3 Full-Reference IQ Measures

Full-reference (FR) IQA methods rely on the availability of a clean undistorted reference image to estimate the quality of the test sample. On order to circumvent this limitation, the same strategy already successfully used for image manipulation detection on and for steganalysis is implemented here [3]. The input gray- scale image **I** (of size N × M) filters with a wiener filter on order to generate a smoothed version ˆ**I**. Then, the quality between both images (**I** and ˆ**I**) is computed according to the corresponding full-reference IQA metric.

2.2.4 No-Reference IQ Measures

Unlike the objective reference IQA methods, on general the human visual system does not require of a reference sample to determine the quality level of an image. Following this same principle, automatic no- reference image quality assessment (NR-IQA) algorithms try to handle the very complex and challenging problem of assessing the visual quality of images, on the absence of a reference [8]. Presently, NR-IQA methods generally estimate the quality of the test image according to some pre-trained statistical models.

2.3 FINGERPRONTS

Fingerprint analysis, also known on the Unites States as dactylographic, is the discipline of using fingerprints to recognize an individual. Palms and the soles of feet also have distinguishing epidermal patterns. Even identical twins will have contradictory fingerprints patterns. No two persons have been found to have the same prints.

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Fig 3: Fingerprints

There are three basic categories of fingerprint shown in figure3: Visible prints, such as those made on oil, ink or blood. Latent prints which are unseen under normal viewing conditions. And plastic prints which are left on soft surfaces such as new paint. There are now over forty methods available for collecting prints including powders, use of chemicals such as iodine, digital imaging, dye strains, and fumes. Lasers are also used.

III. MATERIALS AND METHODS

3.1 Measuring Fingerprint Image Quality

In this section we discuss our implementation of $L(.)$ and I (.) for fingerprint images. We first apply $L(.)$ to a biometric sample $i\ x$ to get feature vector $\boldsymbol{v}i$ and then use $\boldsymbol{v}i$ as input into a neural network, I (.) . $L(.)$ is realized by computing characteristics and features of biometric sample $i\ x$ that convey information for a matching algorithm.

Function $L(.)$ will be realized by computing characteristics and features of I &x that convey information for a matching algorithm. Applying $L(.)$ to a sample $i\ x$ results in an n-dimensional feature vector $\boldsymbol{v}_i$. For fingerprints, this includes measured clarity of ridges and valleys, size of the image, and measures of number and quality of minutiae.

3.2 FEATURE EXTRACTION

This section explains feature extraction for fingerprints. Our proposed definition and measurement of biometric sample quality can be applied to other biometric modalities if the appropriate feature vectors are defined and computed accordingly. It is known that fingerprint matcher algorithms commonly in use are sensitive to clarity of ridges and valleys, measures of number and quality of minutiae, and size of the image. We have used NIST Fingerprint Image Software (NFIS) [7] package to extract features, i.e. implementation of $L(.)$ of equation 7. The MINDTCT package of NFIS has a fingerprint minutia detector algorithm that accepts a fingerprint image and automatically detects minutia. It also assesses minutia quality and generates an image quality map. To locally analyze a fingerprint image, NFIS divides the image into grids of blocks. To assess the quality of each block, NFIS computes several maps (direction map, low contrast, low flow, and high curve) and summarizes the result in a quality map. All pixels in a block are assigned the same result. It should be noted that the NFIS algorithms and software parameters have been designed and set to process images scanned at 500 pixels per inch (19.69 pixels per millimeter) and quantized at 256 levels of gray. A discussion of MINDTCT parameters and how it is used in our quality assessment follows.

3.2.1 Generate image quality map

MINDTCT measures quality of localized regions in the image including determining the directional flow of ridges in the image and detecting regions of low contrast, low ridge flow, and high curvature. These last three conditions represent unstable areas in the image where minutiae detection is unreliable, and together they can be used to represent levels of quality in the image. Each of these characteristics is discussed below.

