Finger Vein Recognition using Differential Box Counting

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Abstract - The demand for simple, convenient, and high security authentication systems for protecting private information has steadily increased. The personal information can be protected in the form of biometrics which uses human physiological or behavioural features for personal identification. Most existing biometric systems have high complexity in time or space or both. This paper presents a user identification system framework using finger-vein technology for authentication, which provides high security and reliability than the other identification technologies. Finger vein ID is a biometric authentication system that matches the vascular pattern in an individual's finger to previously obtained data. The proposed algorithm is Fractal Model using Differential Box Counting method. The performance parameters of the proposed algorithm are compared with the existing algorithms (Repeated line tracking, Fractal model using blanket technique) and the equal error rate is calculated to be 0.05%. This approach not only has precise estimated parametric values but also consumes less computational time.

Keywords- Biometrics, Vein, Recognition, Authentication, Differential box counting.

I.INTRODUCTION

Private information is traditionally provided by using passwords or Personal Identification Numbers (PINs), which are easy to implement but is vulnerable to the risk of exposure and being forgotten. Biometrics, which uses human physiological or behavioural features for personal identification, is a promising alternative to the traditional password or PIN based authentication techniques [1]. There is a long list of available biometric patterns, and many such systems have been developed and implemented, including those for the face, iris, fingerprint, palmprint, hand shape, voice, signature, and gait. Fingerprints and palmprints are usually frayed. Voice, signatures, hand shapes and iris images are easily forged .Face recognition can be made difficult by occlusions or face-lifts and biometrics, such as fingerprints and iris and face recognition, are susceptible to spoofing attacks [2]. The great challenge to biometrics is thus to improve recognition performance in terms of both accuracy and efficiency and be maximally resistant to deceptive practices. Especially for consumer electronics applications, biometrics authentication systems need to be cost-efficient and easy to implement [3].

The finger-vein is a promising biometric pattern for personal identification in terms of its security and convenience [4]. Compared with other biometric traits, the finger-vein has the following advantages [5].The vein is hidden inside the body and is mostly invisible to human eyes, so it is difficult to forge or steal.

- Vein patterns are distinctive between twins and even between a person's left and right hand.
- They are highly stable and robust.
- The non-invasive and contactless capture of finger veins ensures both convenience and hygiene for the user, and is thus more acceptable.
- The finger vein pattern can only be taken from a live body.

II .VEIN BASED PERSONAL IDENTIFICATION SYSTEM

Finger vein recognition is a method of biometric authentication that uses pattern-recognition techniques based on images of human finger vein patterns beneath the skin's surface. Finger vein recognition is one of the many forms of biometrics used to identify individuals and verify their identity. Finger Vein ID is a biometric authentication system that matches the vascular pattern in an individual's finger to previously obtained data. The technology can be used for a wide variety of applications, including credit card authentication, automobile

security, employee time and attendance tracking, computer and network authentication, end point security and automated teller machines. Blood vessel patterns are unique to each individual, as are other biometric data such as fingerprints or the patterns of the iris. Unlike some biometric systems, blood vessel patterns are almost impossible to counterfeit because they are located beneath the skin's surface. Biometric systems based on fingerprints can be fooled with a dummy finger fitted with a copied fingerprint. Voice and facial characteristic-based systems can be fooled by recordings and high-resolution images. The finger vein ID system is much harder to forge because it can only authenticate the finger of a living person. Vein matching, also called vascular technology, is a technique of biometric identification through the analysis of the patterns of blood vessels visible from the surface of the skin.

III.EXISTING ALGORITHM-REPEATED LINE TRACKING

To develop highly accurate personal identification systems, finger-vein patterns should be extracted precisely from the captured images, and the process must be executed speedily in order to satisfy requirements for user convenience [8]. In the method [7] based on line tracking, local dark lines are identified, and line tracking is executed by moving along the lines, pixel by pixel. When a dark line is not detectable, a new tracking operation starts at another position. All the dark lines in the image can be tracked by repeatedly executing such local line tracking operations. Finally, the loci of the lines overlap and the pattern of finger veins is obtained statistically. As the parts of the dark lines are tracked again and again in the repeated operations, they are increasingly emphasized. This makes line extraction robust. Furthermore, reduction of the number of tracking operations and the spatial reduction of the pattern can reduce computational costs. This is the basis of Repeated Line tracking(RLT) algorithm (Naoto Miura, 2004).

IV. PROPOSED ALGORITHM-DIFFERENTIAL BOX COUNTING

The fractal model developed by Mandelbrot provides an excellent method for representing the ruggedness of natural surfaces and it has served as a successful image analysis tool for image compression and classification [6]. Since different fractal sets with obviously different textures may share the same fractal dimension, the concept of differential box counting is used to discriminate among textures [9]. Fractal Dimension (FD) is an interesting feature for texture segmentation, shape classification and graphic analysis in many fields. Experiments are done on the gray scale images.

