ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 10, October 2013

Fingerprint Recognition Scheme using Assembling Invariant Moments and SVM

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Abstract: Fingerprint recognition is one of the most important Biometric techniques among all biometrics. It provides reliable means of biometric authentication due to its features Universality, Distinctiveness, Permanence and Accuracy. It is the method of identifying an individual and it can be used in various application, such as, medical records, criminal investigation, cloud computing communication etc. In cloud computing communications, information security involves the protection of information elements, only authorized users can access the available contents. However, traditional fingerprint recognition approaches have some demerits of easy losing rich information and poor performances due to the complex inputs, such as image rotation, incomplete input image, poor quality image enrollment, and so on. In order to overcome these shortcomings, a new fingerprint recognition scheme based on a set of assembled invariant moments i.e., Geometric moment and Zernike moment features are used to ensure the secure communications. This scheme is also based on an effective preprocessing, the extraction of local and global features and a powerful classification tool i.e. SVM (Support vector machine), thus it is able to handle the various input conditions encountered in the cloud computing communication. A SVM is used for matching the identification of test fingerprint inputs feature vectors with of the database images. The motivation behind the work is, growing need to identify a person for security. The fingerprint is one of the popular biometric methods used to authenticate human being. It is difficult to design accurate algorithms capable of extracting salient features and matching them in a robust way, especially in poor quality fingerprint images therefore, proposed fingerprint recognition provides reliable and better performance in poor quality images than the existing technique.

Keywords: Assembling, Fingerprint recognition, Invariant moments, SVM.

I. Introduction

Biometrics refers to the identification of humans by their characteristics or traits. It is described as the science of recognizing an individual based on his or her physical or behavioural attributes. Biometric system broadly provides the three functionalities such as, verification, identification and screening. Biometrics can be used in the face recognition, fingerprint recognition, hand geometry, iris recognition, signature etc. The complexity of designing a biometric system based on three main factors viz., accuracy, scale or size of the database, and usability.
Among all the biometric indicators, fingerprints have one of the highest levels of reliability and have been extensively used by forensic experts in criminal investigations.

Fingerprint recognition is one of the popular and effective approaches for priori authorizing the users and protecting the information elements during the communications. Generally, traditional fingerprint recognition approaches are divided into two categories, minutiae based methods [1], [2] and image based methods [3], [4], [5]. In minutiae based methods feature vector may contain features of minutia points such as their positions, orientations, and types. The disadvantage of this method is that they may not utilize the rich discriminatory information available in the fingerprints and may have high computational complexities. On the other hand, image based methods use different types of features obtained from fingerprint ridge patterns, such as their local orientations and frequencies, ridge shapes, and texture information. The features may be extracted more reliably than detecting minutiae from fingerprints. Among various image based methods, a Gabor filter feature based method [3] showed relatively high performance comparing to other previous works but, these methods required a larger storage space and a significantly high processing time as well as the performance degradation due to the approximation.
The performance of fingerprint recognition may be greatly affected by the complex input conditions such as image rotation, incomplete input image, poor quality image enrollment, and so on. Both the geometric moments and zernike moments are invariant to scale, position and rotation, so they are able to handle the various input conditions.

Geometric and Zernike moments are the most useful descriptors for image representation and feature extraction with invariance to scale, position, and rotation. Some comparisons of them are listed in the following.

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
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1. Domain: Geometric moments are calculated from the original image, whereas Zernike moments are calculated from the frequency domain.
2. Stability: Geometric moments have strong representation ability and they are vulnerable to noises due to easy variations of their numerical values, while Zernike moments are invulnerable to noises.
3. Complexity: Geometric moments are simple and fast, while Zernike moments are more complex.

From the above comparing analysis, both of the geometric moments and zernike moments have merits and demerits to represent the image. So assembling the geometric moments and zernike moments is an effective way to overcome the shortcomings of the individual one while improving the performances of the systems.

Remaining part of the paper is organized as follows. In Section II, geometric and zernike moment analysis is discussed. Section III describes proposed methodology, Section IV gives results and discussion and conclusion is shown in Section V.