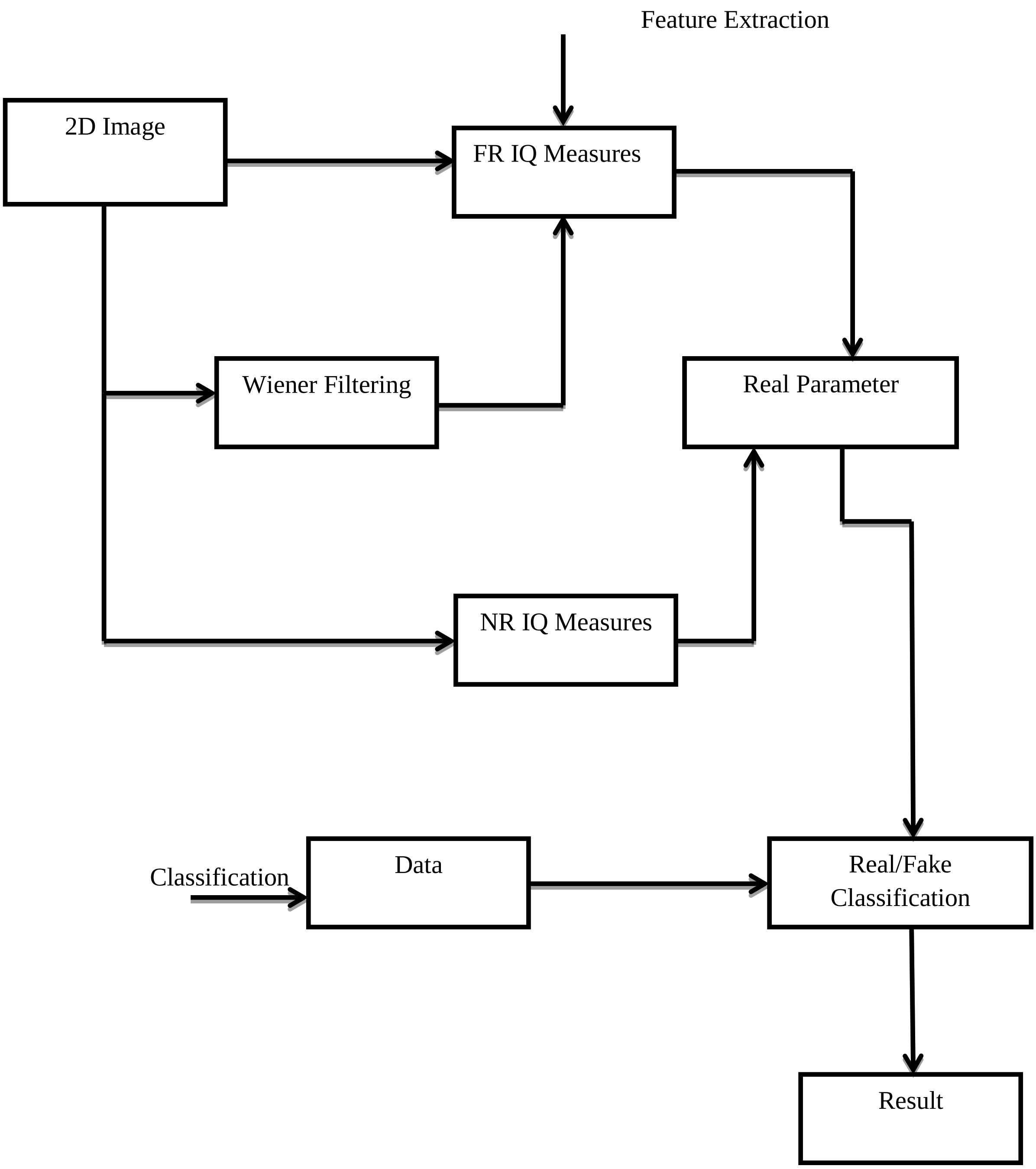


Fig 4: Block Diagram for Feature Extraction

3.2.1.1Direction map

The purpose of this map is to represent areas of the image with sufficient ridge structure. Well-formed and clearly visible ridges are essential to reliably detection of ridge endings and bifurcations. To locally analyze the fingerprint, the image is divided into grid of blocks. All pixels within a block are assigned the same value. To minimize the discontinuity in block values as one move from one block to its neighbour, windows are defined to surround blocks, and windows overlap from one block to the next. For each block in the image, the surrounding window is rotated incrementally and a Discrete Fourier Transform (DFT) is conducted at each orientation. The details are given in [7].

