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FRACTAL ANALYSIS FOR CLASSIFICATION OF REGIONS IN OVERLAPPED FINGERPRINTS

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Abstract- Segmentation of overlapped fingerprint is yet manually carried out by fingerprint examiners, which is a bottleneck in automation of overlapped fingerprints separation. This paper presents method for classification of regions in overlapped fingerprints into overlapped and non overlapped regions based on image fractal analysis. Overlapped fingerprints are decomposed into binary images using a combination multi Otsu thresholding and two threshold binary decomposition algorithms. Fractal dimensions are computed from border images derived from binary images using box counting method. The feature vector includes fractal dimensions, size of the object regions and their average gray value. Naive Bayes classifier is adopted for classification of overlapped fingerprints regions into overlapped and non overlapped regions. The results are evaluated on three databases, i) Standard simulated overlapped fingerprints database, ii) Real overlapped fingerprints database, and iii) Locally simulated overlapped fingerprints. The classification accuracy achieved is 88.33%, the misclassification is mainly due to poor quality of fingerprints in the non overlapped region.

Keywords- fractal, overlapped fingerprint, texture, naïve bayes classifier

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Introduction

Biometrics based personal identification systems have gained tremendous popularity recently, among the various biometrics based personal identification systems, fingerprints based identification systems are the most reliable and proven methods. Development of high performance automatic fingerprints identification systems is a very intense area of research, motivated by the fact that fingerprints based recognition systems are utilized for personal identification in numerous civilian and forensic applications. Despite of the great advancements in fingerprints identification technology, it can be inferred from the recent research that still there is a need for high performance systems especially to handle poor quality degraded latent fingerprints [1].

Latent fingerprints pose critical challenges to the state-of-the-art fingerprint identification systems as these fingerprints generally contain complicated background and unclear ridges. These fingerprints exist on the surfaces of objects that are unintentionally touched by a person in the crime scene [2]. Latent fingerprints are generally unclear and contain artifacts. Feature extraction in latent fingerprints is very difficult as compared with inked and live scan fingerprint images. In some latents the background of a fingerprint is another fingerprint as shown in [Fig-1], such fingerprints are the overlapped fingerprints. Overlapping occurs whenever some object is touched multiple times by people in the scene or due to left over residual fingerprints on the scanning sensor while acquiring fingerprints. In practice, occurrence of overlapped fingerprints is very common in crime scenes. Overlapped fingerprints pose serious challenges to existing fingerprint recognition systems, which are not recognizable even with a state of the art VeriFinger 6.2 SDK. [3], these systems do incorporate any internal module for separation of overlapped fingerprints and thus are unable to identify overlapped fingerprints. In order to take benefits of existing systems there is a need for development of suitable algorithms for separation of overlapped fingerprints.

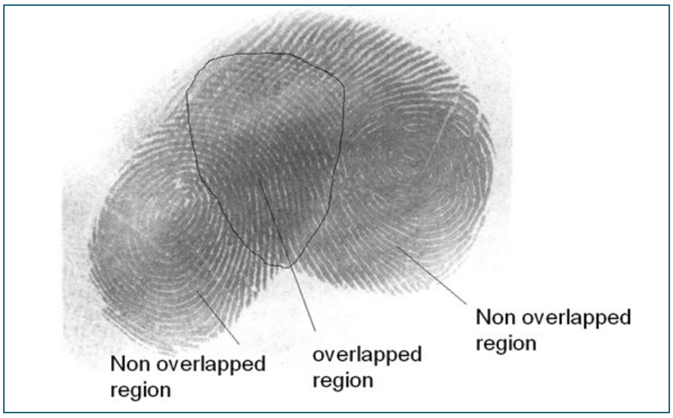

Fig. 1- Typical overlapped fingerprint

In forensic department such overlapped fingerprints are manually separated using gold nano material technology [4]. This method is very tedious and time consuming. Thus automatic separation of overlapped fingerprints is necessary.

Recent research introduces few approaches to solve this problem [3,5-8]. Typical steps involved are:

Segmentation of overlapped fingerprints image into overlapped and non overlapped regions.

- Ridge orientation extraction and classification,
- Separation of overlapped fingerprints through enhancement.

[Fig-2] shows various modules for separation.

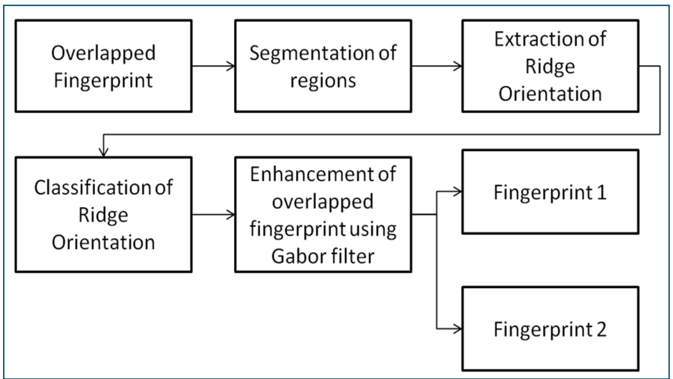

Fig. 2- Modules for separation of overlapped fingerprints.

