Empirical Mode Decomposition Liveness Check in Fingerprint Time Series Captures

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Abstract

This work demonstrates a faster approach for liveness detection in fingerprint devices. The physiological phenomenon of perspiration, observed in time-series fingerprint images of live people, is used as a measure to classify 'live' fingers from 'not live' fingers. Pre-processing involves finding the singularity points using wavelets in the fingerprint images and transforming the information back in the spatial domain to form a spatial domain signal. Wavelet packet sieving is used to tune the modes so as to gain physical significance with reference to the evolving perspiration pattern in 'live' fingers. The percentage of energy contribution in the difference modes is used as a measure to differentiate live fingers from others. The proposed algorithm was applied to a data set of approximately 58 live, 50 spoof and 28 cadaver fingerprint images captured at 0 and after 2 sec, from three different types of scanners. An overall classification rate of 93.7% *was achieved across all the three scanners.*

1. Introduction

In this research a new faster method is proposed for liveness check in fingerprint devices, as a supplement to the fingerprint recognition. Recent studies have demonstrated easy and inexpensive methods to spoof fingerprint recognition systems [11] and liveness detection has been suggested as one of the countermeasures against such attacks [18, 13, 14]. The changing perspiration pattern along the live fingerprint ridges, over time, is used as a measure to classify 'live' fingers from 'not live' fingers. Previous methods, as described in [2, 15, 1], are computationally expensive. A more efficient method has been developed by calculating the singularity points in the fingerprint image. The singularity points are obtained using wavelet domain energy thresholding in the fingerprint images and transforming the information back in the spatial domain to form a spatial domain signal. Wavelet analysis of the images is performed using Daubechies wavelet. Wavelet packet analysis is used to maintain scalable structure of the information content. If sufficient number of singularity points are obtained, only then, the obtained signal is subjected to Hilbert Huang Technique. Wavelet packet sieving is used to tune the modes so as to gain physical significance with reference to the evolving perspiration pattern in 'live' fingers. The percentage of the energy contribution in the difference modes is used as a quantified measure to differentiate live fingers from others. It was observed that the singularity points act as 'quality check' points and hence bad quality cadaver images and partial spoof images were rejected due to number of singularity points below the selected threshold, before further processing.

In this paper, section 2 presents data management. Section 3 describes the singularity point detection part of the algorithm. Section 4 gives the background for empirical mode decomposition (EMD), Hilbert-Huang transform (HHT) and wavelet packet transform (WPT). Section 5 presents the overall algorithm and sections 6 and 7 present results and conclusion.

2. Data management

Data previously collected in our lab is used to test the algorithm. This data set is diverse as far as age, sex, and ethnicity is concerned. Different age groups (23 people between ages 20-30 years, 18 people between 30-40, 9 people between 40-50, and 8 people greater than 50), ethnicities (Asian-Indian, Caucasian, Middle Eastern), and approximately equal numbers of men and women are represented. The data was collected using three different fingerprint scanners, with different underlying technologies including: optical (Secugen model FDU01), electro-optical (Ethentica model Ethenticator USB 2500) and capacitive DC (Precise Biometrics model PS100) techniques of capturing a fingerprint. For spoof finger images, a cast was made from each live subject using dental material and spoofs were

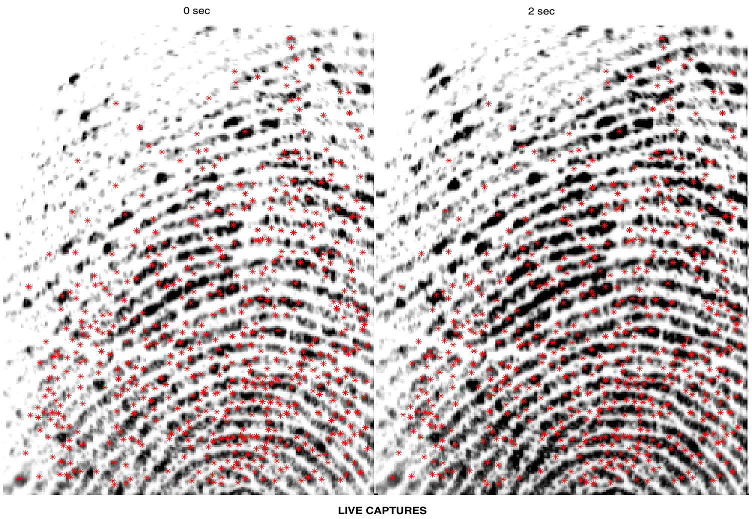

Figure 1. Live fingerprint captures at $0sec$ and after $2sec$ are shown with the key points marked.