3.2.1.2 Low contrast map

An image map called the low contrast map is computed where the blocks of sufficiently low contrast are flagged. This map separates the background of the image from the fingerprint, and maps out smudges and lightly inked areas of the fingerprint. Minutiae are not detected within low contrast blocks in the image. This software computes the pixel intensity distribution within the block's surrounding window. A specified percent (10%) of the distribution's high and low tails are trimmed as possible outliers and the width of the remaining distribution is measured. A pixel intensity threshold was derived empirically from a training sample of low and high contrast blocks extracted from real fingerprint images. Blocks that have narrow dynamic range in pixel intensity are flagged as low contrast areas.

3.2.1.3 Low flow map

Low flow map marks the blocks that could not initially be assigned a dominant ridge flow. Minutiae detected in low flow areas are not reliable.

3.2.1.4 High curve map

Minutiae detected in high curvature areas are not reliable. This is especially true of the core and delta regions of a fingerprint. A high curve map is used to marks blocks that are in high curvature areas of the fingerprint.

3.2.1.5 Quality map

As discussed, the low contrast map, low flow map, and the high curve map all point to different low quality regions of the image. The information in these maps is integrated into one general map, and contains 5 levels of quality (4 being the highest quality and 0 being the lowest). The background has a score of 0, a score of 4 means a very good region of fingerprint. The quality assigned to a specific block is determined based on its proximity to blocks flagged in the above-mentioned maps. We display quality map grayscale image with black, dark gray, medium gray, light gray, and white corresponding to scores of 0 to 4 respectively.

Fig 5: An example of a fingerprint subjectively assessed to be of good quality

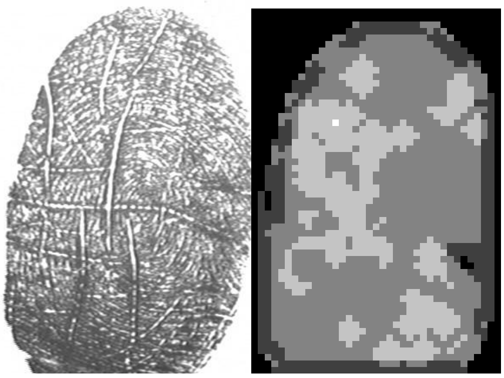


Fig 6: An example of a fingerprint subjectively assessed to be of bad quality

3.2.2 Assess Minutia Quality

NFIS computes a quality/reliability to be associated with each detected minutia point. Although NFIS performs several steps of false minutiae removal, false minutiae usually remain in the candidate list. A robust quality measure can help manage this in that false minutiae should be assigned a lower quality than true minutiae. Two factors are combined to produce a quality measure for each detected minutia point. The first is taken directly from the location of the minutia point within the quality map described above. The second factor is based on simple pixel intensity statistics (mean and standard deviation) within the immediate neighbourhood of the minutia point. An area with clear ridges and valleys will have a significant contrast that will cover the full grayscale spectrum. Consequently, the mean pixel intensity of the neighborhoods will be very close to 127. For similar reasons, the pixel intensities of an ideal neighbourhood will have a standard deviation ≥ 64. Based on this logic and using quality map discussed in 4.1.2.5, NFIS assigns a quality value on the range 0.01 to 0.99 to each minutia. A low quality minutia value represents a minutia detected in a lower quality region of the image, whereas a high quality minutia value represents a minutia detected in a higher quality region.

Q	QUALITY	RANGE
5	poor	$[0, W^{-1}(0.75)]$
4	fair	$(C^{-1}(0.75)], C^{-1}(0.05)]$
3	good	$(C^{-1}(0.05), C^{-1}(0.2)]$
2	very good	$(C^{-1}(0.2), C^{-1}(0.6)]$
1	excellent	$(C^{-1}(0.6), C^{-1}(1)]$

Table 1: Bin boundary for normalized match scores o(.). The boundaries were set by inspection to give useful categorization of the normalized match scores statistic.

For a fingerprint, NFIS detects and assesses quality of each minutia. Minutiae with quality lower than 0.5 are not reliable. We compute the number of minutiae of quality 0.5 or better, 0.6 or better, 0.75 or better, 0.8 and better, and 0.9 and better.

