A Novel Fingerprint Liveness Detection Method using Empirical Mode Decomposition and Neural Network

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***Abstract*—One of the most common biometric systems is fingerprint identification, which has been misused due to issues such as fraud. Hence, intelligent methods should be designed and used to recognize real-live fingerprints. Therefore, in the current work, we proposed a novel liveness fingerprint detection framework with low computational cost and excellent accuracy based on empirical mode decomposition and neural network to distinguish real from fake fingerprints. Our proposed scheme works based on empirical mode decomposition technique. The fingerprint images were cropped into 200 × 200 images and then the two-dimensional (2D) images were converted into one-dimensional (1D) data, greatly reducing the computational process. The empirical mode decomposition (EMD) technique decomposed the data and the first five intrinsic mode functions (IMFs) were targeted for feature extraction through simple statistical features. The findings revealed that our suggested system can yield an average accuracy of 97.72% in distinguishing fake from real fingerprints through multilayer perceptron (MLP) neural network. This framework is very efficient compared to other techniques because only one piece of fingerprint image is enough to defend against spoof attacks. Therefore, such framework can reduce the cost of the fingerprint biometric systems, as no further hardware is needed. In addition, our framework method gives the best classification results in comparison to other previous techniques in real-live fingerprint recognition while being simple with lower computational cost. Therefore, this framework can be practically used in commercial biometric systems.**

Keywords*—Fingerprint; liveness; biometric; neural network; empirical mode decomposition

I. Introduction

People's fingerprints have been used in criminology for many years, and today they are used in biometrics. The fingertip and its unique line pattern originate from the individual DNA pattern in each subject [1]. There are lines on the fingers of all people, which have been of interest to everyone for a long time. These important lines play different roles. One of them is to introduce frictions between finger and objects, by using this friction we can grab, write or touch objects [2]. Fingerprint is the oldest method of recognition and the progress in technology has increased its variety. One issue and difficulty in a biometric system is the lack of discrimination of fake fingerprints, to the extent that it leads to unauthorized entry into the system [3]. Hence, intelligent methods should be designed and used to recognize real-live fingerprints. Liveness identification is an anti-spoofing technique that ensures that only the biometrics of a real and authorized individual are sent for recognition. Liveness detection relies on the fact that extra data can be collected from an authorization system, and that this extra data may be utilized to check the authenticity of an image [4]. Liveness detection utilizes either software- or hardware-based systems along with an authentication system to supply more protection. Hardware-related systems utilize more equipment and readers to capture biometric measures other than fingerprints to detect liveness. Such systems used additional equipment to record biological signals such as fingertip temperature, electric resistance, blood pressure, odor, or heartbeat [5-7]. Nixon and Rowe proposed a multispectral reader in which several light wavelengths and multiple polarizations provide extra data not available from a traditional system. According to several spectral pictures, they introduced a spoof recognition technique [8]. However, this technique has limitations due to additional hardware and remains vulnerable and unreliable. On the other side, software-related approaches utilize different image processing methods to directly process fingerprint image details for liveness detection. For example, Kiss et al. developed a hardware-related system for liveness detection, whereas Schukers et al. investigated software approaches for this purpose [9].

In general, despite the many efforts that have been made in this field, a comprehensive software-based system that is accepted by everyone has not yet been developed, and previous studies have emphasized the necessity of developing this work. Therefore, in this study, inspired by software-based systems and texture features extracted from different layers of fingerprint images, a novel feature calculation scheme was suggested using empirical mode decomposition (EMD) in a one-dimensional framework. One of the key benefits of EMD is its ability to extract hidden information from nonlinear data [10]. In the proposed method, the two-dimensional (2D) data is first converted into one-dimensional (1D) data, and then liveness is predicted through statistical features extracted from five layers of fingerprint images.

This paper is organized as follows. In Section II, various software-based solutions in the fingerprint anti-spoofing were described. Section III provides the procedure proposed in the present work. Section IV reports the experimental. Section V discusses the obtained results and Section VI makes a conclusion.

