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Palmprint recognition based on Mel frequency Cepstral coefficients feature extraction

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Abstract Palmprint identification is a measurement of palmprint features for recognizing the identity of a user. Palmprint is universal, easy to capture and it does not change much across time. This paper presents an application of Mel frequency Cepstral coefficients (MFCCs) for identification of palmprint. Palmprint feature extraction is based on transforming the palmprint image into one dimensional (1-D) signal and then extracting MFCCs from this signal. Wavelet transform (DWT) of the 1-D palmprint signals are used for extracting additional features to help in the recognition process. The features from MFCCs of this DWT vector are added to the MFCCs feature vector, generated from the original palmprint signal, to form a large feature vector that can be used for palmprint identification. Feature matching is performed in this research using feed forward back propagation error neural network. Experimental results show that the proposed method is robust in the presence of noise.

1. Introduction

Biometrics has been currently used for identity, authentication, and forensic purposes. One of the most important applications of palmprint recognition is criminal investigation cases. Biometric technologies have been broadly grouped into four areas with several techniques in each: Hands, heads and face, other physical characteristics, and behavioral characteristics [1–4]. Fingerprints are well accepted as a biometric measure [5–11]. Other techniques related to hands, including hand geometry and vein patterns recognition, are perhaps less well known or accepted. Automatic personal identification based on palmprints has been considered as a novel and promising technology in biometrics family during recent years. One of the most important applications of palmprint recognition is criminal investigation cases. In pursuit of accurate palmprint

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recognition approaches, it is a key issue to design proper image representation to describe skin textures in palm regions. Palmprint recognition in spirit implements many of the same matching characteristics that have allowed fingerprint recognition to be one of the most well-known and best revealed biometrics. The biometric use of palmprints uses ridge patterns to identify an individual. Similar in many respects to fingerprint identification, palmprint identification systems measure and compare ridges, lines and minutiae found on the palm. The palmprint recognition is referred to as APRS (Automatic Palmprint Recognition System) which is program-based. This is in contrast to manual approach for palmprint recognition by experts. The palmprint recognition problem can be grouped into two sub-domains; palmprint verification and palmprint identification. Palmprint verification is to prove the legitimacy of one person by his palmprint. The user provides his palmprint together with his identity information such as his ID number. The palmprint verification system retrieves the palmprint template according to the ID number and matches the template with the online palmprint image acquired from the user. Palmprint identification is to state a person's identity by his palmprint(s) without prior knowledge of the person's identity, tries to match his palmprint acquired image with those in the whole palmprint database. All palmprint recognition problems, either verification or identification are eventually based on a well-defined representation of a palmprint. The palmprint matching, either for the 1-to-1 verification case or 1-to-*m* identification case, is straightforward and easy as long as the representation of palmprints remains unique and simple.

A reliable and robust feature extraction is important for pattern recognition tasks. Palmprints in general are irregular due to imperfections such as ridge gaps caused by skin-fold. Usually these inconsistencies, obtained by a sensor or a camera, are used to capture palmprint images, preprocessed to get feature points or details. Recently, a lot of research work has been directed towards using wavelet based features. The discrete wavelet transform (DWT) has a good time and frequency resolution and hence it can be used for extracting the localized contributions of the signal of interest. This proposed palmprint identification method is based on transforming palmprint image into 1-D signals and performing the same operations performed on speech signals.

This paper presents a new palmprint recognition method based on the Mel-frequency cepstral coefficients (MFCCs) for extracting features composite with wavelet transform. MFCCs are widely used in speech recognition and MFCCs values are not very robust in the presence of additive noise. In the proposed method, features extracted from MFCC composite with wavelet transform of the image will assist in achieving a higher recognition rate. Feed forward error back propagation neural network is used as the classifier in this proposed palmprint recognition method. The comparison between the use of the wavelet transform with MFCCs and the MFCCs only is presented in this paper. The rest of the paper is organized as follows: An overview on the palmprint structure, problem statement, and brief survey on current research area in this field is explained Section 2. The process of extracting features existing in captured palmprint image using MFCCs is discussed in Section 3. Discrete wavelet transform is summarized in Section 4. Feature matching (classification) is discussed in Section 5. Palm print recognition system as a whole is explained in Section 6. Experimental results are given in Section 7. Finally, Section 8 summarizes the concluding remarks.