3.3. Algorithm for SVM Classification

3.3.1 Training Algorithm

Step 1: Read the fingerprint Input training Images from the database.
Step 2: Fond 25 Image Quality Assessment Measures (No Reference & Full Reference) for the fingerprint training images. Example: peak signal to noise ratio, average difference, maximum difference and other quality features.
Step 3: Combine all Quality Measure as an image quality assessment feature.
Step 4: Create Target for SVM classification Training.
Step 5: Make SVM classifier training with two classes (Fake and Real).

3.3.2 Testing Algorithm

Step 1: Read the finger print Test Image from the database.
Step 2: Fond 25 Image Quality Measures (No Reference & Full Reference) for the fingerprint test image. Example: peak signal to noise ratio, average difference, maximum difference and other quality features.
Step 3: Combine all Quality Measure as a feature. **Step 4:** Feature compared with trained Feature using SVM classification.
Step 5: Final result given test image is fake or real finger print image.

3.4 THE SECURITY PROTECTION METHODS

The difficulty of fake biometric detection can be seen as a two-class categorization problem where an input biometric model has to be assigned to one of two classes: real or fake. The solution point of the methods is to find a set of discriminate features which permits to build an appropriate classifier which gives the probability of the image —realism given the extracted set of features. The four selection criteria are:

1.Performance: Only widely used image quality approaches which have been consistently tested showing well performance for different applications have been considered.

2.Complementarity: On order to generate a system as general as possible on terms of attack detected and biometric modalities supported, we have given priority to IQMs based on complementary properties of the image.

3. Complexity: On order to keep the simplicity of the methods, low complexity features have been preferred over those which require a high computational load.

4. Speed: This is, on general, closely related to the previous complexity. To assure a user-friendly non-intrusive application, users should not be kept waiting for a response from the recognition system. For this reason, big importance has been given to the feature extraction time, which has a very big impact on the overall speed of the fake detection algorithm.

IV. RESULTS AND DISCUSSION

A Number of unique subjects on training and testing, as well as the average number of images. It should also be noted that Identic, Cross match and biometric were collected by multiple persons (Table I). [3]

Table I
Number of unique subjects in training and testing

Scanners	Training Subjects	Testing Subjects	Aver Images / subject
Identix	35	125	18.75
Crossmatch	63	191	15.75
Biometrika	13	37	40.0

4.1 GAUSSIAN FILTERED FINGERPRINT IMAGE

The output grey-scale image $\mathbf{I}$ (of size N × M) is filtered with a low-pass Gaussian kernel ($\sigma = 0.5$ and size 3 × 3) on order to generate a smoothed version $\hat{\mathbf{I}}$. Then, the quality between both images ($\mathbf{I}$ and $\hat{\mathbf{I}}$) is computed according to the corresponding full-reference IQA metric.

Fig 6: Gaussian Filtered Fingerprint Image

In figure6 the PSNR value obtained for Gaussian filtered input fingerprint image is only 22.5231.The noise reduced by Gaussian filtered input fingerprint image is not capable for IQA technique So wiener filtering is also used for reducingnoise on input fingerprint image.

4.2 WIENER FILTERED FINGER PRINT IMAGE

The output gray-scale image $\mathbf{I}$ (of size N × M) is filtered with wiener filtering on order to generate a smoothed version $\hat{\mathbf{I}}$. Then, the quality between both images ($\mathbf{I}$ and $\hat{\mathbf{I}}$) is computed according to the corresponding full-reference IQA metric.

Fig 7: Wiener Filtered Finger Print Image

The following message box appears after finding 25 image quality assessment parameters for training the fingerprint image on SVM classifier.

- The most remarkable finding is that the whole group of 25 quality measures is consistently selected as the best performing feature set for all the considered scenarios and traits, showing the high complementarity of the proposed metrics for the biometric security task studied in the work.
- The first observation implies that other quality-related features could still be added to the proposed set in order to further improve its overall performance (until, eventually, adding new features starts decreasing its detection rates).
- For all cases, the best performing 5-feature and even 10-feature subsets present around a 50% HTER, which reinforces the idea that the competitive performance of the system does not rely on the high discriminative power of certain specific features but on the diversity and complementarily of the whole set.
- The results achieved by the proposed protection method based on IQA on this attacking scenario. In spite of the similarity of real andfake images, the global error of the algorithm in this scenariois 2.1%.
- The gummy fingers were generated using three different materials: silicone, gelatine and playdoh, always following a consensual procedure (with the cooperation of the user). As a whole, the database contains over 18,000 samples coming from more than 100 different fingers.
- First, evaluate the "multi-biometric" dimension of the protection method. That is, its ability to achieve a good performance, compared to other trait-specific approaches, under different biometric modalities. For this purpose three of the most extended image-based biometric modalities have been considered in the experiment fingerprints.
- Second, evaluate the "multi-attack" dimension of the protection method. That is, its ability to detect not only spoofing attacks (such as other liveness detection specific approaches) but also fraudulent access attempts carried out with synthetic or reconstructed samples.