created from Play-Doh using the procedure given in [4]. Images from cadaver subjects were collected in collaboration with the Musculoskeletal Research Center at West Virginia University (WVU). Protocols for data collection from the subjects were followed that were approved by the West Virginia University Institutional Review Board (IRB) (HS#14517 and HS#15322). Two images were collected as a time-series live scan, at 0 seconds and, 2 seconds after placement. The data set consists of 130 to 136 fingerprints from live, spoof, and cadavers, depending on the scanner used. Table (1) summarizes the available data. Differences in the number of images per scanner are due to inclusion criteria which requires an accepted enrollment image within five tries. Image collection was performed using custom software developed from device SDKs. All algorithm development was performed using MATLAB.

Table 1. Data set: Distribution

	Capacitive DC Precise Biometric	Electro-optical Ethentica	Optical Secugen
Live	58	55	58
Spoof	50	50	52
Cadaver	33	22	28

3. Singularity point detection

For this particular algorithm, Daubechies wavelet is selected as the mother wavelet. This is in accordance with the following properties of Daubechies wavelets [3]:

- orthonormality, having finite support.
- optimal, compact representation of the original signal from a sub-band coding point of view, thus producing multiresolution effect.
- capability to select maximum vanishing moments and minimum phase, so as to extract even minute details from smoother parts.
- cascade algorithm which can zoom-in on particular features of ϕ.

Daubechies filters used for this algorithm are designed so that the phase of the filter is minimum and the number of vanishing moments are maximum. This is of particular importance as not all the images are well focused and it is crucial to extract the changing information even from the smoother parts of the images [3].

3.1. Localization of ridge information through singularity detection

The method to localize ridge information through singularity detection is based on the observation that for each location (x, y) the time course of a pixel can be considered as a piecewise regular function. Thus, a wavelet transform along the temporal dimension yields a sparse representation of the data with most coefficients close to zero (vanishing property of the wavelet transform). A few large coefficients are obtained at time points, where the signal consists of jump-like changes or singularities from a baseline to an activation state or vice versa. Singularity detection can be undertaken by describing the local regularity of a signal. In our approach we took advantage of the ability of the wavelet transform to characterize the local regularity of the ridge functions. The mathematical background justifying this method is described in [3]. For the fingerprint image all modulus maxima of its wavelet transform and chain maxima across scales to obtain maxima lines are computed. If the image is noisy, maxima lines due to noise are mostly concentrated at fine scales, whereas maxima lines due to signal changes should be persistent across coarser scales. Mathematically, singularity detection can be carried out by finding the abscissa where the wavelet modulus maxima converge at finer scales. If no wavelet modulus maxima exist at fine scales for a point $t = u$, it was shown that the signal is regular in u.

The major task was to distinguish singularities caused by noise fluctuations from those that are generated from sharp signal transitions. Similar to the approach given in [8] three criteria were used namely ridge length, ridge orientation strength, and ridge reliability. Only maxima lines that persist across all scales of analysis are considered as true ridge signal transitions, since noise fluctuations should have less persistence in scale-space. In addition, the strength of a ridge maxima line is computed as the sum of the modulus maxima along the line (across scales). This criterion reinforces the first criteria, since longer maxima lines tend to have larger values for their strength, and strong signal variations yield wavelet coefficients with large amplitudes resulting in values of greater magnitude. These two criteria essentially filter out noisy and partial images for further analysis.