2. Palmprint structure and current recognition systems

Since this research aims at palmprint recognition, it is worth to mention the structure of a palmprint itself. Palmprint is worldwide, easy to capture, and it does not change much across time. Palmprint biometric system does not require particular acquirement devices. It is user-friendly and more acceptable by the public. Besides, palmprint of a human contains different types of features, such as geometrical features, line features, point features, statistical features, and texture features. Line features consist mainly of a group of lines different in their lengths and extended on the surface. In Palmistry each of these lines has a name. Some of the lines of the palmprint are commonly known as: 1 – life line, 2 – head line, 3 – heart line, 4 – girdle of Venus, 5 – sun line, 6 – Mercury line, and 7 – fate line. These lines are numbered as it is shown in Fig. 1. Life line extends from the edge of the palm above the thumb and travels in an arc towards the wrist. Head line starts at the edge of the palm under the index finger and flows across the palm towards the outside edge. Heart line is the first of the major lines existing on palmprint and it is found towards the top of the palm, under the fingers. Girdle of Venus line starts between the little and ring fingers, runs in a rough arc under the ring and middle fingers to end between the middle and pointer fingers. Sun line is parallel to the fate line, under the ring finger. Mercury line runs from the bottom of the palm near the wrist, up through the palm towards the little finger. Fate line runs from the bottom of the palm near the wrist, up through the center of the palm towards the middle finger. Apollo line travels from the Mount of the Moon at the wrist to beneath the Apollo finger. Other lines exist also on a palmprint. Union lines are short horizontal lines found on the percussive edge of the palm between the heart line and the bottom of the little finger. Travel lines are horizontal lines found on the percussive edge of the palm between the wrist and the heart line. Other markings

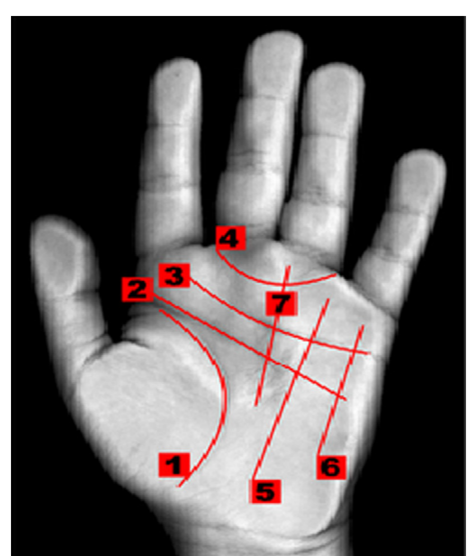

Figure 1 Main lines of a palmprint (Wikipedia).

on palmprint include stars, crosses, triangles, squares, tridents, and rings under each of the fingers.

There are also mounts in Palmprint. These are called: Jupiter, Saturn, Apollo, Mercury, Mars positive, Mars negative, plain of mars, Luna mount, Neptune mount, Venus mount. The thumb, Rhea, is above the mount of Venus. Lower Mars mount is located beneath the mount of Jupiter. The plain of Mars is located in the center of the palm (beneath the mount of Saturn). Upper Mars mount is located beneath the mounts of Apollo and Mercury. Earth mount is located on the fleshy mount created on the back side of the hand. The mount of Luna (or Moon) is located on lower part of the palm directly below the lower plain of Mars. Other features also exist on human palmprint (Fig. 2).

Many research work regarding palmprint recognition has been recently conducted. CASIA researchers develop fast palmprint recognition system working on PDA and common PCs using CMOS web cameras for capturing palmprint images [12]. Describing palmprint images by constructing rank correlation statistics of appearance patterns within local image areas is explained [13]. A robust image coordinate system to facilitate image alignment for feature extraction, and a 2-D Gabor phase encoding scheme for palmprint image and representation is proposed [14]. An experimental study about verification rate of the palmprint authentication system using Zernike, pseudo Zernike, and Legendre orthogonal moments as feature descriptors has been discussed [15]. Linear projection techniques, namely Principle Component Analysis (PCA) and Independent Component Analysis (ICA) are used to extract the palmprint texture features [16]. An algorithm for fully integrated palmprint and fingerprint multi-biometric system for identification and verification of criminal subjects as well as in security access applications is reported [17]. A new algorithm of crease extraction by using non-separable wavelet filter banks with linear phase is reported [18]. Sequential modified Haar transform is applied to the resized palmprint image to obtain modified haar energy (MHE) feature, which is compared with the feature vectors stored in the database using Euclidean Distance [19]. A multimodal biometric identification system is achieved by extracting eigenfinger and eigenpalm features and identification is done based on the (k, l)-NN classifier and thresholding [20]. Many other research work leading to commercial palmprint recognition systems has been recently conducted as well; some of them are reported [21–23].