II. Related Works

In the last two decades, many solutions have been proposed to address fingerprint spoofing vulnerabilities. Marasco et al. introduced a fingerprint liveness recognition system according to several textural properties and multiple classifiers (e.g., Bayesian classifier, decision tree, and multilayer perceptron) and achieved an accuracy of 87.5% [11]. The same authors published another paper two years later based on perspiration and morphological-based static features and reported an accuracy of 87.5% for fingerprint liveness detection [12]. Galbally et al. used image quality related features along with linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA) classifiers and reported an accuracy of 91.8% for fingerprint liveness detection [13]. Gragnaniello et al. introduced a complex liveness detection system based on Wavelet-Markov local-based features and support vector machine (SVM) and reported a good accuracy of 97.2% [14]. Nogueira et al. utilized convolutional networks with random weight and localized binary pattern along with SVM classifier and achieved an accuracy of 96.1% for liveness detection [15]. In 2015, Jiang et al. proposed co-occurrence matrix for feature extraction from fingerprint images along with SVM classifier and reported an accuracy of 93.2% for liveness detection [16]. Gottschlich et al. achieved an accuracy of 93.3% for fingerprint liveness detection using histogram of constant gradients [17]. Zhang and his colleagues used wavelet transform and localized binary patterns and reported an excellent accuracy of 97.9% [18]. Given that fingerprints show oriented texture like paradigm, Nikam et al. used Gabor filter based features to obtain local frequency and orientation data [19]. A novel feature extraction method for detecting fingerprint liveness according to the localized phase quantization has been introduced by Ghiani and his colleagues [20]. In addition, some studies have used other features such as skin deformation and fingerprint pores to detect liveness [21, 22]. For example, Espinoza and his colleagues suggested an approach through comparing pore numbers between real live and fake fingerprints [23]. Generally, previous studies show that the use of nonlinear analysis methods can achieve better classification results due to the nonlinear nature of fingerprint data. However, none of the previous researches have used the EMD method as a robust nonlinear analysis technique to extract hidden patterns in fingerprint data. Therefore, this study aims to integrate this nonlinear analysis technique with neural network in order to distinguish real fingerprints from fake ones.

III. Methodology

In this section, the dataset used, processing algorithms and classification methods were explained in detail.

A. Dataset

In this study, the well-known reliable database of the Liveness Detection Competition 2011 (LivDet 2011) was used that is publicly available [24]. This dataset includes 4 different subsets of fingerprint pictures captured through the Biometrrika FX2000, Sagem MSO300, ItalData ET10 and Digital Persona 4000B sensors. 4000 fingerprint images are available for every sensor. 2000 images are real-live fingerprints and the others are fake fingerprints. The fake images are synthesized by latex, gelatin, ecoflex, wood glue and silicone. Indeed, 400 fake fingerprint images were captured for each of these five materials. Fig. 1 displays fingerprint images from the LivDet 2011 dataset.

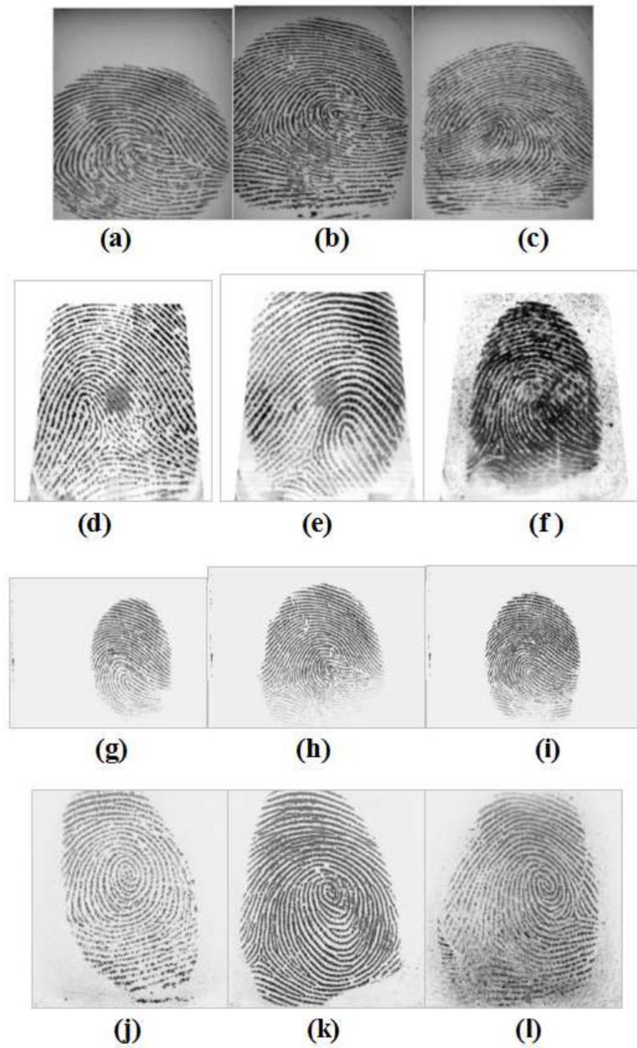

Fig. 1. Instances of spoof fingerprint pictures of the LivDet 2011 database, from Biometrika: (a) latex, (b) gelatin, (c) silicone; from Digital Persona: (d) latex, (e) gelatin, (f) silicone; from ItalData: (g) latex, (h) gelatin, (i) silicone; from Sagem: (j) latex, (k) gelatin, (l) silicone.