II. Invariant Moments

Geometric moments and Zernike moments are invariant moments which are used in this fingerprint recognition scheme.

A. Geometric Moments Analysis

Geometric moments [4] can provide the properties of invariance to scale, position, and rotation. Geometric moment analysis is used to extract invariant features from fingerprint image. This section gives brief description of the moment analysis.

For a 2-D continuous function $f(x, y)$, the moment of order $(p+q)$ is defined as,

$$m_{pq} = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} x^p y^q f(x,y)\,dx\,dy \quad for\ p,q = 0,1,2,\ \dots \quad (1)$$

A uniqueness theorem states that if $f(x,y)$ is piecewise continuous and has nonzero values only in a finite part of the xy-plane, moments of all orders exist, and the moment sequence (m_{pq}) is uniquely determined by $f(x,y)$. Conversely, (m_{pq}) is uniquely determined by $f(x, y)$. The central moments are defined as,

$$\mu_{pq} = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} (x-x')^p (y-y')^q f(x,y)\,dx\,dy \quad (2)$$

where $x' = m_{10}/m_{00}$ and $y' = m_{01}/m_{00}$.

If $f(x, y)$ is a digital image, then (2) becomes,

$$\mu_{pq} = \sum_x \sum_y (x-x')^p (y-y')^q f(x,y) \quad (3)$$

and the normalized central moments, denoted by η_{pq} are defined as follows:

$$\eta_{pq} = \mu_{pq} / \mu^{\gamma}_{00} \quad (4)$$

where $\gamma = (p+q)/2+1$ for $p+q = 2,3\dots$.

A set of seven invariant moments can be derived from the second and third moments. The set consist of groups of nonlinear centralized moment expression and it is a set of absolute orthogonal moment invariants that can be used for a pattern identification invariant to scale, position, and rotation as follows:

$$\begin{aligned}
\phi_1 &= \eta_{20} + \eta_{02}\\
\phi_2 &= (\eta_{20} - \eta_{02})^2 + 4\eta^2_{11}\\
\phi_3 &= (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - 3\eta_{03})^2\\
\phi_4 &= (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2\\
\phi_5 &= (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2]\\
&\quad + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]\\
\phi_6 &= (\eta_{20} + \eta_{02})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]\\
&\quad + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})\\
\phi_7 &= (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2]\\
&\quad + (3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]
\end{aligned} \quad (5)$$

B. Zernike Moments Analysis

Zernike moment [4] can also provide the properties of invariance to scale, position, and rotation. Zernike moment analysis is used to extract invariant features from fingerprint image. This section gives brief description of the Zernike moment analysis.

The magnitudes of Zernike moments have been treated as rotation-invariant features. It has also been shown that Zernike moments can have translation and scale invariant properties by their simple geometric transformations.

The Zernike radial polynomials of order n with repetition m, $V_{nm}(x, y)$, are given by,

$$V_{nm}(x, y) = R_{nm}(x, y)\, e^{jm\theta} \quad (6)$$

where

$$j = \sqrt{-1},\ \ \theta = tan^{-1} y/x \quad (7)$$

and

$$R_{nm}(x,y) = \sum_{s=0}^{(n-|m|)/2} \times \frac{(-1)^s (x^2+y^2)^{(n-2s)/2}(n-s)!}{s!((n+|m|-2s)/2)!((n-|m|-2s)/2)!} \quad (8)$$

where $s = 0,1,\dots,(n-|m|)/2$, $n \geq 0$, $|m| < n$, and $n - |m|$ is even.

The angle θ is between 0 and 2π and is measured with respect to the x-axis in counter clockwise direction. The origin of the coordinate scheme is at the center of an image.

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
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For a digital image, the Zernike moments of order n and repetition m are given by,

$$A_{nm} = \frac{n+1}{\pi} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) V_{nm}^{*}(x,y) \qquad (9)$$

where $V^{*}_{nm}(x, y)$ is the complex conjugate of $V_{nm}(x, y)$.