Figure 2 Mounts on a palmprint (Wikipedia)

3. Extraction of palmprint image features by Mel-frequency cepstral coefficient

Feature extraction can be defined as the process of reducing the amount of data present in a given image sample while retaining image discriminative information. The concept of feature extraction contributes to the goal of identifying palmprint image based on producing sufficient information for good palmprint discrimination, capturing this information in a form and size which allows efficient modeling. Several features extraction techniques are used in signal recognition system such linear prediction coefficients (LPC), linear predictive cepstral coefficients (LPCC), perceptual linear predictive analysis (PLP), and Mel-Frequency Spectrum Coefficients (MFCC) which is currently the most popular and it is discussed in this paper. Mel-frequency cepstral coefficients (MFCCs) are coefficients that have been used to represent signal distribution. MFCCs are commonly used as features in speech recognition systems. MFCC features are derived through cepstral analysis and are warped according to the Mel-scale which emphasizes low frequency components over the higher frequency components. The steps from image to coefficients by MFCC (Fig. 3):

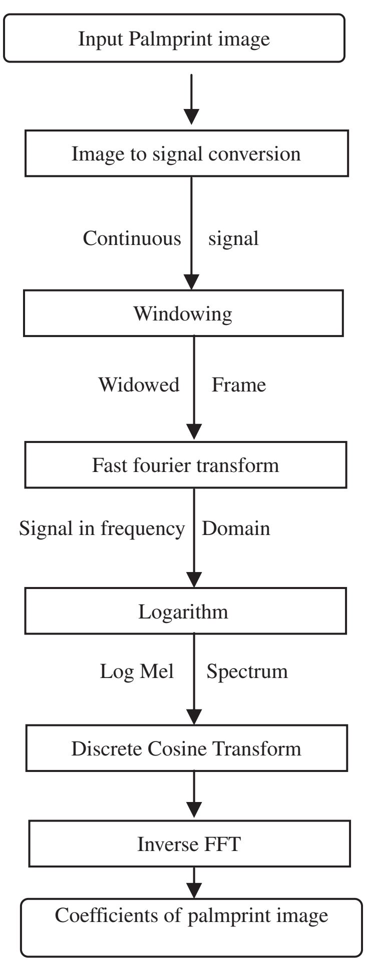

Figure 3 MFCC feature extraction process.

(1) Slicing of the original waveform into predetermined window size.
(2) Performing Fourier Transformation (FFT) on the sliced signal.
(3) Mapping the log amplitudes of the spectrum onto the Mel scale, using triangular overlapping filters.
(4) Performing Discrete Cosine Transformation (DCT) on the Mel log amplitudes.
(5) The resulting amplitudes of the spectrum are the MFCCs.

Calculation of MFCC features proceeds similarly to the Cepstral transformation process: the input converted image is firstly framed and windowed. The Fourier Transform is then taken and the magnitude of the resulting spectrum is warped by the Mel-scale. The log of this spectrum is then taken and a Discrete Cosine Transform is applied [24]. The Mel is a unit of measure of perceived pitch or frequency of a tune. The Mel-scale is therefore a mapping between the real frequency scale (Hz) and the perceived frequency scale (Mels). The name Mel comes from the word melody to indicate that the scale is based on pitch comparisons. The Mapping is virtually linear below 1 KHz and logarithmic above. A popular formula to convert f hertz into m Mel is given in Eq. (1):

$$m = 2595\log_{10}\left(\frac{f}{700} + 1\right) \tag{1}$$

MFCC is based on the short term analysis, and thus for each frame of data a MFCC vector is computed.

For feature extraction to take place, the signal must first be broken up into small sections of N samples each (called frames). In this step the continuous signal is blocked into frames of N samples where the number of samples per frame N will depend on the sampling rate of the data. To avoid a loss of information, frame overlap is used, adjacent frames being separated by M, where $M < N$. The first frame consists of the first N samples. The second frame begins M samples after the first frame, and overlaps it by $N - M$ samples and so on. Typically, around 60% of overlapping is sufficient to embrace the lost information [25,26]. Typical values for N and M are $N = 256$ and $M = 100$.

3.1. Windowing

Windowing in time domain is a point wise multiplication of the frame and the window function. Common windowing functions include the rectangular window, the hamming window, the Blackman window, and flattop window. For each frame, a windowing function is usually applied to increase the continuity between adjacent frames. The concept here is to minimize the spectral distortion by using the window to narrow the signal to zero at the beginning and end of each frame. If we define the window as: as $w(n),\ 0 \leqslant n \leqslant N-1$, where N is the number of samples in each frame. Result of windowing the signal is: $y_l(n) = x_l(n)w(n),\ 0 \leqslant n \leqslant N-1$.

A good window function has a narrow main lobe and low side lobe levels in their transfer functions. The most commonly used window function is the hamming window (used in this research) and it has the form:

$$S_k = \sum_{n=0}^{N-1} s_n e^{-j2\pi kn/N}, \quad k = 0, 1, 2, \ldots, N-1 \tag{2}$$

3.2. Discrete Fourier Transform (DFT)

The next processing step is computing Discrete Fourier Transform (DFT) of the frame to obtain the magnitude spectrum. Fourier Transform theory is based on the idea that any signal can be represented as the sum of properly chosen sinusoidal waves. This is of profound importance in digital signal processing since the transform effectively decomposes a signal into its component frequencies and their amplitudes. By taking the DFT of the signal, transformation from the time domain into the frequency domain is achieved, and the coefficients of the obtained sinusoidal components are called the spectral components. Fast Fourier Transform which converts each frame of N samples from the time domain into the frequency domain. The FFT is a fast algorithm to implement the Discrete Fourier Transform (DFT), which is defined on the set of N samples S_k's as follow:

$$w(n) = 0.54 - 0.46\cos\left(\frac{2\pi n}{N-1}\right), \quad 0 \leqslant n \leqslant N-1 \tag{3}$$