The singularity detection is performed for both the images captured after zeroth and two second in the time series capture sequence. The obtained singularity points are further filtered out using ridge length, ridge orientation strength and ridge reliability, and the retained points are used as the key points for further processing. The obtained key points in case of 'live' captures is shown in figure (1) while figure (2) demonstrates the linking between the points. The points without any linking might be directly related to the perspiration changes. This is getting reflected in the bottom row of the table (2).

The obtained point linking is mapped into a time domain signal $f(t)$ using B-spline interpolation. This signal is further processed using EMD based technique as described in section 2. Table (2) demonstrates the average number of singularity points obtained and matches found for all the three categories. The numbers given in table (2) are averaged for all the three scanner technologies.

Table 2. Wavelet Singularity Detection

	Live	Spoof	Cadaver
Avg. Keypoints (0 sec)	2111	1345	899
Avg. Keypoints (2 sec)	2832	1366	1341
Avg. Matches Found	**932**	**98**	**167**

4. Hilbert-Huang analysis

Huang et. al. [12, 5] developed a signal analysis method, called as the Empirical Mode Decomposition (EMD) method. This method analyzes the signal under the consideration, by decomposing it into mono-components called Intrinsic Mode Functions (IMF). The empirical nature of the approach may be partially attributed to a subjective definition of the envelope and the intrinsic mode function involved in its sifting process. The EMD method used in conjunction with Hilbert Transform is also known as Hilbert-Huang Transform (HHT). By the EMD method, the obtained signal $f(t)$ can be represented in terms of IMFs as:

$$f(t) = \sum_{i=1}^{n} c_i(t) + r_n \tag{1}$$

where, $c_i(t)$ is the i^{th} Intrinsic Mode Function and r_n is the residue.

A set of analytic functions can be constructed for these IMFs. The analytic function $z(t)$ of a typical IMF $c(t)$ is a complex signal having the original signal $c(t)$ as the real part and its Hilbert transform of the signal as its imaginary part. By representing the signal in the polar coordinate form one has

$$z(t) = c(t) + jH[c(t)] = a(t)e^{j\phi(t)} \tag{2}$$

where $a(t)$ is the instantaneous amplitude and $\phi(t)$ is the instantaneous phase function. The instantaneous amplitude $a(t)$ and is the instantaneous phase function $\phi(t)$ can be calculated as,

$$a(t) = \sqrt{\{c(t)\}^2 + \{H[c(t)]\}^2} \tag{3}$$

$$\phi(t) = \tan^{-1}\left\{\frac{H[c(t)]}{c(t)}\right\} \tag{4}$$

The instantaneous frequency of a signal at time t can be expressed as the rate of change of phase angle function of the analytic function obtained by Hilbert Transform of the signal. The expression for instantaneous frequency is given in equation (5).

$$\omega(t) = \frac{d\phi(t)}{dt} \tag{5}$$

Because of a capability of extracting instantaneous amplitude $a(t)$ and instantaneous frequency $\omega(t)$ from the signal, this method can be used to analyze an obtained non-stationary signal. In a special case of a single harmonic signal, the phase angle of its Hilbert transform is a linear function of time and therefore its instantaneous frequency is constant and is exactly equal to the frequency of the harmonic. In general, the concept of instantaneous frequency