The main issues in separation of overlapped fingerprints are accurate ridge orientation extraction in overlapped and non overlapped regions of overlapped fingerprint, classification of orientation fields that belongs to individual fingerprints in the overlapped region, and design of Gabor filter which enhances fingerprints based on the orientations.

In the process of feature extraction method of ridge orientation extraction is selected based on whether the region in the image is overlapped or non overlapped. The reason for this is extraction of ridge orientation in non overlapped region can be done using gradient based methods which are simple and less complex. And overlapped region needs a novel method, since overlapped region contains two dominant orientations and gradient based methods in this case are not satisfactory.

Thus region based methods for orientation extraction are adopted. At present the algorithms for separation of overlapped fingerprints incorporate manual marking of overlapped region by the fingerprints expert. Thus the existing separation algorithms do not support complete automation.

Literature has presented few algorithms for separation of overlapped fingerprints. These algorithms are centered towards development of robust algorithms for ridge orientation extraction and classification. However, no attention is given to the segmentation of overlapped region and it is a major bottleneck in designing automatic fingerprints separation systems. In addition, manual marking is a subjective process and demands expert decision from fingerprints examiners. In practice, latent fingerprints identification involve large number of overlapped fingerprints, and thus, manual marking needs to be avoided as it becomes a tedious and time consuming job. Therefore automatic segmentation of overlapped fingerprint into overlapped and non overlapped regions is required. Work in this paper focuses on developing an innovative algorithm for automatic identification of overlapped and non overlapped regions in overlapped fingerprint, which helps in complete automation of separation process.

Following sections of the paper presents fractals based analysis methodology to classify image regions as overlapped and non overlapped regions, demonstrates experimental results and presents conclusions and future work.

Identification of Regions in Overlapped Fingerprints using Texture Analysis

Image texture is an important property and represents visual description of images. This property is estimated using statistical measurements and other local measurements. Most of the texture extraction methods are not invariant to distortions, which are serious limitations for many applications that involve texture analysis [9].

Image fractals paradigm is one of the most popular methods in image analysis which characterizes image based fractal dimension. The concept of image fractals is applied in many areas of image processing like texture analysis, segmentation and compression [9] [10].

Image fractals are the good descriptors of texture and they are robust to noise and distortions, thus helps in designing robust texture analysis and classification algorithms. Mathematically fractal dimension is invariant to scaling, rotation and smooth deformations. Fractal features are usually used for description of natural texture or computer generated fractals image surfaces.

Distribution of fingerprints ridges in fingerprints produces a kind of texture patterns [11], which motivates for considering fingerprints as a texture image. In this work overlapped fingerprints are considered are texture images and mage fractal is explored for identification of regions in overlapped fingerprints.

Fractal Dimension Using Box Counting Method

Box counting is a widely used method for computing image fractal dimensions. In box counting, image is covered with a grid and the how many boxes are required for covering the image pattern is calculated. This computation is repeated for different sizes of box. Smaller size boxes capture more detailed image structure. A graph is plotted with log (N) on Y-axis and log(r) on the X-axis and the fractal dimension D is the slope of this line as in (1)

$$D = \frac{\log(N)}{\log(r)} \qquad (1)$$

Where, N is the number of boxes required to cover image pattern and r is the corresponding size of the box.

Fractal Based Overlapped Fingerprints Analysis

In this work image fractal dimension is computed for the identification of overlapped and non overlapped regions in the overlapped fingerprint. In general image fractals feature alone is not sufficient to obtain highly unique texture description of image, they give better results when combined with other pixel features. Therefore in this work image fractal dimension is combined with other features such as average gray value and size of object regions, thus fractal dimension, average gray value and area of objects comprises complete feature set. [Fig-3] shows complete feature extraction process.

Feature extraction consists of decomposing a given input image into a set of binary images using a combined method of Otsu multi thresholding algorithm and two threshold binary decomposition algorithms [12].

Features including fractals dimensions, average gray value and object size are computed from these binary images which are used in analysis and classification of regions in overlapped fingerprints.

