IDENTIFYING FINGERPRINTS WITH WAVELET COEFFICIENTS AND RADIAL BASIS FUNCTION

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Abstract

This paper implements wavelet decomposition with radial basis function artificial neural network for identifying fingerprints. Sample fingerprints are taken from database from the internet resource. The fingerprints are decomposed using daubechi wavelet 1(db1) to 5 levels. The coefficients of approximation at the fifth level is used for calculating statistical features. These statistical features are used for training the RBF network.

Keywords: Fingerprint, wavelet, radial basis function.

1. INTRODUCTION

Fingerprints are graphical ridge patterns present on human fingers, which, due to their uniqueness and permanence, are among the most reliable human characteristics that can be used for people identification. A common hypothesis is that certain features of the fingerprint ridges, called minutiae, are able to capture the invariant and discriminatory information present in the fingerprint image. A minutia detected in a fingerprint image can be characterized by a list of attributes that includes the minutia position, the minutia direction, and the type of minutia (ending or bifurcation). The representation of a fingerprint pattern thus comprises the attributes of all detected minutiae in a so-called minutiae set. By representing the minutiae set as a point pattern, the fingerprint verification problem can be reduced to a minutiae point pattern matching problem. Due to variations that may occur between two minutiae sets extracted from different impressions of the same finger, determining whether they indeed represent the same finger can be an extremely difficult problem. Both minutiae sets may suffer from false, missed, and
displaced minutiae, caused by poor fingerprint image quality and imperfections in the minutiae extraction stage. Two fingerprints may be translated, rotated, and scaled with respect to each other and fingers may exert an unevenly distributed pressure across the acquisition sensor resulting in local nonlinear deformations due to the elasticity of the skin.

We use texture analysis using wavelet transform to overcome the above problems. The study of surface texture is commonly referred to as Surface Metrology. Texture is a fundamental characteristic in many natural images and also plays an important role in computer vision and pattern recognition. Texture analysis is an essential step for many image processing applications such as industrial inspection, document segmentation, remote sensing of earth resources, and medical imaging. For that reason, a great number of approaches to texture analysis have been investigated earlier. Typical fingerprint surface consists of a range of spatial wavelengths with different amplitudes.

1.1. Proposed method

Step 1: Fingerprint image is decomposed using db1 to 5 levels.
Step 2: The coefficients of approximation at 5th level is used for training the RBF network.
Step 3: At the end of training process, the final weights are stored in a file.
Step 4: During the testing process, the decomposition to 5th level using db1 and statistical feature extraction are done. The features are processed with final weights of RBF to identify fingerprint.

2. WAVELETS

Wavelet transform based method (Shabana, et al., 2010), pseudo Zernike moments (PZMs) has been used for identifying fingerprints (Avinash et al., 2010), DWT based non minutiae features (Shashi, et al., 2011), 64-subband structure proposed by the FBI WSQ standard is used to decompose the frequency of the image (Linlin et al, 2009), multi-scale and multi-directional recognition of fingerprints (Thaiyalnayaki et al., 2010) are explored.

The wavelet (WT) was developed as an alternative to the short time fourier transform (STFT). A wavelet is a waveform of effectively limited duration that has an average value of zero. Compare wavelets with sine waves, which are the basis of Fourier analysis. Sinusoids do not have limited duration, they extend from minus to plus infinity and where sinusoids are smooth and predictable, wavelets tend to be. Wavelet analysis is the breaking up of a signal into
shifted and scaled versions of the original (or mother) wavelet. Mathematically, the process of Fourier analysis is represented by the Fourier transform: which is the sum over all time of the signal \( f(t) \) multiplied by a complex exponential. The results of the transform are the Fourier coefficients, which when multiplied by a sinusoid of frequency, yield the constituent sinusoidal components of the original signal.

The continuous wavelet transform (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function. The result of the CWT are many wavelet coefficients \( C \), which are a function of scale and position. Multiplying each coefficient by the appropriately scaled and shifted wavelet yields the constituent wavelets of the original signal.

![Fig.1. Decomposition using wavelet](http://software.intel.com/sites/products/documentation/hpc/ipp/ippi/ippi_ch13/ch13_Intro.html)

An image can be analyzed for various information by decomposing the image using wavelet of our choice. Decomposition (Figure 1) operation applied to a source image produces four output images of equal size: approximation image, horizontal detail image, vertical detail image, and diagonal detail image.
The flow of decomposition process is shown in Figure 1. Fingerprint image is given as input to the system and level 1 to level decompositions take place. Initially, Approximation, horizontal, vertical and diagonal matrices are obtained from the original image. Each matrix is \( \frac{1}{4} \)th size of the input image. In the level two and subsequent levels, Approximation matrix of the previous levels are used for subsequent decompositions.