One of the major properties of Zernike moments is that the image can be reconstructed by using the inverse transformation.

$$f^{\wedge}(x,y) = \sum_{n=0}^{n_{max}} \sum_{m=-n}^{n} A_{nm} V_{nm}(x,y) \qquad (10)$$

where n_{max} is the maximum order of the Zernike moments considered for a particular application.

The magnitudes of the Zernike moments $|A_{nm}|$ are rotation invariant. They also can be invariant to translation and scale.

The Zernike moment $|A_{nm}|$ is order n with repetition m, where n is a nonnegative integer, m is an integer and subject to the constraint $n-|m|$ = even, $|m| \leq n$. It has been found that low-order Zernike moments are stable under linear transformations while the high-order moments have large variations, therefore choose the order n which is less than 5, and the first ten Zernike moments ($n \leq 5$) can be defined as $A_{0,0}$, $A_{1,1}$, $A_{2,0}$, $A_{2,2}$, $A_{3,1}$, $A_{3,3}$, $A_{4,0}$, $A_{4,2}$, $A_{4,4}$, $A_{5,1}$, $A_{5,3}$ and $A_{5,5}$.

III. PROPOSED METHOD

Figure 1. shows an overview [6] of the proposed fingerprint recognition system. Fingerprint image is input to the system. Extract the features of input image and check those extracted features with already stored features of fingerprint images in the database.

Following figure contains two stages, offline processing and online processing. In the offline stage, fingerprint images of the different individuals are firstly processed by the feature extraction module and then their extracted features are stored in the database. In the on-line stage, a fingerprint image of an individual is processed by the feature extraction module, its extracted features are then fed to the matching module, which matches them against own templates in the database.

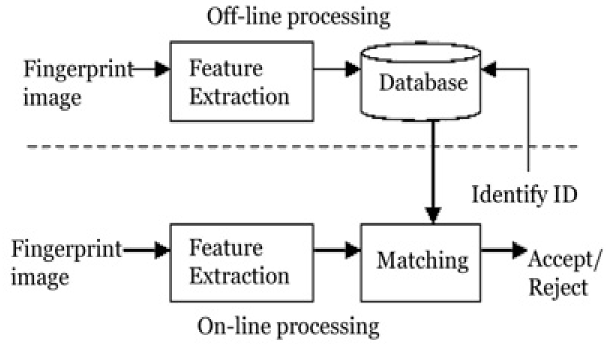

Fig. 1 Overview of the fingerprint recognition system

Both online and offline process contains feature extraction module, which consists of five stages as shown in Figure 2, such as, image enhancement, determination of reference point, determination and partition of ROI, assembling of invariant moment analysis, and PCA (Principal component analysis).

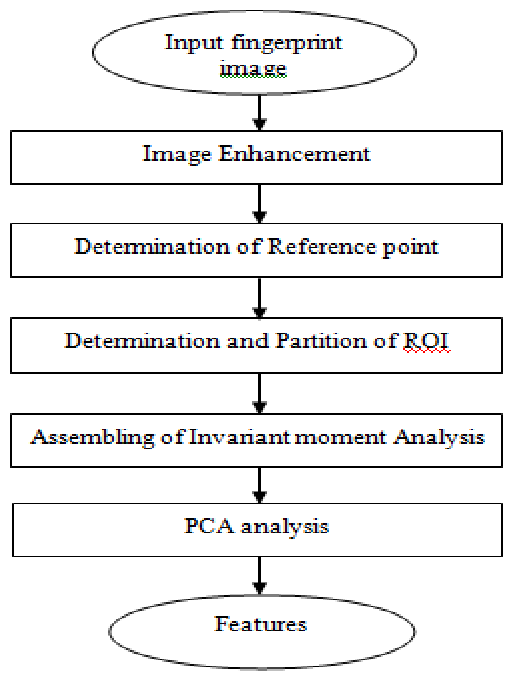

Fig. 2 Flowchart of the feature extraction module

A. Image Enhancement

This algorithm consists of two stages, STFT (short time Fourier transform) analysis and Enhancement. The performance of a fingerprint recognition system depends on the quality of the input images and it roughly corresponds to the clarity of the ridge structure in the fingerprint image, hence it is necessary to enhance the fingerprint in advance.