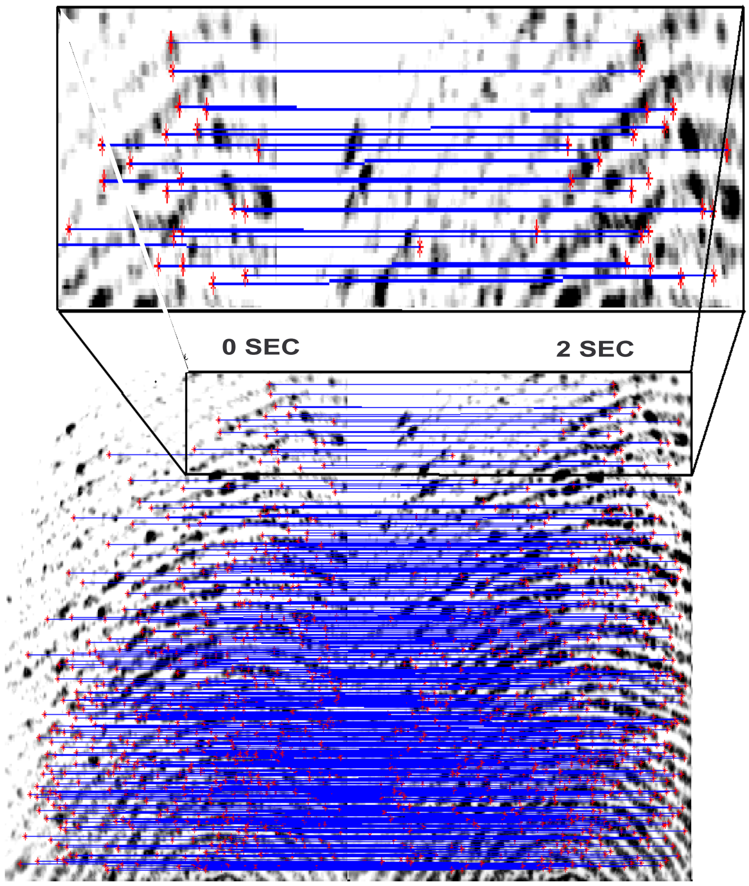

Figure 2. Live fingerprint captures at $0sec$ and after $2sec$ are shown with the key points linked.

provides an insightful description as how the frequency content of the signal varies with the time.

The empirical mode decomposition (EMD) method proposed by [12, 5] decomposes a signal into IMFs by an innovative sifting process. The IMF is defined as a function which satisfy following two criterion,

- The number of extrema and the number of zero crossings in the component must either equal or differ at most by one.
- At any point, the mean value of the envelope defined by the local maxima and the envelope defined by local minima is zero.

A sifting process proposed to extract IMFs from the signal processes the signal iteratively in order to obtain a component which satisfies above mentioned conditions. An intention behind application of these constraints on the decomposed components is to obtain a symmetrical mono-frequency component to guarantee a well-behaved Hilbert transform. It is shown that the Hilbert transform behaves erratically if the original function is not symmetric with x-axis or there is sudden change in phase of the signal without crossing x-axis [5].

The sifting process separates the IMFs with decreasing order of frequency i.e it separates high frequency component first and decomposes the residue obtained after separating each IMF till a residue of nearly zero frequency content does not obtained. To date, there is no mathematical formulation derived for EMD method and the studies done in order to analyze the behavior of this method in stochastic situations involving broadband noise shows that the method behaves as a dyadic filter bank when applied to analyze a fractional Gaussian noise [6]. In this sense, the sifting process in the EMD method may be viewed as an implicit wavelet analysis and the concept of the intrinsic mode function in the EMD method is parallel to the wavelet details in wavelet analysis.

The wavelet packet analysis of the signal was seen as a filter bank with adjustable time and frequency resolution. It resulted in symmetrical orthonormal components when a symmetrical orthogonal wavelet is used as a decomposition wavelet. As a signal can be decomposed into symmetrical orthonormal components with wavelet packet decomposition, they also guarantee well behaved Hilbert transform. These facts motivate formulating a sifting process based on wavelet packet decomposition to analyze a non-stationary signal obtained from the fingerprint images. This procedure may be used to detect what type of fingerprint the said signal has generated.

4.1. Wavelet packet transform

A wavelet packet is represented as a function, $\psi^i_{j,k}$ where i is the modulation parameter, j is the dilation parameter and k is the translation parameter.

$$\psi^i_{j,k}(t) = 2^{-j/2}\psi^i(2^{-j}t - k) \tag{6}$$

Here $i = 1, 2j^n$ and n is the level of decomposition in wavelet packet tree.