These decomposition components have the following meaning:

1. The ‘approximation’ image is obtained by vertical and horizontal lowpass filtering.
2. The ‘horizontal detail’ image is obtained by vertical highpass and horizontal lowpass filtering.
3. The ‘vertical detail’ image is obtained by vertical lowpass and horizontal highpass filtering.
4. The ‘diagonal detail’ image is obtained by vertical and horizontal highpass filtering.

2.1. WAVELET FEATURES EXTRACTION

The wavelet transform (WT) was developed as an alternative to the short time Fourier transform (STFT). A wavelet is a waveform with limited duration that has an average value of zero. Comparing wavelets with sine waves, sinusoids do not have limited duration, they extend from minus to plus infinity and where sinusoids are smooth and predictable. Wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (or mother) wavelet. The features are obtained from the Approximation and Details of the 5th level by using the following equations

\[
V1 = \frac{1}{d} \sum (\text{Approximation details})
\]

Where \( d \) = Samples in a frame and

\[
V1 = \text{Mean value of approximation}
\]

\[
V2 = \frac{1}{d} \sum (\text{Approximation or details} - V1)
\]

Where \( V2 = \text{Standard Deviation of approximation} \)

\[
V3 = \text{maximum (Approximation or details)}
\]

\[
V4 = \text{minimum (Approximation or details)}
\]

\[
V5 = \text{norm (Approximation or Details)}^2
\]

Where \( V5 = \text{Energy value of frequency} \)
3. RADIAL BASIS FUNCTION (RBF)

An RBF neural network consists of an input and output layer of nodes and a single hidden layer, Cowan et al. (1996), Grant et al. (1992), Chen et al. (1992), Moody et al. (1989), Robert et al. (1991). Each node in the hidden layer implements a basis function $G(x, x_i)$ and the number of hidden nodes is equal to the number of data points in the training database. The RBFNN approximates the unknown function that maps the input to the output in terms of a basis function expansion, with the functions, $G(x, x_i)$, as the basis functions. The input-output relation for the RBFNN is given by equation (6)

$$y_l = \sum_{j=1}^{N} w_{lj} G(x, x_j), \quad l = 1, 2, \ldots, M$$

(6)

where $N$ is the number of basis functions used, $y=(y_1, y_2, \ldots, y_m)^T$, is the output of the RBFNN, $x$ is the test input, $X_j$ is the center of the basis function and $w_{lj}$ are the expansion coefficients or weights associated with each basis function. Each training data sample is selected as the center of a basis function. Basis functions $G(x, x_i)$ that are radially symmetric are called radial basis functions. Commonly used radial basis functions include the Gaussian and inverse multiquadrics.

![Fig. 2. The Radial basis function neural network](image)

The network (Figure 2) described is called an exact RBFNN, since each training data point is used as a basis center. The storage costs of an exact RBFNN can be enormous, especially when the training database is large. An alternative to an exact RBFNN is a generalized RBFNN where the number of basis functions is less than the number of training data points. The problem then changes from strict interpolation to an approximation, where certain error constraints are to be satisfied. The operation of the generalized RBFNN is summarized in the following steps.
Step 1: Center selection: This is achieved by using optimization techniques that select the basis function locations by minimizing the error in the approximation. The input-output relation for a generalized RBFNN using Gaussian basis functions is given by

$$y_i = \sum_{j=1}^{H} w_j \exp \left( -\frac{\|x-c_j\|^2}{2\sigma_j^2} \right)$$  \hspace{1cm} (7)

where $H$ is the total number of basis functions used, $c_j$ is the center of the $j^{th}$ Gaussian basis function and $\sigma_j$ is the width of the Gaussian. The neural network architecture is then selected by setting the number of input nodes equal to the input dimension, the number of hidden nodes to the number of centers obtained in Step 1, and the number of output nodes equal to the output dimension.