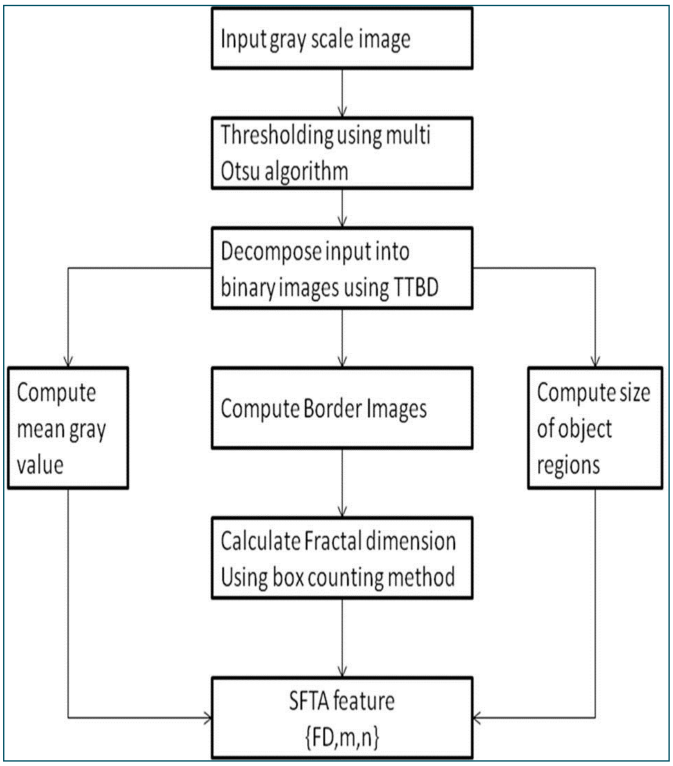

Fig. 3- Feature extraction for region analysis

Two - Thershold Binary Decomposition (TTBD)

This algorithm decomposes a given grayscale image into a set of T binary images. First step is, TTBD calculates a set of threshold values by exploiting gray level distribution in the input image. This is accomplished by employing multi-level Otsu thresholding algorithm [12].

Otsu algorithm computes thresholds recursively, such that in every step the image intra-class variance is decreased. Otsu algorithm is applied to each image region until the proper number of thresholds (T) is obtained. TTBD algorithm decomposes given input image into binary images by selecting a pair of thresholds from T using [Eq-2].

$$I_b(x,y) = \begin{cases} 1 \text{ if } t_\ell < I(x,y) \le t_u \\ 0, \text{ otherwise.} \end{cases} \qquad (2)$$

Where t_l is the lower threshold value and t_u upper threshold value. The set of binary images are obtained by applying the two threshold segmentation method [Eq-1] to the input image using all pairs of consecutive thresholds from T U $\{n_l\}$ and all pairs of thresholds from the set $\{t, n_l\}$, $\{t, n_l\}$ where n_l corresponds to the maximum possible gray level in I(x, y). Thus, the number of resulting binary images is $2n_t$.

After applying Two Thresholds Binary Decomposition algorithm to the input gray level image, mean gray scale value and objects size are computed directly from the binary image. The fractal dimensions represent the boundary complexity of objects and structures segmented in the input image. The regions boundaries of a binary image $I_b(x, y)$ are represented as a border image denoted by Δ(x, y) and computed using [Eq-3] and fractal dimensions are calculated using algorithm 1.

$$\Delta(x,y) = \begin{cases} 1 \text{ if } \exists (x',y') \in N_8[(x,y)] : \\ \quad I_b(x',y') = 0 \ \wedge \\ \quad I_b(x,y) = 1, \\ 0, \text{ otherwise.} \end{cases} \qquad (3)$$

Algorithm 1: Computation of Haussdorf Fractal Dimension

1. Pad the image with background pixels to adjust its dimensions to the power of 2.
2. Initialize the box size to value 'e' which is equal to the image size.
3. Calculate N (e), which is the number of boxes of size 'e' that contains at least one object pixel
4. If e > 1 then set e, e = e / 2 and go to step 3.
5. Compute the points log (N (e)) x log (1/e).
6. Use least squares method for line fitting.

Experimental Results

Classification of regions as overlapped and non overlapped is carried out in two phases. In the training phase, Naivebayes classifier is trained to recognize a set of reference feature vectors for given set overlapped and non overlapped image patterns, and during testing phase, unknown vectors of input patterns are classified according to a best match criterion.

[Fig-4](a&b) depict a typical input image and [Fig-5](a&b) depict border images along with corresponding fractal dimensions.

Test images are derived from three different databases, they are as follows. Database1 is generated as a part work proposed in this paper.

