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Palmprint Texture Analysis using 1D Log-Gabor Filter

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Abstract: Biometrics is the study of automated methods for recognizing a person based on his physical or behavioral characteristic. Biometric systems can be divided into two categories- identification systems and verification systems. Identification systems tell "who you are?" and verification system tell "are you the one who you claim to be?" Security has become a paramount concern in today's arena. Hence palmprint identification plays a very significant role to address issues of authentication. This involves image acquisition, preprocessing, feature extraction, and pattern matching. Here 1D Log-Gabor filter is used for texture analysis and feature extraction. Support Vector Machine (SVM) classifier is used in this project for pattern matching as against conventional hamming distance. By the incorporation of this SVM classifier the performance of the whole application has significantly increased duly yielding concise accurate results.

***Index Terms*: CCD, SVM.**

I. INTRODUCTION

Biometric systems usually use a enrollment process to capture a biometric image, extract the desired features and subsequently encode to create a biometric template. This template is then stored in a database against which future comparisons will be made. When the biometric is used for verification (e.g., access control), the biometric system confirms the validity of the claimed identity. When used for identification the biometric technology compares a specific person's biometric with all of the stored biometric database to see if there is a match. For biometric technology to be effective, the database must be precisely accurate and reasonably comprehensive. The inner surface of the palm normally contains three flexion creases, secondary creases and ridges. The flexion creases are also called principal lines and the secondary creases are called wrinkles. Even it is found that identical twins have different palm prints. These non-genetically deterministic and complex patterns are very useful in personal authentication. . Palm print identification can be divided into two categories- high resolution or low resolution images. High resolution images are suitable for forensic applications such as criminal detection whereas low resolution images are more suitable for civil and commercial applications such as access control. Points and minutia points as features from high resolution images while in low resolution images they generally extract principal lines, wrinkles and texture. Initially palm print research focused on high-resolution images but now almost all research is on low resolution images for civil and commercial applications. The design of a biometric system takes account of five objectives: cost, user acceptance and environment constraints, accuracy, computation speed and security. Reducing accuracy can increase speed. Examples are hierarchical approaches Reducing user acceptance can improve accuracy. For instance, users are required to provide more samples for training. Increasing cost can enhance security. In some applications, environmental constraints such as memory usage, power consumption, size of templates and size of devices have to be fulfilled.

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II. SYSTEM DESIGN

A typical palm print recognition system consists of five parts: palm print scanner, preprocessing, feature extraction, matcher and database. The palm print scanner collects palm print images. Researchers utilize four types of sensors, CCD-based palm print scanners, digital cameras, digital scanners and video cameras to collect palm print images. CCD-based palm print scanners capture high quality palm print images and align palms accurately because the scanners have pegs for guiding the placement of hands. Pre processing sets up a coordinate system to align palm print images and to segment a part of palm print image for feature extraction. Feature extraction obtains effective features from the pre processed palm prints. Features of palm can be extracted by using 1D Log-Gabor filter. Once the central part is segmented, features can be extracted for matching. A palm print images are matched with the trained images located in database using Support Vector Machine (SVM) classifier.

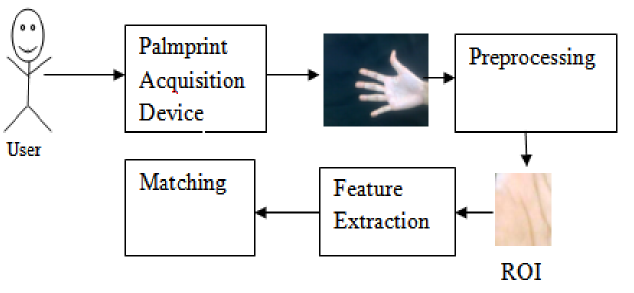

Fig.1 Proposed Model for Palmprint Recognition System

III. LOG-GABOR FEATURE EXTRACTION

Gabor filters are a traditional choice for obtaining localized frequency information. They offer the best simultaneous localization of spatial and frequency information. However they have two main limitations.

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The maximum bandwidth of a Gabor filter is limited to approximately one octave and Gabor filters are not optimal if one is seeking broad spectral information with maximal spatial localization. An alternative to the Gabor function is the log-Gabor function proposed by Field [1987]. Field suggests that natural images are better coded by filters that have Gaussian transfer functions when viewed on the logarithmic frequency scale. (Gabor functions have Gaussian transfer functions when viewed on the linear frequency scale). On the linear frequency scale the log-Gabor function has a transfer function of the form.

$$G(w) = e^{(-\log (w/w0)2) / (2(\log (k/w0)2)} \quad (1)$$

Where w_o is the filter's centre frequency. To obtain constant shape ratio filters the term k/w_o must also be held constant for varying w_o.

Filters are constructed in terms of two components.