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

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The algorithm simultaneously estimates all the intrinsic properties of the fingerprints such as the foreground region mask, local ridge orientation and local ridge frequency, and used these properties to enhance the fingerprint image. Thus, it can enhance the image completely.

The STFT [7] image enhancement algorithm consists of two stages as summarized in following algorithm.

Algorithm: Enhanced the fingerprint image with STFT algorithm

Input: Fingerprint image
Output: Enhanced fingerprint image

Stage 1: STFT analysis
1) Read input fingerprint image from fingerprint database.
2) Divide input image into overlapping blocks.
3) For each overlapping block generate and reconstruct a ridge orientation image by computing gradients of pixels in a block.
4) Get a ridge frequency image by applying FFT into the block, then take an energy image by summing the power of FFT value.
5) Smooth the orientation image using average vector and generate a coherence image using smoothed orientation image.
6) Generate a region mask by thresholding the energy image.

Stage 2: Enhancement
1) Generate angular filter F_a which is centered on the orientation of the smoothed orientation image.
2) Generate radial filter F_r centered on the frequency image.
3) Apply the filter, $F = F * F_a * F_r$ into the block in the FFT domain.
4) Generate the enhanced block by inverse Fourier transform IFFT(F).
5) Reconstruct the enhanced image by composing enhanced blocks, and get the final enhanced image.

B. Determination of Reference Point

Core and delta are singular points and they are unique landmarks of fingerprints as a global feature. They are commonly used as reference points for fingerprint indexing, classification, and matching. However, some of the partial fingerprint images or plain-arch-type fingerprints may exists without the delta points. It may possible to get two core points from the whorl type fingerprints. This step determines a reference point from the enhanced image instead of from the original image directly.

The orientation field obtained from the enhanced image will increase the reliability and accuracy for detection. The reliable detection of a reference point can be accomplished by detecting the maximum curvature using complex filtering methods [8] and it is summarized in algorithm as below.

Algorithm: Reference point determination

Input: Enhanced fingerprint image
Output: Reference point determination in the fingerprint image

1) Read enhanced fingerprint image.
2) Apply corresponding complex filter, $h = (x + iy)^m g(x, y)$ on each block of the image, where m and $g(x, y) = exp\{ - ((x^2 + y^2)/(2\sigma^2))\}$ indicate the order of complex filter and Gaussian window respectively.
3) For $m=1$, obtain filter response of each block by a convolution, $h * O(x, y) = g(y) * ((xg(x))^t * O(x, y)) + ig(x)^t * ((yg(y) * O(x, y)))$ where $O(x, y)$ represents the pixel orientation in the orientation image.
4) Reconstruct the filtered image by composing filtered blocks.
5) The maximum response of complex filter in the filtered image can be considered as the reference point.

Since there is only one unique output point is taken as reference point of an image.

C. Determination and Partition of ROI

In order to speed up the overall process for feature extraction, use only a predefined area (ROI) around the reference point of fingerprint image for feature extraction instead of using the entire fingerprint. The center of the cropped ROI image is the position of the reference point which is determined in the previous step.

To cover both global and local information of fingerprint, reduce the effects of noise and nonlinear distortions, the determined ROI region is divided into four sub-ROIs which provides four sets of geometric moment and zernike moment features.

D. Assembling Invariant Moments analysis

At the fourth step, apply the geometric moments and Zernike moments analysis introduced in Section II on fingerprint image. Geometric moments provide a set of seven invariant moments and Zernike moments provide twelve features.

Let $\phi_{k,l}$ for k = 1, 2, 3, 4and l = 1, 2, 3,...,19, where $\phi_{k,l}$ for l = 1, 2, 3,...,7 consist of geometric moments, and $\phi_{k,l}$ for l = 8, 9, 10,...,19 consist of zernike moments, k is used for index of image. Each sub-ROI contains 19 features. So feature vector is enclosed with 76 features.