4.3 TRAINING RESULTS FOR FINGERPRONT IMAGES

4.3.1 REAL FINGERPRINT IMAGES

Table II. Training Results For Real Fingerpront Images

PARAMETER	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
MSE(e^+2)	1.74	1.43	1.40	1.90	1.77	1.43	1.63	1.30	1.37	1.44	1.27	1.06
PSNR(e^+1)	2.57	2.65	2.66	2.55	2.56	2.65	2.68	2.59	2.69	2.67	3.70	3.78
SNR(e^+1)	2.33	2.45	2.42	2.25	2.31	2.42	2.44	2.23	2.39	2.31	2.58	2.74
SC(e^+0)	1.10	1.13	1.14	1.16	1.12	1.10	1.18	1.02	1.04	1.05	1.17	1.04
MD	86	82	91	85	94	81	91	87	84	89	88	95
AD(e^+1)	2.33	2.45	2.42	2.25	2.32	2.42	2.44	2.23	2.29	2.31	2.58	2.74
NAE(e^-2)	5.18	4.23	4.35	5.81	4.96	4.34	4.07	5.94	5.55	5.43	3.77	2.99
RAMD	8.6	8.2	9.1	8.5	9.4	8.1	9.1	8.7	8.4	8.9	8.8	9.5
LMSE(e^+1)	8.12	9.45	7.43	8.04	8.44	6.34	5.87	7.89	5.98	8.34	8.56	7.43
NXC(e^-1)	9.90	9.91	9.93	9.87	9.89	9.95	9.78	9.71	9.34	9.81	9.56	9.76
MAS(e^-2)	4.12	4.23	5.78	6.32	4.98	5.89	4.87	5.32	5.87	4.67	4.29	4.56
MAMS(e^+6)	24.4	22.5	21.8	22.9	24.6	23.8	26.8	22.6	23.4	25.6	23.9	25.5
TED(e^2)	10.2	9.31	8.94	7.21	11.2	8.98	10.4	11.8	12.5	10.8	9.34	11.8
TCD(e^-1)	15.3	12.5	11.8	13.2	17.3	12.4	11.5	12.8	13.8	15.8	14.9	13.1
SME(e^-3)	2.33	3.44	4.89	2.44	3.89	4.76	2.43	3.97	5.34	4.12	3.23	4.21
SPE(e^-7)	10.3	11.7	13.5	12.8	13.9	9.32	10.9	12.3	14.2	8.34	10.2	9.34
GME(e^4)	5.22	6.34	7.32	5.54	4.22	5.23	6.22	7.23	5.89	4.12	5.32	7.44
GPE(e^2)	3.12	3.56	4.12	5.23	6.23	4.23	7.34	5.34	6.39	5.23	3.45	5.32
SSIM(e^-1)	8.21	8.45	8.87	8.64	8.91	8.02	8.23	8.75	8.50	8.98	8.12	8,04
VIF	84	87	98	78	94	74	81	96	82	93	83	91
RRED	123	134	164	173	183	153	182	172	133	152	132	143
JQI(e^+1)	1.43	2.54	2.12	3.19	4.21	1.01	1.32	1.54	2.09	2.89	3.23	1.02
HLFI(e^-2)	7.23	6.34	7.45	8.56	8.67	9.34	8.34	7.03	6.92	8.44	7.87	7.94
BIQI(e^-1)	2.87	3.29	1.34	2.80	1.87	2.21	3.84	1.09	2.82	1.07	3.98	3.98
NIQE(e^+1)	9.01	8.87	7.18	7.34	9.23	8.12	9.5	6.33	7.22	8.32	5.88	2.98