1. Radial component, which controls the frequency band that the filter responds to
2. The angular component, which controls the orientation that the filter responds to.

The two components are multiplied together to construct the overall filter. Here are the parameters you have to decide on, several are interdependent.

- The minimum and maximum frequencies you wish to cover.
- The filter bandwidth to use.
- The scaling between centre frequencies of successive filters.
- The number of filter scales.
- The number of filter orientations to use.
- The angular spread of each filter.

A. Maximum Frequency

The maximum frequency is set by the wavelength of the smallest scale filter, this is controlled by the parameter minWaveLength. The smallest value you can sensibly use here is the Nyquist wavelength of 2 pixels, however at this wavelength you will get considerable aliasing and I prefer to keep the minimum value to 3 pixels or above.

B. Minimum Frequency

The minimum frequency is set by the wavelength of the largest scale filter. This is implicitly defined once you have set the number of filter scales (nscale), the scaling between centre frequencies of successive filters (mult), and the wavelength of the smallest scale filter.

maximum wavelength = minWavelength * mult^(nscale-1)

minimum frequency = 1 / maximum wavelength

C. Filter Bandwidth

The filter bandwidth is set by specifying the ratio of the standard deviation of the Gaussian describing the log Gabor filter's transfer function in the log-frequency domain to the filter center frequency. This is set by the parameter sigmaOnf The smaller sigmaOnf is the larger the bandwidth of the filter. I have not worked out an expression relating sigmaOnf to bandwidth, but empirically a sigmaOnf value of 0.75 will result in a filter with a bandwidth of approximately 1 octave and a value of 0.55 will result in a bandwidth of roughly 2 octaves.

D. Scaling Between Centre Frequencies

Having set a filter bandwidth one is then in a position to decide on the scaling between centre frequencies of successive filters (mult). It is here one has to play off the conflicting demands of even spectral coverage and independence of filter output. Here is a table of values, determined experimentally, that result in the minimal overlap necessary to achieve fairly even spectral coverage.

sigmaOnf .85	mult 1.3	
sigmaOnf .75	mult 1.6	(bandwidth ~1 octave)
sigmaOnf .65	mult 2.1	
sigmaOnf .55	mult 3	(bandwidth ~2 octaves)

E. The Number of Filter Orientations

This, in conjunction with the angular spread of each filter, specifies the resolution of the orientation information you obtain from the filters. I have traditionally used six orientations.

F. The Angular Spread of Each Filter

Here again one plays off the demands of even spectral coverage and independence of filter output. The angular interval between filter orientations is fixed by the number of filter orientations. In the frequency domain the spread of 2D log-Gabor filter in the angular direction is simply a Gaussian with respect to the polar angle around the centre. The angular overlap of the filter transfer functions is controlled by the ratio of the angular interval between filter orientations and the standard deviation of the angular Gaussian spreading function. Within the code this ratio is controlled by the parameter dThetaOnSigma. A value of dThetaOnSigma = 1.5 results in approximately the minimum overlap needed to get even spectral coverage.

IV. SVM PATTERN MATCHING

To match palm prints, we are going to compute a matching score between two palm prints according to the points of their palm lines. The central part of the image, which is 256 x 256, is then cropped to represent the whole palm print. Such preprocessing greatly reduces the translation and rotation of the palm prints captured from the same palms. Matching of palm is done by using SVM(Support Vector Machine). The Support Vector Machine (SVM) is a widely used classifier. And yet, obtaining the best results with SVMs requires an understanding of their workings and the various ways a user can influence their accuracy. The SVM classifier is widely used in bioinformatics (and other disciplines) due to its high accuracy, ability to deal with high-dimensional data such as gene expression, and flexibility in modeling diverse sources of data [2].SVMs belong to the general category of kernel methods [4, 5]. A kernel method is an algorithm that depends on the data only through dot-products. When this is the case, the dot product can be replaced by a kernel function which computes a dot product in some possibly high dimensional feature space. This has two advantages: First, the ability to generate non-linear decision boundaries using methods designed for linear classifiers.

Second, the use of kernel functions allows the user to apply a classifier to data that have no obvious fixed-dimensional vector space representation. The prime example of such data in bioinformatics are sequence, either DNA or protein, and protein structure. Using SVMs selectively requires an understanding of how they work. When training an SVM the practitioner needs to make a number of decisions: how to preprocess the data, what kernel to use, and finally, setting the parameters of the SVM and the kernel. Uninformed choices may result in severely reduced performance [6].

V. RESULTS AND DISCUSSION

A. Main Toolbox

Contains a set of icon buttons used to select choices.