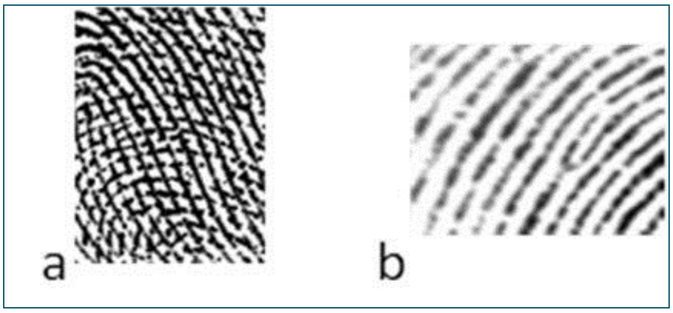

Fig. 4- (a) overlapped image, (b) Non overlapped image

Database 1- A database of overlapped fingerprints is generated using ink impression of fingerprints on paper by local subjects in overlapped fashion. This database contains 100 samples of overlapped fingerprints. These overlapped fingerprints are collected through guiding the subjects for different finger pressure, different overlap angle, and amount of ink on the finger to ensure that samples cover varied conditions of overlapped fingerprints with varied quality.

Database 2- This database contains 100 samples of simulated latent overlapped fingerprints.

Database 3- This database contains 100 samples of real latent overlapped fingerprints lifted from the crime scene includes good quality as well as poor quality overlapped fingerprints.

Classification performance was evaluated through rigorous testing with images of selected from all three databases. The Naivebayes classifier is selected as a suitable classifier in this work as there no dependency between features- fractal dimension, average gray value and region size of the object. Built in Naive ayes classifier existing in Matlab R2014a is utilized and the results obtained are tabulated in [Table-1].

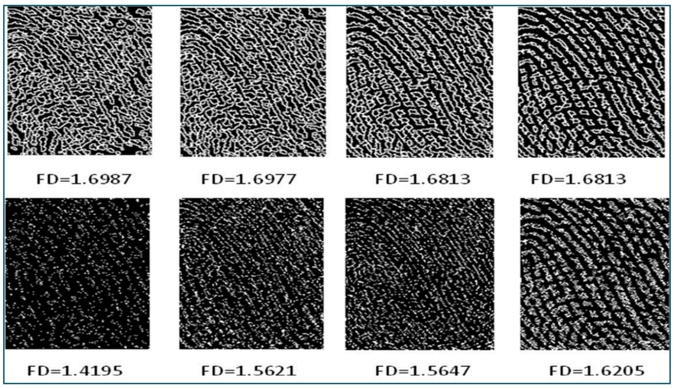

Fig. 5a- Border images for image in 4(a)

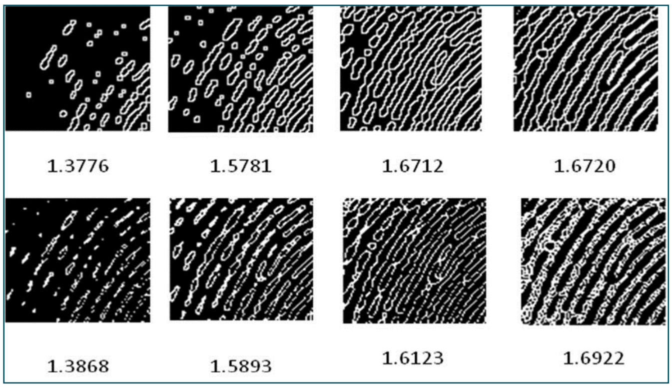

Fig. 5b- Border images for image in 4(b)

The confusion matrix of Naivebayes classifier is given in table 1. The average classification accuracy calculated from Table 1 is 88.33%. It is a ratio of correct number of image classifications to the total number of images. The misclassification is mainly due to poor quality of fingerprints in the non overlapped region.

Table 1- Confusion Matrix

Actual Class	Predicted Class		
	Overlapped	Non Overlapped	Total No. Of Images
Overlapped	280	20	300
Non Overlapped	50	250	300

Conclusions

This paper provides a method for classification of regions in overlapped fingerprints into overlapped and non overlapped regions. Feature extraction includes computation of image fractal dimension, size of object regions and average gray value. Input images are decomposed into binary images using two threshold binary decomposition algorithms. Haussdorf fractal dimension is computed from border images using box counting method. Naive Bayes classifier is adopted for classification of patterns as overlapped and non overlapped regions. The results are evaluated on standard simulated overlapped fingerprints database, real overlapped fingerprints database, and locally simulated overlapped fingerprints. The classification accuracy achieved is 88.33%. In future the work can be extended by adopting other classifiers for proper validation of accuracy. However, it is concluded at this stage that the misclassification is mainly due to poor quality of fingerprints in the non overlapped region. In order to reduce the percentage misclassification, this work could be extended to explore other texture features like Gabor texture features and Haralick texture features. This work could also be extended for evaluation on larger database with different classifiers.

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Conflicts of Interest: None declared.

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