In general S_k's are complex numbers and only their absolute values (frequency magnitudes) are considered. The resulting sequence S_k's are interpreted as: positive frequencies $0 \leqslant f < F_s/2$ correspond to values $0 \leqslant n \leqslant N/2 - 1$, while negative frequencies $-F_s/2 < f < 0$ correspond to values $N/2 + 1 \leqslant n \leqslant N-1$, F_s denotes the sampling frequency. The result after this step is often referred to as spectrum or periodogram.

The magnitude spectrum is frequency warped in order to transform the spectrum into Mel frequency. The Mel frequency warping is performed using a Mel filter bank: a set of bandpass filters with constant bandwidth and spacing on the Mel-scale. The bank consists of one filter for each desired Mel-frequency component, where each filter has triangular filter bandpass frequency response. The triangular filters are spread over the entire frequency range from zero to the Nyquist frequency. The number of filters is one of the parameters which affect the recognition accuracy of the system. Thus, for each tone with an actual frequency, f, measured in Hz, a subjective pitch is measured on a scale called the 'Mel' scale.

3.3. Discrete Cosine Transform

The last stage involves performing a Discrete Cosine Transform on the log of the Mel-spectrum. In this final step, the log Mel spectrum is converted back to time. The result is called the Mel frequency cepstrum coefficients (MFCC). The cepstral representation of the speech spectrum provides a good representation of the local spectral properties of the signal for the given frame analysis. Because the Mel spectrum coefficients (and so their logarithm) are real numbers, it could be converted to the time domain using the Discrete Cosine Transform (DCT). MFCC's (Mel power spectrum coefficients) that are the result of the last step are given as:

$$c_n = \sum_{k=1}^{k} (\log S_k)\cos\left[n\left(k - \frac{1}{2}\right)\frac{\pi}{K}\right], \quad n = 0, 1, \ldots, K-1 \tag{4}$$

where $n = 0,1, \ldots, N-1$, K is the number of filters, N is the number coefficients and $c(n)$ are the Mel-frequency cepstral coefficients. The number of resulting Mel-frequency cepstral coefficients are chosen between 12 and 20, since most of the signal information is represented by the first few coefficients. The first component, C_0 is excluded from the DCT since it represents the mean value of the input signal, which carried little signal specific information.

4. Discrete Wavelet Transform (DWT)

Wavelets are a mathematical tool for hierarchically decomposing functions. They allow a function to be described in terms of a coarse overall shape, plus details that range from broad to narrow. Regardless of whether the function of interest is an image, a curve, or a surface, wavelets offer an elegant technique for representing the levels of detail present. The Discrete Wavelet Transform (DWT) is a very popular tool for the analysis of non-stationary signals. The idea of it is to represent a signal as a series of approximations: low pass version corresponds to the signal, and high pass version corresponds to details. This is done at different resolutions. It is almost equivalent to filtering the signal with a bank of bandpass filters whose impulse responses are all roughly given by scaled versions of a mother wavelet [27–29]. The outputs of the filters are usually maximally decimated so that the number of DWT output samples equals the number of input samples and thus no redundancy occurs in this transform. The one level DWT decomposition reconstruction filter bank is shown in Fig. 4. The art of finding a good wavelet lies in the design of the set of filters, H_0, H_1, G_0, and G_1 to achieve various trade-offs between spatial and frequency domain characteristics while satisfying the perfect reconstruction (PR) condition. In Fig. 4, the process of decimation and interpolation by 2:1 at the output of H_0, H_1 effectively sets all odd samples of these signals to zero.

The Haar wavelet is the simplest type of wavelets. In the discrete form, Haar wavelets are related to a mathematical operation called the Haar transform. The Haar transform serves as a prototype for all other wavelet transforms. Like all wavelet transforms, the Haar transform decomposes a discrete signal into two sub-signals of half its length. One sub-signal is a running average or trend; the other sub-signal is a running difference or fluctuation. The two outputs of $H_0(Z)$ and $H_1(Z)$ are concatenated to form a single vector of the same length as the original palmprint image converted signal. Both the approximation and the detail coefficients of the palmprint image signal are thus contained in the wavelet transformed signal vector. So, features from the low pass as well as the high pass components of the signal are forming feature presented in this vector. The features from this DWT vector are added to the MFCCs feature vector generated from the original palmprint signal to form a large feature vector that can be used for palmprint identification. These are more robust features in case of the presence of degradations.