B. Preprocessing

Preprocessing is a crucial step in image processing. In the present work, images were prepared for further processing in terms of light intensity, color and other physical characteristics. This step provides a same condition for fake and real fingerprints. The actions performed in the preprocessing stage were image conversion to gray levels, image matching, image cropping, normalization, etc. Since the segments of the images were subjected to analysis, image equalization was performed after segmenting the image so that the effects of pixels around these segments do not appear in the image being processed [25]. In fact, since this work is only focused on fingerprint liveness and non-liveness, there is no need to process whole image. In addition, image cropping has two advantages: (1) analysis is performed on the fake and real fingerprint textures and the noise surrounding the picture is not processed, and (2) processing only a small segment of the image reduces the computational cost and accelerates the processing speed. As a result, the processing system designed in this way will be more practical. Therefore, in the current research, a 200 × 200 foursquare window was located on the fingerprint picture and subsequent analysis was performed on it (Fig. 2).

Fig. 2. Image segmentation and cropping used in this work.

1) Conversion 2D data into 1D: Since this work aimed to introduce a simple and effective system with minimum computational cost and maximum processing speed, an attempt was done to convert the 2D image data into 1D data in a simple way after cropping. This reduces the complexity of computations and simplifies the processing process. In this method, all the rows of the image pixel values matrix are sequentially placed in one row and form a vector of image pixel values. Therefore, the 2D matrix of image pixel values are transformed into a 1D vector similar to a time series, which is further processed on. This simple scheme is shown in Fig. 3.

C. Empirical Mode Decomposition

In 1998, Huang developed a new decomposition algorithm based on the Hilbert transform called EMD. This algorithm decomposes a time series into some oscillatory signals called intrinsic mode functions (IMF) [26, 27]. Due to the ability of EMD to provide short time variations in frequency that are not attainable from Fourier transform, it may be utilized to analyze nonstationary and nonlinear signals [28]. EMD is developed in the Hilbert-Huang transform (HHT) under the supposition that each signal comprises of ordinary intrinsic functions of fluctuations [29, 30]. The nature of the algorithm is to determine the intrinsic fluctuating functions through their characteristic temporal subscales in the signal empirically and separate it into simpler compounds correspondingly [31]. The resultant compounds obtained from the algorithm form the IMFs. IMFs are functions that satisfy two stipulates: (1) in the entire dataset, the count of extrema and the count of zero-crossings should be equal or differ not more than one; and (2) at each sample, the averaged value of the envelope determined through the local maxima and the envelope determined through the local minima approaches zero [26]. The process to produce an IMF in the EMD is known as sifting mechanism. The sifting framework to generate the IMFs of a time series s(t), consists of the following stages:

1) Find all local maxima and minima of time series s(t);

2) Interpolation among the local maxima to produce lower envelope, $s_L(t)$, as well as interpolation among the local maxima to produce upper envelope, $s_U(t)$;

3) For every time point t, compute the average of the lower and upper envelopes;

$$e(t) = \frac{s_L(t)+s_U(t)}{2} \tag{1}$$

4) Subtract the averaged resultant from the input time series;

$$d(t) = s(t) - e(t) \tag{2}$$

This is a single iteration of the sifting framework. The next stage is to verify if the time series d(t) from the previous stage is an IMF or not.

5) Replicate the sifting mechanism on the residue time series.

Practically, of the averaged envelop approaches zero, the sifting framework stops. This stopping condition guarantees the symmetrical property of the resultant envelop as well as the accurate relationship between the count of extremes and count of zero crossings that determine the IMFs [32].

Here, EMD was first applied to 1D data and then seven statistical features were calculated from the five first IMFs obtained from the EMD decomposition process. Previous studies on biomedical data have shown that the first five IMFs extracted from EMD contain very important details and information from the original data [33-35]. Therefore, according to previous studies and to keep the computation cost low, the first five IMFs were used in this work for feature extraction. Fig. 4 shows our proposed process according to preprocessing, EMD and feature selection approaches for fingerprint liveness identification.

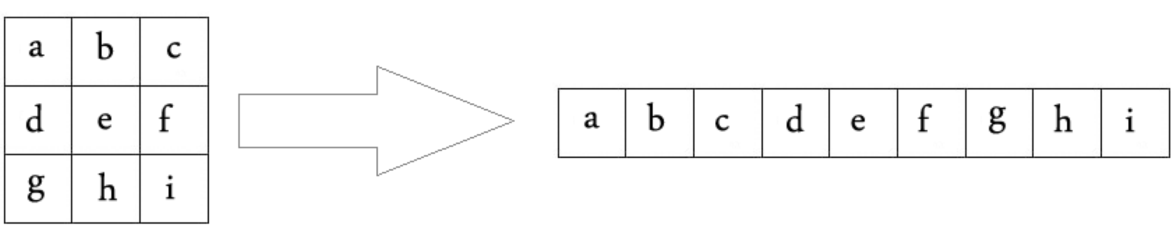

Fig. 3. A proposed scheme for converting two-dimensional data into one-dimensional data.