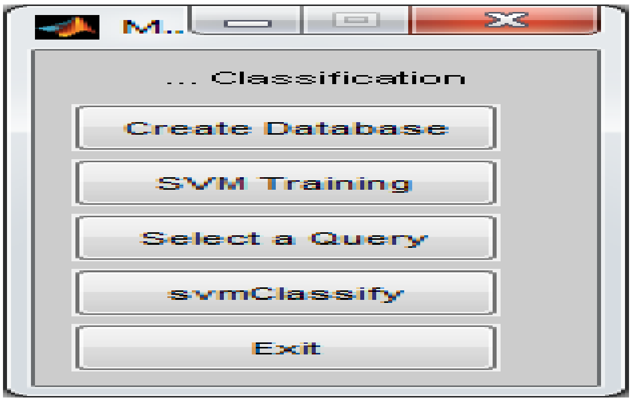

Fig.2 Main Toolbox

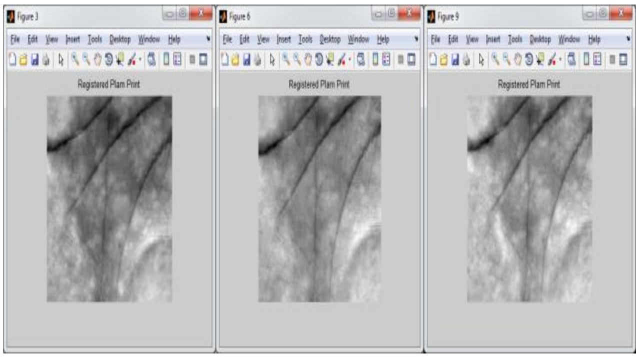

Fig. 3 Feature Extracted Images

B. SVM Training

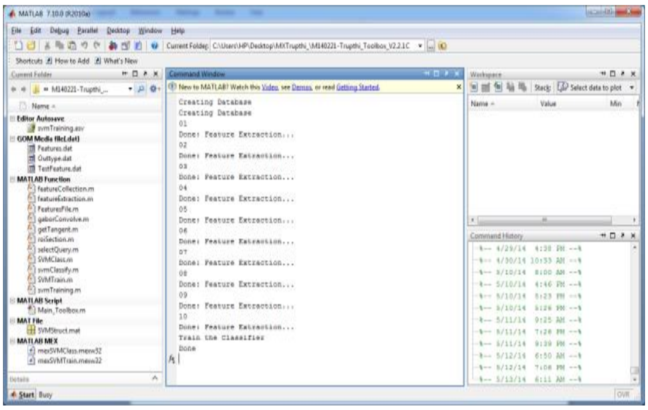

Fig. 4 Training Database

C. Select Query

One of the image is selected from test folder.

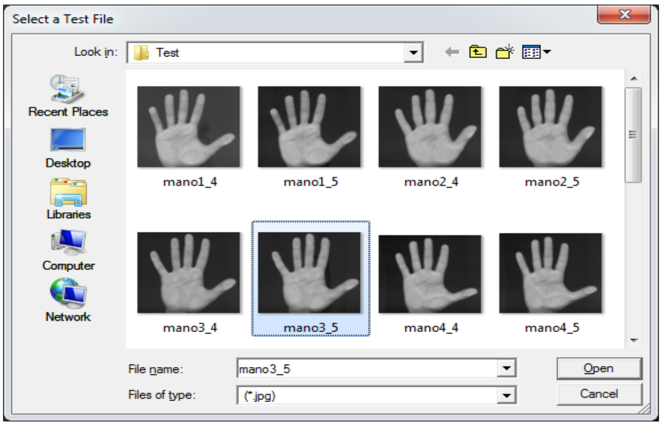

Fig. 5 Test Database

D. SVM Classify

The classified image is of third person

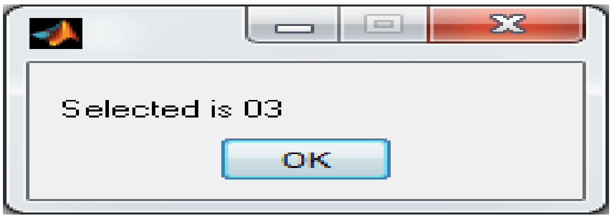

Fig. 6. Selected Image

E. Dataset

The system performance is evaluated using sample palm of our database .A dataset consist of test and train folder. In test folder all the palm images are stored, where as in train folder ten individuals each of three images with different angle and rotation. A dataset of 36 palms, which are collected from different people.

VI. CONCLUSION AND FUTURE SCOPE

In this project we have implemented new method for feature extraction and template matching. Image is captured by capturing device which is user friendly and constraint free. A preprocessing algorithm extracts a central part of the image for feature extraction. To represent low resolution palmprint image and match different palmprint images, we use 1D log Gabor filter for texture feature extraction and matching is done using SVM(Support Vector Machine)classifier. In future, the work can be extended to a larger database containing more palmprint images where in images could be identified as to whether they belong to men or women ,of certain age group and hosts .

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