R1-R12-Real Image

4.3.2 FAKE FINGERPRONT IMAGES

Table III Training Results For Fake fingerprint Images

PARAMETER	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
MSE(e^+2)	1.14	1.10	1.16	1.12	1.10	1.04	1.05	1.17	1.04	1.18	1.02	1.15
PSNR(e^+1)	2.45	2.52	2.23	2.65	2.98	2.43	2.91	2.34	2.78	2.12	3.94	3.63
SNR(e^+1)	2.02	2.12	2.34	2.21	2.39	2.46	2.42	2.21	2.35	2.01	2.87	2.92
SC(e^+0)	1.74	1.43	1.40	1.90	1.77	1.23	1.05	1.78	1.14	1.20	1.19	1.93
MD	81	87	86	91	89	75	83	72	93	82	74	81
AD(e^+1)	3.32	4.55	4.21	5.21	2.99	3.99	4.32	1.24	3.22	2.42	2.53	2.67
NAE(e^-2)	2.18	7.23	5.34	2.31	7.32	2.34	1.07	3.94	2.42	4.31	5.70	6.95
RAMD	8.1	8.7	8.6	9.1	8.9	7.5	8.3	7.2	9.3	8.2	7.4	8.1
LMSE(e^+1)	2.12	5.45	3.43	1.04	2.44	3.34	1.87	3.89	4.98	3.34	2.56	5.43
NXC(e^-1)	9.43	9.21	9.56	9.87	9.01	9.03	9.16	9.26	9.65	8.61	9.01	9.34
MAS(e^-2)	7.12	2.21	1.78	8.30	2.82	1.92	5.81	4.19	7.32	2.73	5.29	4.56
MAMS(e^+6)	19.4	17.5	16.8	27.9	19.6	18.8	21.8	17.6	16.4	31.6	28.9	19.5
TED(e^2)	10.2	9.31	8.94	7.21	11.2	8.98	10.4	11.8	12.5	10.8	9.34	11.8
TCD(e^-1)	15.3	12.5	11.8	13.2	17.3	12.4	11.5	12.8	13.8	15.8	14.9	13.1
SME(e^-3)	2.43	3.23	4.45	2.12	3.56	4.54	2.64	3.12	5.65	4.63	3.97	4.20
SPE(e^-7)	2.35	6.27	8.53	2.81	6.79	4.30	5.19	7.73	9.22	2.36	4.22	4.21
GME(e^4)	2.02	1.43	4.12	7.24	6.32	1.32	3.24	5.21	8.12	5.65	2.42	6.12
GPE(e^2)	3.45	3.16	3.56	5.43	6.07	4.34	7.07	4.13	7.33	5.53	3.78	4.34
SSIM(e^-1)	12.3	4.45	9.87	3.64	5.91	12.2	4.23	5.75	8.50	4.98	2.12	11.4
VIF	78	93	82	74	64	70	84	87	92	78	77	82
RRED	134	111	131	119	136	165	132	176	123	185	123	156
JQI(e^+1)	4.31	5.42	1.42	8.19	6.45	2.01	6.32	2.54	5.09	2.89	7.21	3.01
HLFI(e^-2)	5.34	2.45	1.12	4.32	5.67	2.30	2.59	3.45	2.54	3.22	4.32	2.94
BIQI(e^-1)	1.84	7.33	6.32	5.83	5.54	7.43	6.32	6.23	8.82	7.23	9.23	5.23
NIQE(e^+1)	8.01	5.87	6.18	6.34	2.23	4.12	3.5	9.33	5.22	7.32	4.88	7.98

F1-F12-Fake

V. TESTING RESULTS FOR FINGERPRINT IMAGE

5.1 Real fingerprint Image

Table IV. Testing Results For Real fingerprint Image

PARAMETER	ONPUT IMAGE (REAL)
MSE(e^+2)	1.63
PSNR(e^+1)	2.57
SNR(e^+1)	2.21
SC(e^+0)	1.08
MD	75
AD(e^+1)	7.32
NAE(e^-2)	5.18
RAMD	7.5
LMSE(e^+1)	8.12
NXC(e^-1)	9.60
MAS(e^-2)	2.12
MAMS(e^+6)	19.4
TED(e^2)	3.24
TCD(e^-1)	8.33
SME(e^-3)	2.21
SPE(e^-7)	2.53
GME(e^4)	12.3
GPE(e^2)	3.02
SSIM(e^-1)	8.02
VIF	81
RRED	174
JQI(e^+1)	5.21
HLFI(e^-2)	2.74
BIQI(e^-1)	2.73
NIQE(e^+1)	9.43