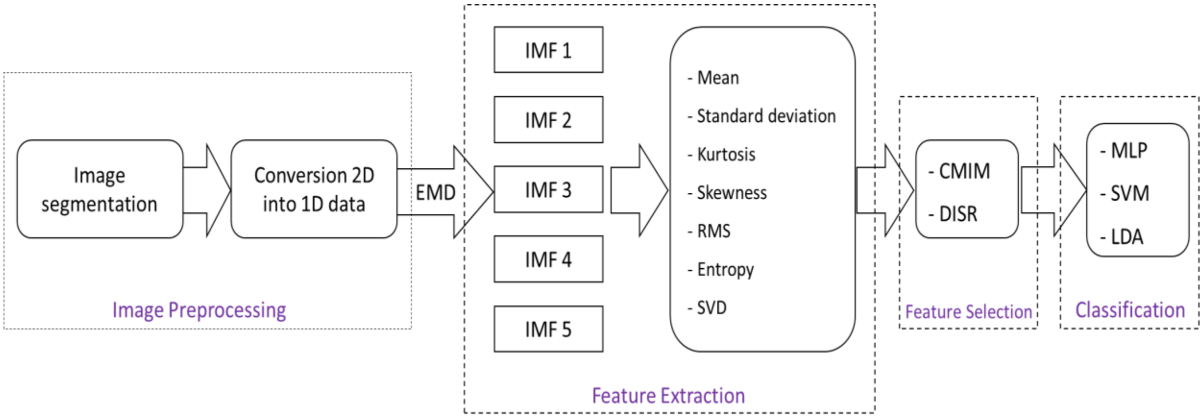

Fig. 4. The proposed process according to preprocessing, EMD and feature selection approaches for fingerprint liveness identification.

After extracting the first five IMFs for each feature vector, seven statistical features [36] (i.e., standard deviation, mean, skewness, root mean square (RMS), kurtosis, singular value decomposition (SVD), entropy) were calculated with the following mathematical definitions for each IMF:

$$Mean = \frac{1}{n}\sum_{i=1}^{n}(x_i) \tag{3}$$

$$Standard\ deviation = \left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right)^{\frac{1}{2}} \tag{4}$$

$$RMS = \sqrt{\frac{1}{n}({x_1}^2 + {x_2}^2 + {x_3}^2 + \cdots + {x_n}^2)} \tag{5}$$

$$Entropy = \sum(P * \log_2 P) \tag{6}$$

$$Skewness(X) = \frac{E[(X-\mu)^3]}{\sigma^3} \tag{7}$$

$$Kurtosis(X) = \frac{E[(X-\mu)^4]}{\sigma^4} \tag{8}$$

$$SVD = U\sum V^T \tag{9}$$

where x or X denote the time series (i.e., each IMF), n represents the count of data points, P represents the count of image histograms, μ denotes the mean of signal, σ denotes the standard deviation, and E[.] is the mathematical expectation.

D. Feature Selection

In this work, all above seven features were calculated for the first five IMFs. Thus, a 5 × 7 feature matrix was produced for every image. Therefore, 35 features were calculated for the entire fingerprint images. However, it should be noted that some features may be redundant or may not be informative for distinguishing real from fake fingerprints. Thus, the CMIM and DISR were utilized in our framework to select best discriminative features, improve the classification results and minimize computational cost.

1) CMIM: This method removes redundant features by making a trade-off between discrimination and independence to choose features that maximize mutual information with the class to anticipate. Conditional mutual information is defined by:

$$CMI(y; x_n|x_m) = H(y|x_n) - H(y|x_n.x_m) \tag{10}$$

Afterward, following relationship is utilized for selecting the (F+1)th feature while F features have been chosen.

$$f(F+1) = \arg\max_n(\min_{1\le l\le F} I(y; x_n|x_{f(l)})) \tag{11}$$

2) DISR: This algorithm utilizes the following equation for feature selection [37, 38]:

$$F_{DISR} = \arg\max_{X_i\in X_s}\left\{\sum_{X_j\in X_s}\frac{MI(X_{i.j}.Y)}{H(X_{i.j}.Y)}\right\} \tag{12}$$

where $H(X_{i.j}.Y)$ is the information entropy and $MI(X_{i.j}.Y)$ is the mutual information.