The wavelet packet coefficients $c^i_{j,k}$ corresponding to the signal $f(t)$ can be obtained as,

$$c^i_{j,k} = \int_{-\infty}^{\infty} f(t)\psi^i_{j,k}(t)dt \tag{7}$$

The entropy E is an additive cost function such that $E(0) = 0$. The entropy indicates the amount of information stored in the signal i.e. higher the entropy, more is the information stored in the signal and vice-versa. There are various definitions of entropy in the literature [3]. Among them, two representative ones are used here i.e. the energy entropy and the Shannon entropy. The wavelet packet node energy entropy at a particular node n in the wavelet packet tree of a signal is a special case of $P = 2$ of the P-norm entropy which is defined as,

$$e_n = \sum_k |c^i_{j,k}|^P \quad (P \geq 1) \tag{8}$$

where $c^i_{j,k}$ are the wavelet packet coefficients at particular node of wavelet packet tree. It was demonstrated that the wavelet packet node energy has more potential for use in signal classification as compared to the wavelet packet node coefficients alone [7]. The wavelet packet node energy represents energy stored in a particular frequency band and is mainly used to extract the dominant frequency components of the signal. The Shannon entropy is defined as,

$$e_n = -\sum_k (c^i_{j,k})^2 \log[(c^i_{j,k})^2] \tag{9}$$

Note that one can define his own entropy function if necessary. Here the entropy index (EI) is defined as a difference between the number of zero crossings and the number of extrema in a component corresponding to a particular node of the wavelet packet tree as,

$$EI = |No\,of\ zero\ crossings - No\,of\ extrema| \tag{10}$$

Entropy index value greater than 1 indicates that the component has a potential to reveal more information about the signal and it needs to be decomposed further in order to obtain simple frequency components of the signal.

5. Wavelet-based sieving

The overall algorithm first performs singularity point detection which filters noisy and partial images, and localizes the ridge information for further analysis. Next the localized ridges are interpolated with cubic splines. The interpolated data increases the time resolution of the signal which will in turn increase the regularity of the decomposed components. The cubic spline interpolation assures the conservation of signal data between sampled points without large oscillations.

Table 3. Average Percentage Contribution of Energy (%) for Ethentica

Mode No.	Packet Node	Live	Spoof	Cadaver
2	(8,1)	52.2	6.3	3.9
3	(7,0)	61.3	11.2	14.8
4	(6,1)	91.2	57.3	37.3

The interpolated data is decomposed into different frequency components by using wavelet packet decomposition, described in section 3. A shape of the decomposed components by wavelet analysis depends on the shape of the mother wavelet used for decomposition. Daubechies wavelet of higher order(16) shows good symmetry and leads to symmetrical and regular shaped components.

In case of the binary wavelet packet tree, decomposition at level n results in 2^n components. This number may become very large at a higher decomposition level and necessitate increased computational efforts. An optimum decomposition of the signal can be obtained based on the conditions required to be an IMF. A particular node (N) is split into two nodes N_1 and N_2 if and only if the entropy index of the corresponding node is greater than 1 and thus the entropy of the wavelet packet decomposition is kept as least as possible. Other criteria such as the minimum number of zero crossings and the minimum peak value of components can also be applied to decompose only the potential components in the signal.

Once the decomposition is carried out, the mono-frequency components of the signal can be sieved out from the components corresponding to the terminal nodes of the wavelet packet tree. The percentage energy contribution of the component corresponding to each terminal node to the

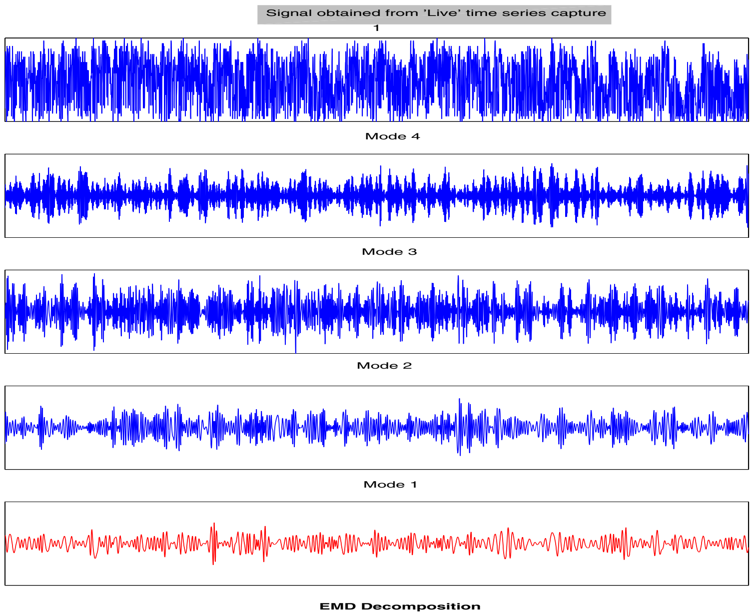

Figure 3. EMD Decomposition for the live fingerprint signal.