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

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E. PCA Analysis

PCA analysis reduces the dimension of feature vector, which examines feature covariance matrix and then selects the most distinct features. It is one of the oldest and greatest known techniques in multivariate analysis. Let x ϵ R_n be a random vector, where n is dimension of the input space. Covariance matrix of x is defined as, $\Xi = E\{[x-E(x)][x-E(x)^T\}$. Let $u_1, u_2 .....u_n$ and $\lambda 1, \lambda 2.... \lambda n$ be eigenvectors and eigenvalues of Ξ respectively and $\lambda 1 \geq \lambda 2 \geq .... \geq \lambda n$, then PCA factorizes Ξ into $\Xi = U \Lambda U^T$ with $U = [u_1, u_2 .....u_n]$ and $\Lambda = diag(\lambda 1, \lambda 2 .... \lambda n)$.

F. Matching with SVM

Support vector networks or SVM [9], [10] are supervised learning models with associated learning algorithms used in machine learning. It analyzes the data and recognize different patterns. It is used for classification and regression analysis. The basic SVM takes a set of input data and predicts for each given input. SVM is used for classifying data sets.

Viewing input data as two sets of vectors in an *n*-dimensional space, then SVM will construct a separating hyperplane in that space, one which maximizes the margin between the two data sets. To calculate the margin, two parallel hyperplanes are constructed, one on each side of the separating hyperplane, which are "pushed up against" the two data sets. Instinctively, a good separation is achieved by the hyperplane that has the largest distance to the neighbouring data points of both classes, since in general the larger the margin the better the generalization error of the classifier.

Usually, there are four kinds of SVM types: the linear SVM, radial-basis SVM, polynomial SVM, and sigmoid SVM. Most of the time nonlinear types of SVM, such as radial-basis SVM, polynomial, and sigmoid SVM can be used for fingerprint matching to achieve high recognition rate.

For each input fingerprint and its template fingerprint, compute the geometric and zernike moments. Since the output is to judge whether the input fingerprint is match or non-match according to the identity ID, So it consider being as matching process as two-class problem. SVM is used to verify a matching between feature vectors of input fingerprint and of template fingerprint image.

There are mainly 2 stages training and testing, In the training stage, training samples are fed to the SVM with indicating their corresponding class. The features are computed from the training data, each contains vector from the training fingerprint. Whereas in the testing stage, test samples are fed to the SVM to produce the output values. Similarly, the features are computed from the testing data, each contains vector from the test fingerprint with the querying ID. If the output number is equal ID, then it means fingerprints are matched, otherwise they are non-matched.

SVM steps are defined in the following algorithm.

Algorithm:

Input: Feature vector
Output: Classification result

1) Get feature vectors of different fingerprints.
2) Use Radial Basis function (RBF) and construct the hyperplane for converting low dimensional data space into high dimensional data space.
3) After constructing hyperplane feature vectors are divided into two classes. So in one class Right Loop, Left Loop, Mixed and Tented Arch type fingerprints are there and in another class Arch and Whorl type fingerprints are there.
4) SVM classifies test fingerprint image according to the class of fingerprint.

To verify test fingerprint image subtract the test fingerprint feature vector from training feature vectors. If test fingerprint is same as that of trained fingerprint image then system gives 0 value it means test fingerprint is exactly matched. If test fingerprint is different from the trained fingerprints then system finds the image which is closer to test fingerprint.

IV. RESULT AND DISCUSSIONS

Fingerprint recognition system is tested on various fingerprint dataset (FVC2002 and FVC2004) [11]. Database is divided into two parts, training dataset and testing dataset.

Each person have eight fingerprints in the database. Among those images some of the images belongs to class 1 (R, L, M) from dataset and some of them belongs to class 2 (A, W). Various parameters that have been analyzed for the system performance, such as, false reject rate, false acceptance rate, equal error rate, EER performance study on different methods, recognition rate, recall time per pattern analysis. These are as discussed below.