E. Classification

1) Multilayer perceptron (MLP) neural network: One of the simplest and effective structure of neural networks is MLP with back propagation learning procedure. MLP has been demonstrated to be effective in various problems, including pattern recognition, prediction, estimation and classification. The architecture of this neural network comprises of an input layer, hidden layer(s) and an output layer. The neurons of every layer are linked to the next layer with a certain weight, which is defined as follows:

$$\Delta W_{ij} = \eta\delta_j(n)y_i(n) \tag{13}$$

The above equation is known as the delta law through which weight correction is done from neuron i to neuron j. η, $\delta_j(n)$ and $y_i(n)$ are learning rate variable, local gradients and input signal of neuron j, respectively. If j is a neuron in the hidden layer, then $\delta_j(n)$ is obtained through:

$$\delta_j(n) = \varphi_j'(v_j(n))\sum_k \delta_k(n)W_{kj}(n) \tag{14}$$

where k is a neuron in the output layer, and $\varphi_j'(v_j(n))$ denotes the activation function for characterizing the input-output relationships of the non-linearity to entity j [39, 40].

2) SVM: In this study, SVM was used for classification because this classifier minimizes the expected risk in the test data and considers a margin around the class boundaries, which leads to increased generalizability of the results. SVM uses a kernel property to convert the nonlinear classification problem into a linear one by increasing the dimensionality of the dataset. In this work, we used the RBF kernel. The mathematical notation of SVM is [41]:

$$a_i = [(\omega \cdot b_i) + x] - 1 \geq 0 . \quad i = 1.2 \dots . l \quad (15)$$

where a_i represents the identifier generated by SVM ($a_i \in -1. +1$). This can be transformed into a dual problem via the Lagrange coefficient as follows:

$$\min Q(y) = \frac{1}{2}\sum_{i.j=1}^{l} y_i y_j a_i a_j \cdot K(b_i b_j) - \sum_{i=1}^{l} y_i \quad (16)$$

y_i represents Lagrange coefficients. K is the kernel function with the following equation:

$$K(a.a_i) = \frac{\exp(-|a-a_i|^2)}{g^2} \quad (17)$$

3) LDA: LDA is an expansion of Fisher's linear discriminant to find linear combinations of samples that separate two classes of events or objects. It is very associated with regression analysis and analysis of variance, which attempt to specify one dependent variable as a linear combination of other samples. LDA attempts to solve an optimal discrimination projection matrix W_{opt}:

$$W_{opt} = \text{argmax}_W \left| \frac{W^T S_b W}{W^T S_t W} \right| \quad (18)$$

where, S_b and S_t are the scatter matrices with the following definitions:

$$S_b = \sum_{p=1}^{q} n_p (\mu_p - \mu)(\mu_p - \mu)^T \quad (19)$$

$$S_t = \sum_{p=1}^{q} n_p (\mu_p - \mu)(\mu_p - \mu)^T + \sum_p (x_p - \mu_{k_p})(x_p - \mu_{k_p})^T \quad (20)$$

where, S_b represents the between-class dispersion matrix and S_t represents the total dispersion matrix. The second term in (20) represents the within-class dispersion matrix. μ_p represents the averaged feature vector of image class p, as well as n_p denotes the count of features in image class p. q denotes the total count of the features. x_p denotes the feature vector of a data point, and μ_{k_p} denotes the vector of the image class that x_p belongs to [42].

IV. Results

After preprocessing and cropping the fingerprint images, the 2D data of the images were converted into 1D data, and then the EMD algorithm was applied to this 1D data, and the IMFs of each data were extracted for real and fake fingerprints. Next, all seven mentioned features were calculated for the first five IMFs. Fig. 5, 6, 7 and 8 show the box plots for the mean, standard deviation, entropy and SVD features for the five IMFs of real and fake fingerprints, respectively.

As shown in the above figures, there are obvious differences in the features extracted from different IMFs between real and fake fingerprints. However, as expected, the rate of change decreases after IMF1. This observation is due to the fact that the IMF 1 has more information and details from the original data, and in the subsequent IMFs, the amount of these details decreases accordingly.

After feature extraction, feature selection was performed with CMIM and DISR methods. Then, feature classification by three different classifiers (i.e., MLP, SVM and LDA) was performed to distinguish real from fake fingerprints. At this stage, 70% of the dataset (i.e., extracted features) was allocated for training classifiers, 10% of the dataset for validation, and the remaining 20% for testing the performance of the classifiers. To assess the classification performance, a random subsampling technique was used that replicates the hold-out cross validation n times. MLP training process was stopped if 1000 iterations executed or error reached less than 0.01%.