Table 4. Average Percentage Contribution of Energy (%) for Secugen

Mode No.	Packet Node	Live	Spoof	Cadaver
2	(8,1)	46.5	12.2	0.6
3	(7,0)	71.3	22	5.5
4	(6,1)	77.2	28.7	41.2

original signal is used as sieving criteria in order to identify the potential components of the signal. This is obtained by summing up the energy entropy corresponding to the terminal nodes of the wavelet packet tree of the signal decomposition in order to get total energy content and then calculating the percentage contribution of energy corresponding to each terminal node to the total energy. The higher the percentage energy contribution is, the more significant the component. Note that the decomposition is unique if the mother wavelet in the wavelet packet analysis is given and the sieving criteria are specified.

6. Results

The technique described in the last section is applied to the obtained fingerprint signals. Figures (3), (4) and (5) demonstrate example EMD decompositions for the three finger categories namely, live, cadaver and spoof.

It should be noted that only those time sequences with number of singularity points greater than threshold are subjected to EMD processing. Percentage contribution of energy in wavelet packet tree at the selected wavelet packet nodes, which best quantified the liveness pattern was calculated for all the four nodes. This is given in tables (3)-(5).

The classification was performed to divide the images into live and not live (spoof and cadaver) categories. 10 images of live and not live category each were used to determine the threshold value for the analysis, and classification to distinguish remaining live fingerprints from the remaining not live images was performed based on this predetermined threshold. The classification was performed by determining whether the node energy is above the threshold (to get classified as live) or below the threshold (to get classified as not live). Classification rates of 93%, 98.9% and 89.2% were achieved for Secugen, Precise Biometrics and Ethentica respectively.

Table 5. Average Percentage Contribution of Energy (%) for Precise Biometrics

Mode No.	Packet Node	Live	Spoof	Cadaver
2	(8,1)	31.2	2	3.1
3	(7,0)	60	19.9	32.6
4	(6,1)	86.5	44.3	56.4

7. Discussion and Conclusion

The proposed wavelet packet based sifting process was able to decompose the fingerprint signal into monocomponents and provides meaningful results. When applied

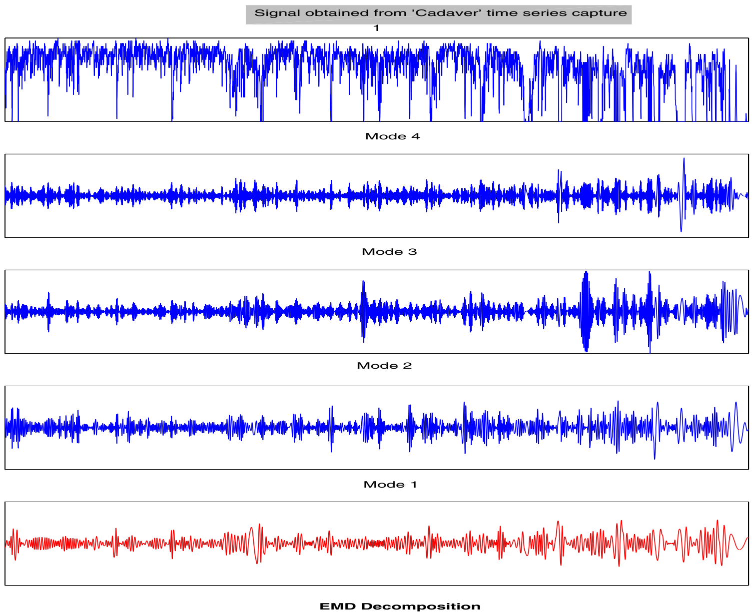

Figure 4. EMD Decomposition for the cadaver fingerprint signal.

to the time stamped fingerprint signals, the proposed sifting process showed good vitality detection rate. This was tested across three different fingerprint scanner technologies namely optical, electro-optical and capacitive DC.