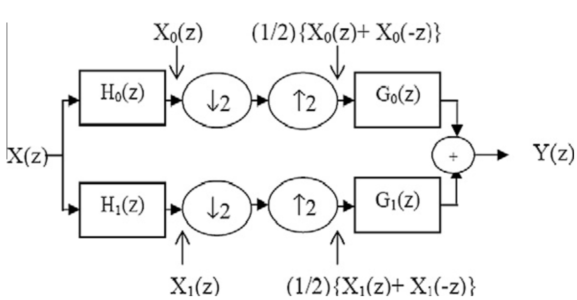

Figure 4 The two band decomposition-reconstruction wavelet filter bank.

5. Pattern matching using artificial neural network (ANN)

Classification is a process which has two phases: signal modeling and pattern matching. The combination of a palmprint model and a matching technique is called a classifier. For successful classification, each palmprint is modeled using a set of data samples in the training mode, from which a set of feature vectors is generated and saved in a database. Features are extracted from the training data, essentially stripping away all unnecessary information in the training palmprint image, leaving only the characteristic information with which palmprint models can be constructed. When features of some unknown palmprint captured image is extracted, pattern matching techniques are used to map the features from the input palmprint image to a model corresponding to a known palmprint. Common classifiers in signal identification include Gaussian Mixture Models (GMMs), Hidden Markov Models (HMMs), Vector Quantization (VQ) and Neural Networks (NNs) which is used in this research. Neural Networks are widely used for feature matching. The classification step in palmprint identification systems is in fact a feature matching process between the features of a new palmprint image and the features saved in the database. Error back-propagation learning algorithm consists mainly of two passes through the different layers of the network. In the forward pass, an input vector is applied to the sensory nodes of the network, and its effect propagates through the network layer by layer. Finally, a set of outputs is produced as the actual response of the network. During the forward pass the synaptic weights of the networks are all fixed. In the backward pass the synaptic weights are all adjusted in accordance with an error correction rule. The actual response of the network is subtracted from a target response to produce an error signal. This error signal then propagated backward through the network [30]. Neural networks function by effectively learning mappings between inputs and outputs and are useful when the underlying statistics of the task are not well understood. The simplest implementation of backpropagation learning updates the network weights and biases in the direction in which the performance function decreases most rapidly the negative of the gradient. Feed forward back propagation error neural networks are a popular type of neural network and consist of an input layer, one or more hidden layers and one output layer as shown in Fig. 5. The structure shown will be used for feature matching in this research. Neurons in the input layer only act as buffers for distributing the input signal x_i to neurons in the hidden layer. Each neuron $_j$ in the hidden layer sums up its input signals x_i after weighting them with the strengths of the respective connections w_{ji} from the input layer and computes its output y_j as a function f of the sum:

$$Y_j = f\left(\sum w_{ji} x_i\right) \tag{5}$$

Training a network consists of adjusting its weights using a training algorithm. The training algorithms adopted the weights by minimizing the sum of squared difference between the desired and actual values of the output neurons:

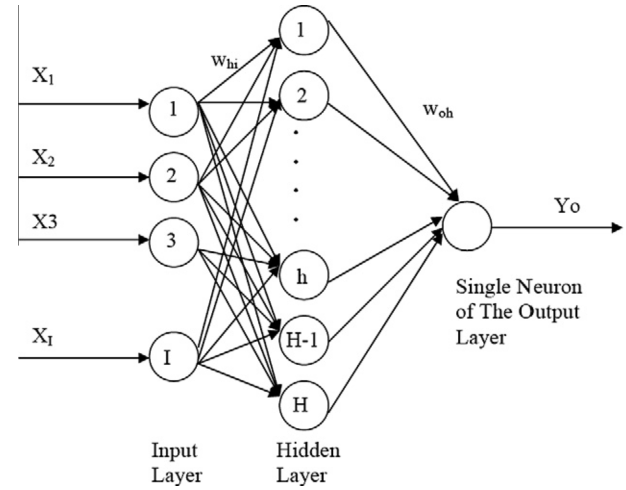

Figure 5 A multilayer feed forward back propagation error neutral network.

$$E = \frac{1}{2} \sum_{f} \left(Y_{dj} - Y_j \right)^2 \tag{6}$$

where Y_{dj} is the desired value of the output neuron j and Y_j is the actual output of that neuron. Each weight w_{ji} is adjusted by adding an increment. w_{ji} is selected to reduce E as rapidly as possible. The adjustment is carried out over several training iterations until a satisfactorily small value of E is obtained. Training process is ended when the maximum number of eras is reached or the required performance has been met. Many training algorithms using error back- propagation could be used and requires that all training set feature vectors be examined to train network. The gradient descent algorithm is generally very slow because it requires small learning rates for stable learning. The momentum variation is usually faster than simple gradient descent, because it allows higher learning rates while maintaining stability, but it is still too slow for many practical applications. These two methods are normally used only when incremental training is desired. Levenberg-Marquardt training is usually used for training small and medium size networks if enough memory is available. Performance is minimized to the goal [31,32].