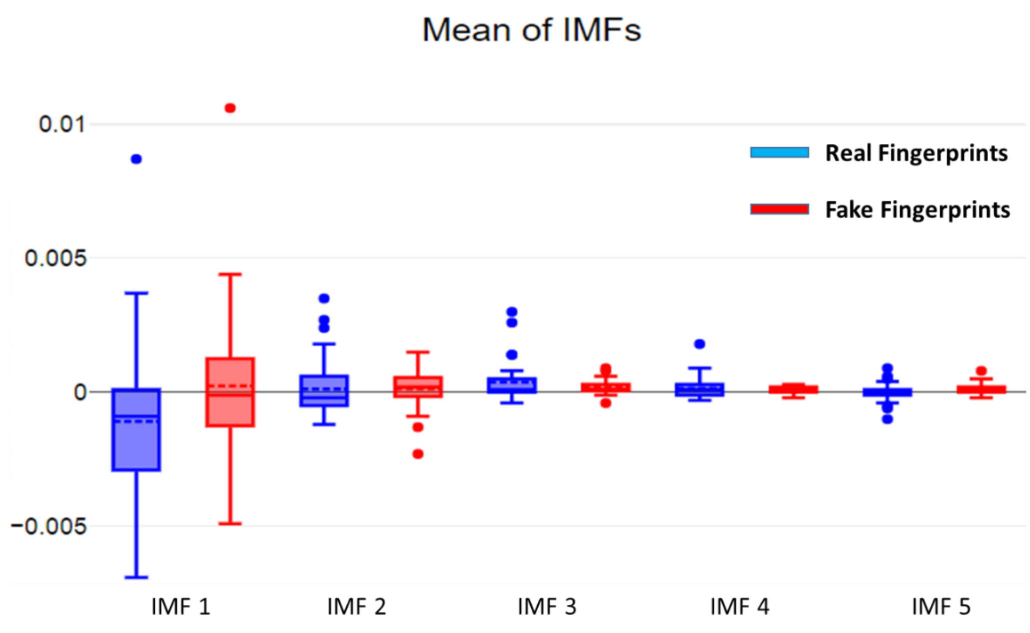

Fig. 5. Mean of the first 5 IMFs computed from one-dimensional data of real and fake fingerprints.

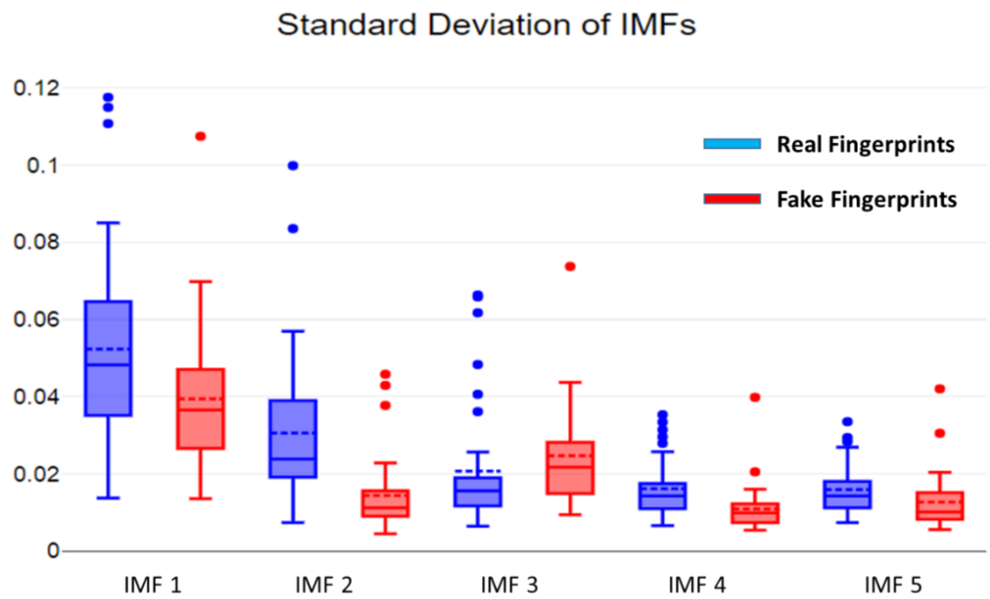

Fig. 6. Standard deviation of the first 5 IMFs computed from one-dimensional data of real and fake fingerprints.