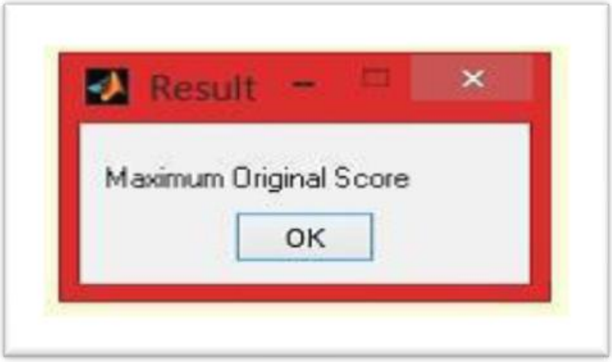
5.2 Fake fingerprint Image

Table V Testing Results for Fake fingerprint Image

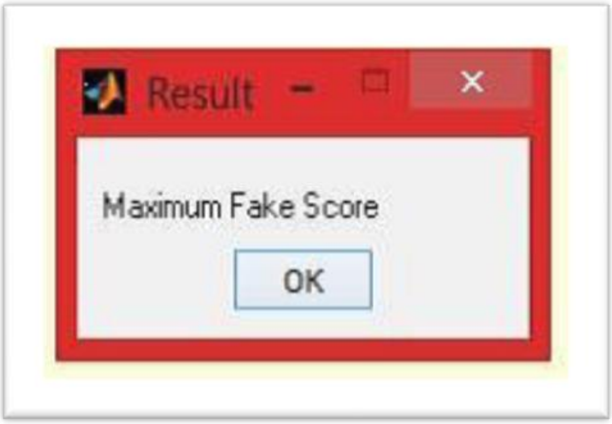
PARAMETER	ONPUT IMAGE(FAKE)
MSE(e^+2)	7.43
PSNR(e^+1)	5.21
SNR(e^+1)	6.06
SC(e^+0)	3.32
MD	84
AD(e^+1)	3.42
NAE(e^-2)	5.18
RAMD	8.4
LMSE(e^+1)	2.32
NXC(e^-1)	2.54
MAS(e^-2)	7.32
MAMS(e^+6)	19.14
TED(e^2)	10.89
TCD(e^-1)	15.01
SME(e^-3)	7.02
SPE(e^-7)	2.39
GME(e^4)	2.23
GPE(e^2)	8.32
SSIM(e^-1)	2.43
VIF	65
RRED	154
JQI(e^+1)	4.02
HLFI(e^-2)	5.93
BIQI(e^-1)	7.48
NIQE(e^+1)	2.10

5.3 Matlab Results

The following result shows that tested fingerprint image is Original.



The following result shows that tested fingerprint image is fake.



5.4 OVERALL RESULTS

Table VI Overall Results

FINGERPRINT IMAGE	FULL REFERENCE	NO REFERENCE
REAL	MSE,PSNR,SNR,NAE, SME,SC, NXC,GPE,SSIM,VIF, RRED	BIQI, NIQI
FAKE	MD,AD,RAMD,LMSE, MAS,MAMS, TED,TCD,SPE,GME	JQI,HLFI

The most remarkable finding is that the whole group of25 quality measures is consistently selected as the best performing feature set for all the considered scenarios and traits, showing the high complementarity of the proposed metrics for the biometric security task studied on the work.

VI. CONCLUSION

Image quality assessment for liveness detection technique is used to detect the fake biometrics. Due to Image quality measurements it is easy to find out real and fake users because fake identities always have some different features than original it always contain different color and luminance, artifacts, quantity of information, and quantity of sharpness, found on both type of images, structural distortions or natural appearance. This paper also opens new possibilities for future work, including: i) extension of the considered 25-feature set with new image quality measures; II) further evaluation on other image-based modalities(e.g., palm print, hand geometry, vein); III) inclusion of temporal information for those cases on which it is available (e.g., systems working with face videos); iv) use of video quality measures for video access attempts; v)Also Real time implementation of Iris and face image application on biometric can be done on efficient way.

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