6. The proposed palmprint recognition system

The proposed palmprint recognition system consists mainly of three phases: signal modeling, feature extraction, and feature matching as shown in Fig. 6. The image, which is converted to one-dimensional signal, is used to extract the MFCC features. In addition, the wavelet transformed signal is used to extract additional features which can be used to assist the MFCC features extracted from the original degraded signal. Features are extracted from the training data essentially stripping away all unnecessary information in the training signals samples leaving only the characteristic information with which signal models can be constructed. In the testing phase, a sample of signals which is converted from an image of unknown person is subjected to feature extraction. The resulting information is compared to the models in the palmprint image database allowing the unknown one to be identified. It is clear that the feature extraction process (obtained from discriminatory information) and classification

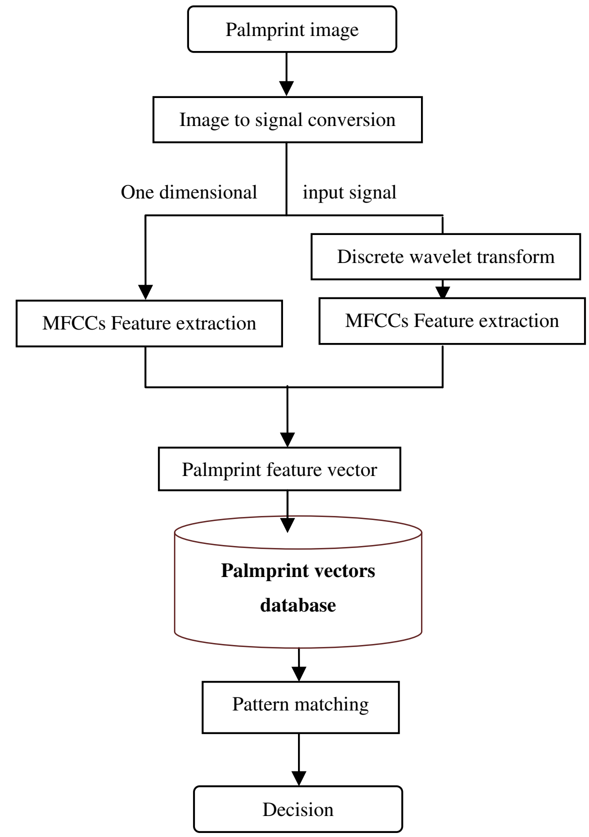

Figure 6 Components of automatic palmprint identification system

process (using the features to determine the correct signal, which corresponds to the correct palmprint image) algorithms are of critical importance to any signal identification system. The process of performing this method of identification consists of two phases: a training or enrollment phase followed by a testing or evaluation phase. During the training phase, each signal in the set is modeled using a set of training data. Both of them include feature extraction which is sometimes called the front end of the system. The feature extractor converts the digital palmprint image signal into a sequence of numerical descriptor called feature vectors. Extraction of the Mel-frequency cepstral features proceeded using standard techniques, involving segmenting the data into frames using a Hamming window, taking the Fourier Transform and inputting the magnitude of this spectrum into a series of Mel-filter banks to perform the warping. The log of the resulting spectrum can then be operated on by a Discrete Cosine Transform (DCT) to produce the cepstral coefficients (Fig. 6).

7. Data set, experiment, and results

7.1. Palmprint images dataset

The palmprint image dataset used in this research is obtained from CASIA Palmprint Image Database V1.0. This database includes 2496 palmprint images of 312 different people (user) and for each one 8 different palmprint images were captured. These images are captured using different camera and optical lenses. Other added images contain much degree of image blurring or over-exposure due to improper hand postures and failure of the LEDs of the imaging device during image capturing process. All palmprint images are 8 bit gray-level JPEG files. In capturing these images, there were no dowels to restrict postures and positions of palms. A human being is to put his palm into the device and lay it on a uniform-colored background. The device supplies an evenly distributed illumination and captures palmprint images using a CMOS camera fixed on the top of the device [32]. Fig. 7 shows eight palmprint images of one user among 312 users in the dataset used in this research.

7.2. Palmprint images dataset representation

After forming palmprints database, the training phase of the automatic palmprint identification system is started. All palmprint images in the database are transformed into 1-D signals. These signals are used to generate both MFCCs and DWTs to form the feature vectors of the database. The features used in the first of this research experiments (techniques) are MFCCs. The digitized waveform is converted into a spectral-domain representation. For the current recognizer, 12 Mel-frequency cepstral coefficients (MFCC coefficients), 12 MFCC delta features that indicate the degree of spectral change, one energy feature, and one delta-energy feature (for a total of 26 features per frame). The features used in second of this research experiments are MFCCs of the extracted DWTs. The features used in the third of this research experiments are MFCCs extracted from original image sinal plus MFCCs of the extracted DWTs. These vectors are equally partitioned and used to train, validate and test the neural network.