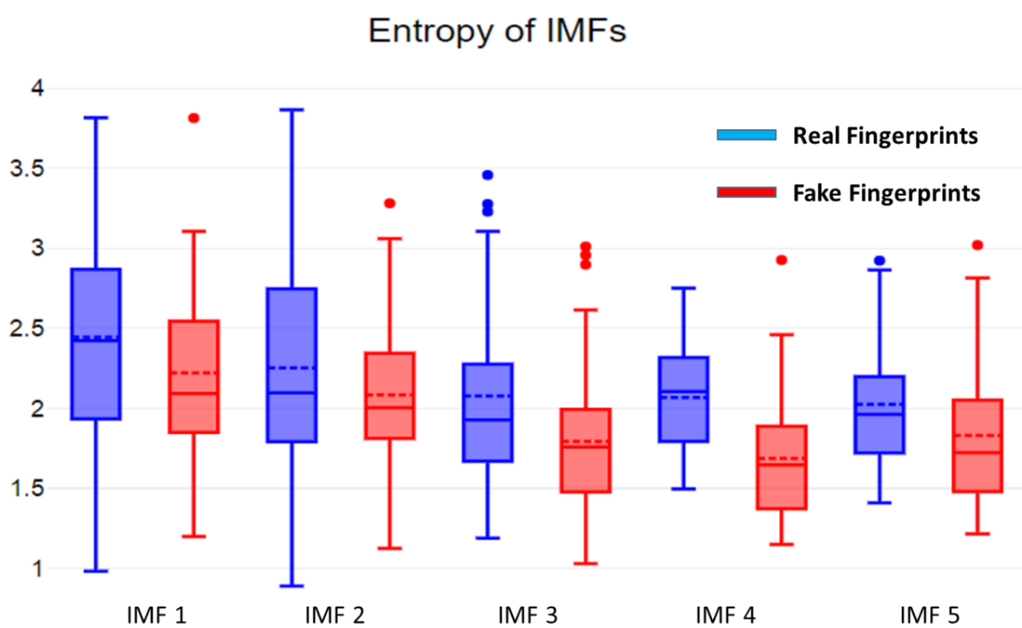

Fig. 7. Entropy of the first 5 IMFs computed from one-dimensional data of real and fake fingerprints.

To evaluate the classification performance, the following error criteria were calculated and used:

False fake rate (FFR) = The number of fake fingerprints that are mistakenly recognized as real.

False real rate (FRR) = The number of real fingerprints that are mistakenly recognized as fake.

Average classification error (ACE) = (FFR + FRR)/2.

Tables I, II and III summarize the classification results obtained by MLP, SVM and LDA classifiers, respectively. All classifiers produced a lower ACE through the features chosen by the DISR feature selection approach as input. Also, all classifiers produced a higher ACE using all features as input. This showed that feature selection is an effective approach to feed classifiers with high discriminative features. Our experiments showed that DISR is a more effective feature selection method than CMIM, which can lead to better classification results. The best results of FFR, FRR and ACE obtained by MLP were 2.48%, 2.08% and 2.28%, respectively (Table I).

Also, the best results of FFR, FRR and ACE obtained by SVM were 3.40%, 2.24% and 2.82% respectively (Table II). Finally, the best results of FFR, FRR and ACE obtained by LDA were 5.53%, 2.64% and 4.09% respectively (Table III).

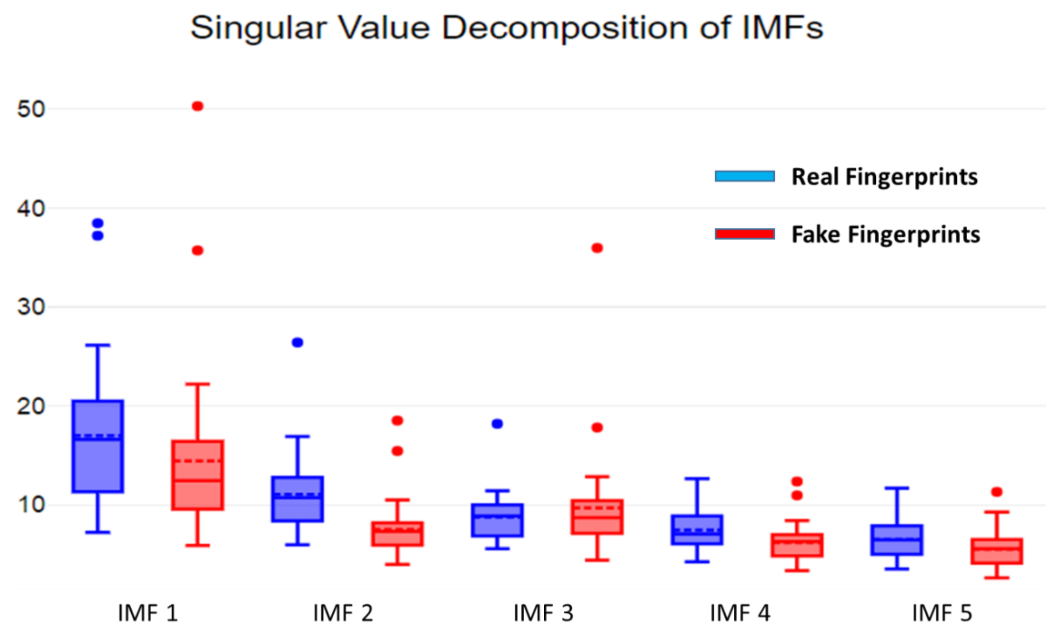

Fig. 8. SVD of the first 5 IMFs computed from one-dimensional data of real and fake fingerprints.