A. False Reject Rate

To compute FRR, the genuine match were performed. For genuine match, each fingerprint of each person is compared with other fingerprints of same person. The FRR is defined as follows,

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
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$$\text{FRR} = \frac{\text{Number of rejected genuine claims}}{\text{Total number of genuine accesses}} \times 100\% \qquad (1)$$

B. False Acceptance Rate

For computing FAR, the imposter match were performed. For imposter match, each test fingerprint is compared with fingerprints belonged to other persons.

$$\text{FAR} = \frac{\text{Number of accepted imposter claims}}{\text{Total number of imposter accesses}} \times 100\% \qquad (2)$$

C. Equal Error Rate

The EER is used as a performance indicator. The EER indicates the point where the FRR and FAR are equal.

D. EER Performance Study

Following Table I provides different EER values for different methods, EER is calculated by averaging FAR and FRR.

TABLE I
EER (%) OF PROPOSED METHOD WITH OTHER METHODS

Methods	**EER %**
Minutiae based	6.68
Geometry moments based	3.57
Zernike moments based	3.23
Proposed	2.18

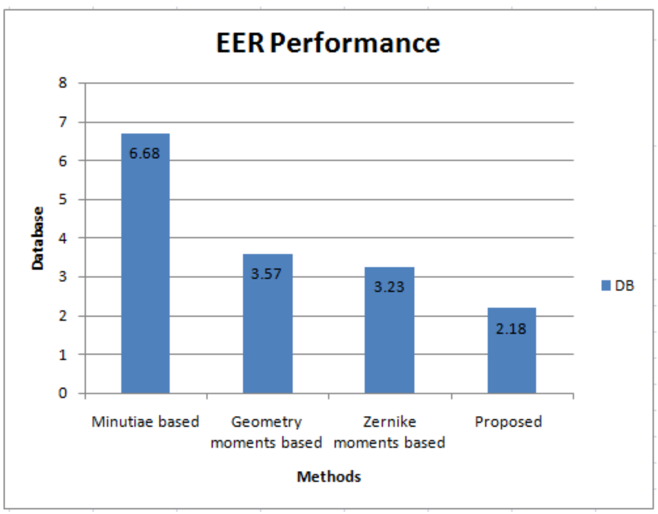

Fig. 3 EER (%) Performance for different methods

The above graph shows the different values of EER for different methods. For proposed method EER value is less than the another EER values so performance of system is improved.

E. Recognition Rate

Recognition rate of SVM classifier for training and testing dataset are as described in following Table II . After getting class of fingerprint and ID, it needs to verify that fingerprint image. So similarity measure is used for verification of testing fingerprint. If testing fingerprint image is given from the training fingerprint dataset then system gives exactly matched fingerprint ID. If testing fingerprint image is not trained then system gives the image ID, which is closer image to that of testing fingerprint.

TABLE II
RECOGNITION RATE

Classifier	**Training Dataset**	**Testing Dataset**	**Average recognition Rate**
SVM	100%	75%	87.5 %

V. CONCLUSION

In order to protect the multimedia contents for security, this new fingerprint recognition scheme based on a set of assembled geometric and zernike moment features in cloud computing communications. This scheme can also used to protect the data or security-focused resources for safety communications. This fingerprint recognition scheme is based on the effective preprocessing, the extraction of local and global invariant moment features and the powerful SVM classification tool, thus it is able to handle the various input conditions. SVM is used to verify matching between fingerprints.

A pre-processing enhancement with the STFT analysis makes the algorithm highly robust to poor-quality fingerprint images and it improves the matching accuracy. Because of the image enhancement, the reference point can be reliably determined by the complex filtering methods. Feature extraction is done by using assembling invariant moment analysis and it covered both local and global properties of fingerprints.

ACKNOWLEDGMENT

I humbly thanks to Prof. C. A. Laulkar (Sinhgad College of Engineering, Pune) for lending her invaluable expertise. I also thankful to my institution for providing guidance and opportunities.

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ISSN (Print) : 2319-5940
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Vol. 2, Issue 10, October 2013

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BIOGRAPHIES

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