7.3. Neural network structure

The feed forward back propagation error artificial neural network (FFBPENN) used in this research consists of three layers: Input layer, hidden layer, and output layer. Three techniques and hence three different network architectures are built. In the first technique, MFCCs extracted from one dimensional palmprint signals are introduced to FFBPENN input layer. In the second technique, MFCCs features extracted from DWT of one dimensional palmprint signals are introduced to input layer of FFBPENN. In the third technique, the extracted features from both MFCCs and MFCCs of DWT of one dimensional palmprint signals are concatenated in a single feature vector and applied to input layer of FFBPENN. The hidden layer consists of 312 neurons which is the number of class patterns (312 users) the networks were trained with. The output neurons are 9 which represent the binary bit patterns representing user (class pattern) identification number (user ID). Total number of palmprint image patterns is 2496 and it is divided into two subsets. The first subset is the training set, used for computing the gradient and updating the network weights and biases. The second subset is used for testing and verifying the network design. The transfer function between input layer and hidden layer is Log-sigmoid which calculates layer's output from its net input squashed into [0, 1]. The transfer function between hidden layer and output layer is pure linear transfer function which gives an output between -1 and $+1$. The function used in training the network is Gradient descent with adaptive learning rate (traingda) that updates weight and bias values according to gradient descent with adaptive learning rate. The training stops if the number of iterations exceeds epochs, if the performance function drops below goal, if the training time is longer than time seconds, or if the magnitude of the gradient is less than minimum gradient (1e$-$10 is the typical value used in this research). While testing the system, both the palmprint image used for testing and that results from recognition are displayed and manually compared. Also, the collected palmprint data (features) is compared with that of palmprint data stored in the palmprint database. The authentication is a success when the two data values are consistent with each other, or else the authentication fails.

7.4. Obtained results and analysis

Experiments are done to see how each of the three neural networks reacts to noisy palmprints. The results of these experiments are given in Figs. 8–10. A comparison between A comparison of recognition rates in case of each of the three

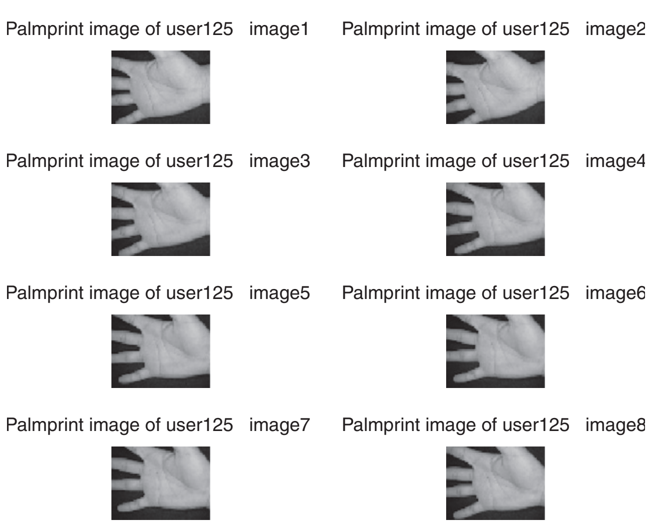

Figure 7 Eight images of palmprints of a user used in this research.

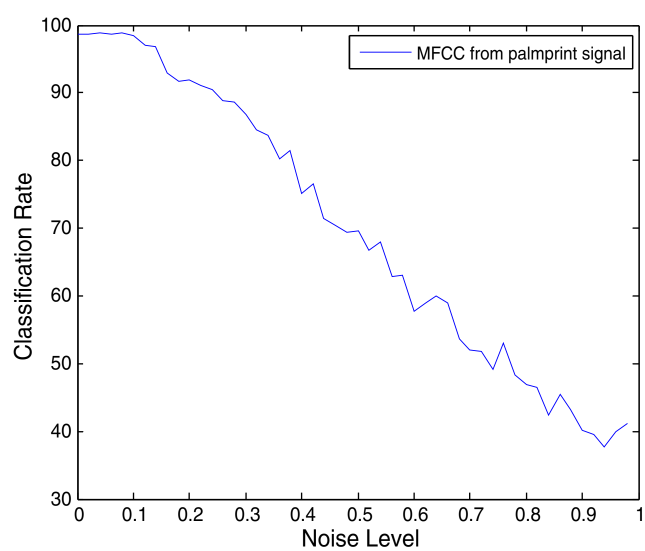

Figure 8 Recognition Rates when using MFCCs features extracted from Palmprint images.