Step 2: Training of the neural network involves determining the weights $w_{ij}$, in addition to the centers and widths of the basis functions given in equation (8)

$$Y = GW$$  \hspace{1cm} (8)

Where

$$Y = \begin{bmatrix} d_1^T \\ d_2^T \\ \vdots \\ d_P^T \end{bmatrix}$$  \hspace{1cm} (9)

is the desired M-dimensional output for all P input samples

$$G = \begin{bmatrix} G(x_1, c_1) & G(x_2, c_1) & \cdots & G(x_H, c_1) \\ G(x_1, c_2) & G(x_2, c_2) & \cdots & G(x_H, c_2) \\ \vdots & \vdots & \ddots & \vdots \\ G(x_1, c_M) & G(x_2, c_M) & \cdots & G(x_H, c_M) \end{bmatrix}$$  \hspace{1cm} (10)

is the output of the basis functions,

$$W = \begin{bmatrix} w_{11} \\ w_{12} \\ \vdots \\ w_{H,M} \end{bmatrix}$$  \hspace{1cm} (11)

is the weight matrix and $M$ is the output dimension.

Equation (12) can be solved for $w$ as

$$W = G^+Y$$  \hspace{1cm} (12)

where $G^+$ is the pseudoinverse defined as
Fig. 3. Radial basis function flow chart

\[ G^* = (G^T G)^{-1} G^T. \]

**Step 3:** Generalization: In the test phase, the unknown pattern is mapped using the relation
Radial basis function is a supervised neural network. The network has an input layer, hidden layer (RBF layer) and output layer. The eight features obtained are used as inputs for the network along with target values.

**Training RBF is done as follows**, 

**Step 1:** Finding distance between pattern and centers.  
**Step 2:** Creating an RBF matrix whose size will be (np X cp), where np= number of fingerprint patterns (10 fingerprint patterns X number of images) used for training and cp is number of centers which is equal to 10. The number of centers chosen should make the RBF network learn the maximum number of training patterns under consideration. 
**Step 3:** Calculate final weights which are inverse of RBF matrix multiplied with Target values.  
**Step 4:** During testing the performance of the RBF network, RBF values are formed from the features obtained from fingerprint image and processed with the final weights obtained during training. Based on the result obtained, the image is classified to particular fingerprint.

<table>
<thead>
<tr>
<th>Table 1 Training RBF</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Step 1:</strong> Apply Radial Basis Function.</td>
</tr>
<tr>
<td>No. of Input = 8</td>
</tr>
<tr>
<td>No. of Patterns = 10</td>
</tr>
<tr>
<td>No. of Centres = 10</td>
</tr>
<tr>
<td>Calculate RBF as</td>
</tr>
<tr>
<td>RBF = ( \exp(-X) )</td>
</tr>
<tr>
<td>Calculate Matrix as</td>
</tr>
<tr>
<td>( G = RBF )</td>
</tr>
<tr>
<td>( A = G^T \times G )</td>
</tr>
<tr>
<td>Calculate</td>
</tr>
<tr>
<td>( B = A^{-1} )</td>
</tr>
</tbody>
</table>
Calculate
\[ E = B * G^T \]

**Step 2:** Calculate the Final Weight.
\[ F = E * D \]

**Step 3:** Store the Final Weights in a File

<table>
<thead>
<tr>
<th>Table 2 Testing RBF</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Step 1:</strong> Read the Input</td>
</tr>
<tr>
<td><strong>Step 2:</strong> Read the final weights</td>
</tr>
<tr>
<td><strong>Step 3</strong> Calculate.</td>
</tr>
<tr>
<td>Numerals = F * E</td>
</tr>
<tr>
<td><strong>Step 4:</strong> Check the output with the templates</td>
</tr>
</tbody>
</table>

Figure 3 gives the flow-chart for RBF implementation. Table 1 gives the steps involved in training an RBF. Table 2 gives the steps for testing the RBF for identifying the fingerprint.

<table>
<thead>
<tr>
<th>Table 4 Sample fingerprint database</th>
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<tbody>
<tr>
<td><strong>Event 1</strong></td>
</tr>
<tr>
<td>Person 1</td>
</tr>
<tr>
<td>Person 2</td>
</tr>
<tr>
<td>Person 3</td>
</tr>
</tbody>
</table>
4. EXPERIMENTAL DATABASE AND RESULTS

A sample database is presented for 3 people in Table 3. Each row presents 4 fingerprints of a person. Similarly, there are 3 rows showing 3 people. The coefficient values are presented ‘approximation’ (Figure 4), ‘horizontal’ (Figure 5), ‘vertical’ (Figure 6) and ‘details (Figure 7) at 5th level of decomposition using ‘db1’ wavelet. Figure 8 presents fingerprints at all 5 levels for the fingerprint of person 1 with event 1.

5. CONCLUSION

This paper presents an approach to implement wavelet decomposition of fingerprint image. The coefficients of approximation of the decomposed image at the 5th level is used as input data for training the RBF network. The network is trained with 5 X 11 X 1 topology. The performance of the network is more than 92%.
Reference