TABLE I. PERFORMANCE OF MLP NEURAL NETWORK IN REAL AND FAKE FINGERPRINT CLASSIFICATION

Feature set	FFR (%)	FRR (%)	ACE (%)
All features	2.55	3.30	2.93
Selected features by CMIM	2.57	2.80	2.69
Selected features by DISR	2.48	2.08	2.28

TABLE II. PERFORMANCE OF SVM CLASSIFIER WITH RBF KERNEL IN REAL AND FAKE FINGERPRINT CLASSIFICATION

Feature set	FFR (%)	FRR (%)	ACE (%)
All features	4.51	3.51	4.01
Selected features by CMIM	3.20	3.10	3.16
Selected features by DISR	3.40	2.24	2.82

TABLE III. PERFORMANCE OF LDA CLASSIFIER WITH IN REAL AND FAKE FINGERPRINT CLASSIFICATION

Feature set	FFR (%)	FRR (%)	ACE (%)
All features	6.68	5.72	6.20
Selected features by CMIM	4.95	4.45	4.70
Selected features by DISR	5.53	2.64	4.09

V. DISCUSSION

Spoof attacks with non-real replications substantially threaten the security of different fingerprint identification systems. Thus, it is necessary to develop efficient countermeasures against these deceive attacks. In the current work, a novel liveness fingerprint detection framework with low computational cost and excellent accuracy was proposed. Our proposed scheme works based on empirical mode decomposition technique. The fingerprint images were cropped into 200 × 200 images and then converted the 2D images into 1D data, greatly reducing the computational process. The EMD technique decomposed the data and the first five IMFs were targeted for feature extraction through simple statistical features. Consistent with previous studies [15, 16], our findings also demonstrated the efficacy of textural features to detect fingerprint viability. The findings revealed that our suggested system can yield an average accuracy of 97.72% in distinguishing fake from real fingerprints through MLP neural network. This framework is very efficient compared to other techniques because only one piece of fingerprint image is enough to defend against spoof attacks. Therefore, such framework can reduce the cost of the fingerprint biometric systems, as no further hardware is needed. Image cropping, 2D to 1D data conversion and the use of nonlinear EMD analysis are the innovations of this study that distinguish our work from previous studies. As will be explained in the next paragraph, this framework led to the improvement and development of previous results and was a step forward in the development of software-based methods for fingerprint liveness detection.

In this section, our proposed framework was compared with other techniques examined on the same database (i.e., LivDet 2011 database). Table IV indicates the characteristics and results of similar papers conducted on the LivDet 2011 database to discriminate fake from real fingerprints in terms of ACE. As indicated, seven papers have worked on this dataset with various computational algorithms to detect real-live fingerprints. Most of the previous techniques utilized texture features and all of them utilized SVM classifier. Gragnaniello et al. [43] reported the best classification results with the ACE = 5.7%. Their system works based on local contrast phase descriptor. As shown in Table IV, our introduced technique gives the best classification results compared to other previous methods in real-live fingerprint recognition while being simple with lower computational cost. Therefore, this framework can be practically used in commercial biometric systems.

TABLE IV. CHARACTERISTICS AND RESULTS OF SIMILAR STUDIES CONDUCTED ON THE LIVDET 2011 DATASET TO DISTINGUISH REAL FROM FAKE FINGERPRINTS

Author (year)	Algorithm	Classifier	Result
Nogueira et al. (2014) [15]	Convolutional network with random weight and local binary pattern	SVM	ACE = 6.5%
Jian et al. (2015) [16]	Co-occurrence matrix	SVM	ACE = 11%
Jia et al. (2014) [44]	Multiscale local binary pattern	SVM	ACE = 7.5%
Gragnaniello et al. (2015) [43]	Local contrast phase descriptor	SVM	ACE = 5.7%
Jia et al. (2013) [45]	Multiscale local ternary patterns	SVM	ACE = 9.8%
Zhang et al. (2014) [18]	Wavelet transform and local binary patterns	SVM	ACE = 12.5%
Johnson et al. (2014) [46]	Pore characteristics	SVM	ACE = 12%
Our proposed system	Empirical mode decomposition and statistical features	MLP, SVM, LDA	ACE = 2.28%

VI. CONCLUSION

In summary, the proposed framework includes preprocessing along with image cropping incorporation, feature extraction using nonlinear analysis, feature selection by two different information-based approach, and classification stage through neural network, improved accuracy of previous techniques for fingerprint liveness detection. The findings of the present study support the use of nonlinear analysis and texture features for liveness fingerprint detection. However, the results of this study need to be validated by additional databases. In addition, future studies should explore other advanced classification techniques, especially deep learning models, to improve our findings.

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