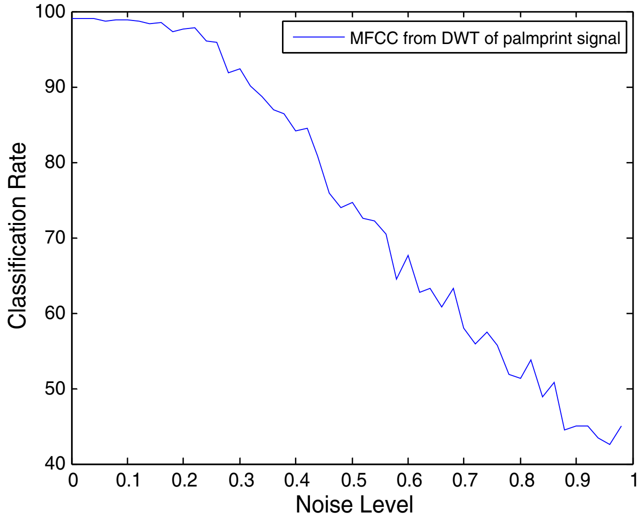

Figure 9 Recognition rates when using MFCCs of DWTs features extracted from palmprint modeled images.

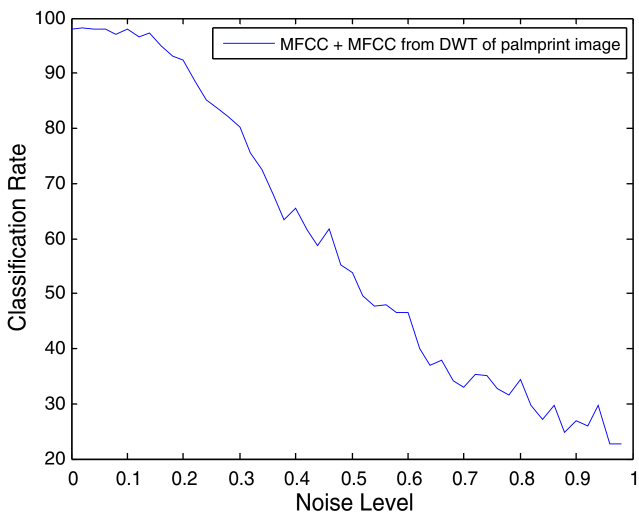

Figure 10 Recognition rates when using MFCCs plus MFCCs of DWTs features extracted from palmprint modeled images.

used techniques is given in Fig. 11. Networks are trained with clean images and tested with noisy images. Recognition rates deteriorate reasonably in case of high added noise levels.

8. Conclusions

In the field of biometrics, palmprint is a novel but promising technology. Limited work has been reported on palmprint identification and verification although the importance of palmprint features. There are many sole features in a palmprint image that can be used for personal identification. Principal lines, wrinkles, ridges, minutiae points, singular points, and texture are regarded as useful features for palmprint representation. Palmprint recognition based on extracting previously mentioned features is tedious work and

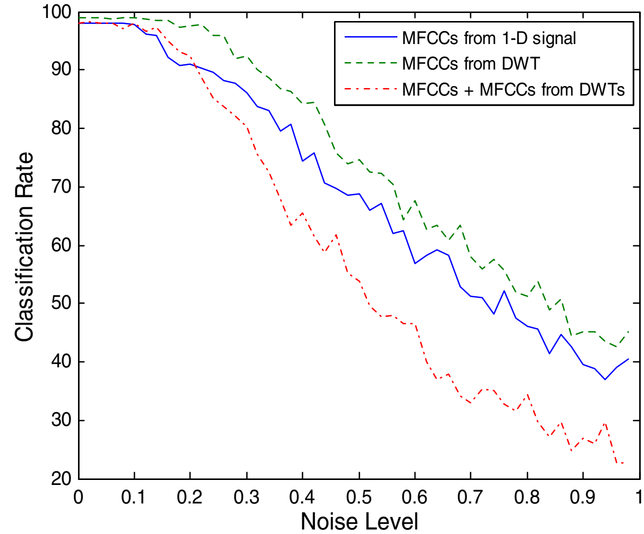

Figure 11 Comparison of recognition rates for three used techniques when training networks with noisy images and testing it with these noisy images.

requires high computational complexities. This paper presents a new method for palmprint identification based on converting palmprint image into one dimensional signal, then extracting MFCCs features of this modeled signal. Other technique is done by extracting MFCCs features from extracted DWTs features of this modeled signal. Third technique is done combining both. In each of these used techniques, feedforward back propagation error neural network is used for recognition process. This proposed approach is to avoid tedious tasks of geometrical feature extraction from palmprint images. Other experiment is done to find out how the recognition rates of each of the three used techniques can be affected when adding noise of palmprint images. Results show that recognition rates are defying in the cases of low SNR. Future work is to compare the performance of this proposed approach to others that use the same palmprint database.

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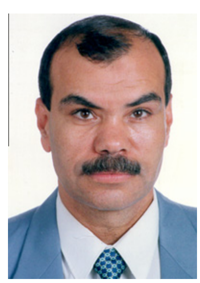

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