Previous algorithms to quantify perspiration for liveness are given in [2, 15] and enhanced in [1]. While these algorithms were able to achieve complete classification, the main drawback associated with these algorithms is that, they are computationally complex. The presented algorithm is faster and was able to achieve an overall classification rate of 93.7% across all the three scanners.

Liveness detection has been suggested as a countermeasure against spoofing of fingerprint scanners. Previously, to strengthen fingerprint recognition, several hardware based liveness measures including [16, 10, 9, 11, 17, 19] are suggested. These methods being hardware based are bulky and expensive. The proposed method, being purely software based, is cheaper and more flexible for future adaptations.

As the physiological phenomenon of perspiration is at the base of the detection process, it would be interesting to study variations in the perspiration, and how the algorithm behaves for those variations. While the algorithm is shown to give reasonable classification for the limited data used, more data with multiple scanners and with different underlying technologies is required to validate the perspiration phenomenon across the population. It is desired to test the performance of the algorithm under different environmental settings including hot weather, cold weather and different finger conditions including dirty fingers, wet fingers and dry fingers and even deliberately distorted fingers. The algorithm should be evaluated in the light of the fact that the above conditions are problematic for performing the fingerprint recognition, irrespective of liveness detection.

One of the important findings of this work is, this method provides a framework to analyze the ridge signals node wise, thus enabling concentration and characterization of the changing information at every node. This property can be further extended and used to classify the real perspiration changes from remaining natural or deliberate attempts like pressure changes etc. and can be linked with the perspiration pattern characterization method described in [1].

Lastly, the algorithm was developed using MATLAB 7, using pentium processor, with 1GB RAM. The entire algorithm steps take roughly 120 milliseconds to formulate result for each subject and is much faster than the original wavelet based algorithm. It is possible to select different nodes to calculate the energy activity. This makes the algorithm more flexible than previous algorithm and can provide better resistance to the deliberate attempts to spoof the system. The drawback of the algorithm is, as can be seen from the results, it is less accurate as compared to the original wavelet based algorithm. Another limitation of the presented results is, the algorithm is not tested on variety of types of spoof fingers, e.g. gummy fingers.

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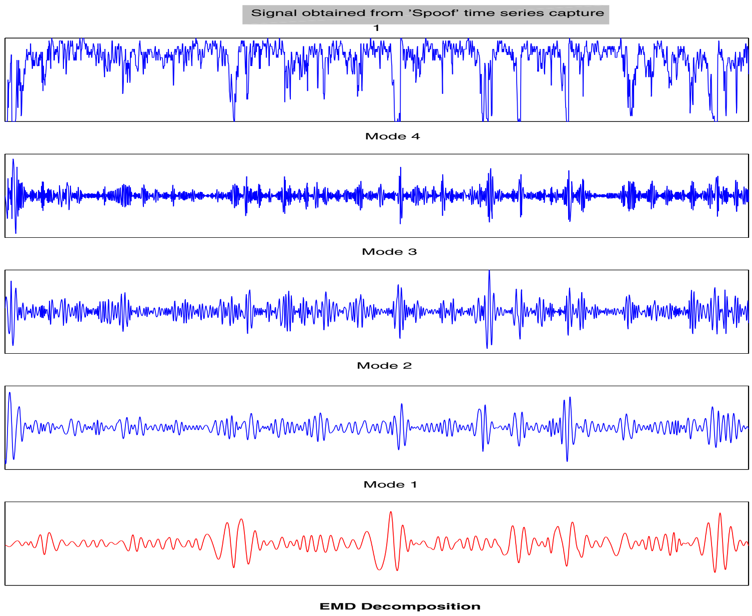

Figure 5. EMD Decomposition for the spoof fingerprint signal.

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