The concept of fractal is used to describe objects that possess self similarity at all scales and levels of magnification. Fractal objects have irregular shapes and complex structures that cannot be represented adequately by the traditional Euclidian dimension. Fractal dimension (FD) assigns non integral dimension values to objects that do not fit to the traditional Euclidean space of objects. For example, the dimension of a straight line is unity, but the dimension of a jagged line is a fractional value falling between unity and two, depending on its degree of jaggedness .The fractal dimension has been used in image classification to measure surface roughness where different natural scenes such as mountains, clouds, trees, and deserts generate different fractal dimensions.

Fractal theory is widely used in image processing and is based on the accurate estimation of fractal dimension. Since manmade designs usually have simple surface texture and regular geometry shape, it can be easily used for many pattern recognition applications including classification and segmentation. One of the important properties of fractal is the self-similarity. A bounded set A is said to be self-similar, if A is the union of a number (N_r) of non-overlapping scaled copies of itself, where r is the scaling factor. The box-counting dimension is the most frequently used for measurements in various application fields [11]. The reason for dominance lies in its simplicity and automatic computability.

The box counting method consists in partitioning the image space into square boxes of equal size. The box covers the image space of the function or pattern of interest and the number of boxes that contain at least one pixel of the function is counted. The process is repeated with different box sizes.

The basic principle to estimate FD is based on the concept of self-similarity. The FD of a bounded set A in Euclidian n-shape is defined as,

$$D= \log (N_r) / \log (1/r)$$

Where N_r is the least number of distinct copies of A in the scale r. The union of N_r distinct copies must be cover set A completely.

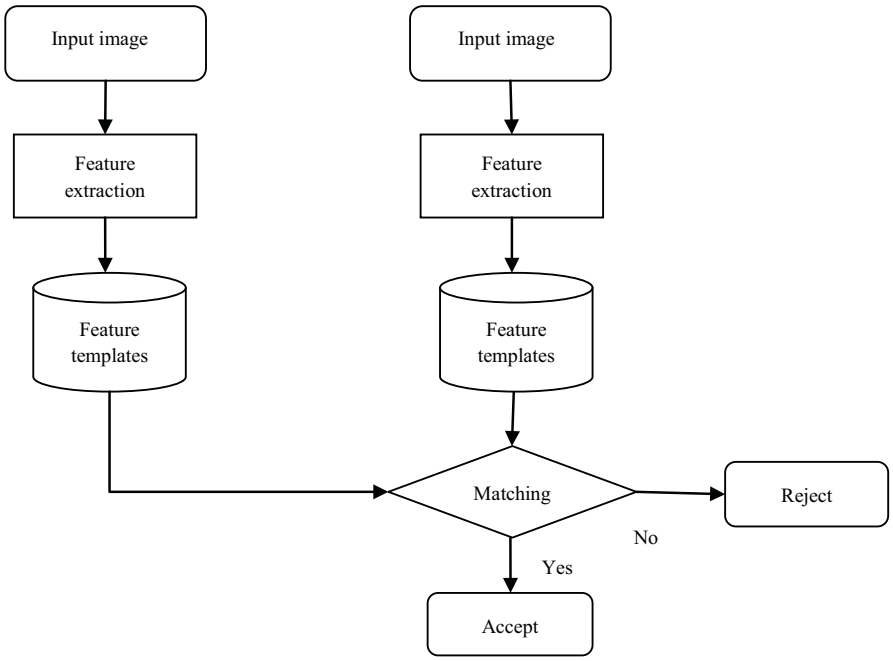

Figure 1.Flow Chart of the proposed system

Figure 1. shows the flow chart of the proposed algorithm.

A.Steps in feature extraction by Differential Box Counting

Step 1: The image of size MxM is scaled down to a size of lxl ,where $M/2 \geq l > 1$ and l is an integer.

Step 2: $r=l/M$ is estimated .

Step 3: The image is considered as a 3-D space with(x, y) denoting 2-D position and the third coordinate (z) denoting gray level. The (x, y) space is partitioned into grids of size lxl. **.** On each grid there is a column of boxes of size $lxl\ xl'$.If the total number of gray levels is G then $l' = \lfloor x\ G/M \rfloor$.

Step 4: The minimum and maximum gray level of the image in the (i, j) th grid fall in box number p and q respectively. Then,

$n_r\ (i, j) = q - p + 1$

is the contribution of N_r in (i, j)th grid.

Step 5 : N_r is calculated for different values of r.

Step 6: D**,** the fractal dimension, can be estimated from the least square linear fit of log(N_r) against log (1/r)

$$D = \log(N_r) / \log(1/r)$$

V.EXPERIMENTAL RESULTS

A. Database

The database used is the SDUMLA-HMT Database obtained from Machine Learning and Data Mining Lab, Shandong University. This is the first open finger vein database. The device used to capture finger vein images was designed by Joint Lab for Intelligent Systems of Wuhan University. In the capturing process, each subject was asked to provide images of the index finger, middle finger and ring finger of both the hands to obtain 6 finger vein images. Therefore, the finger vein database is composed of 3816 images from 636 subjects. Every image is stored in “bmp” format with 320*640 pixel size. A few sample images are shown in Figure 2.

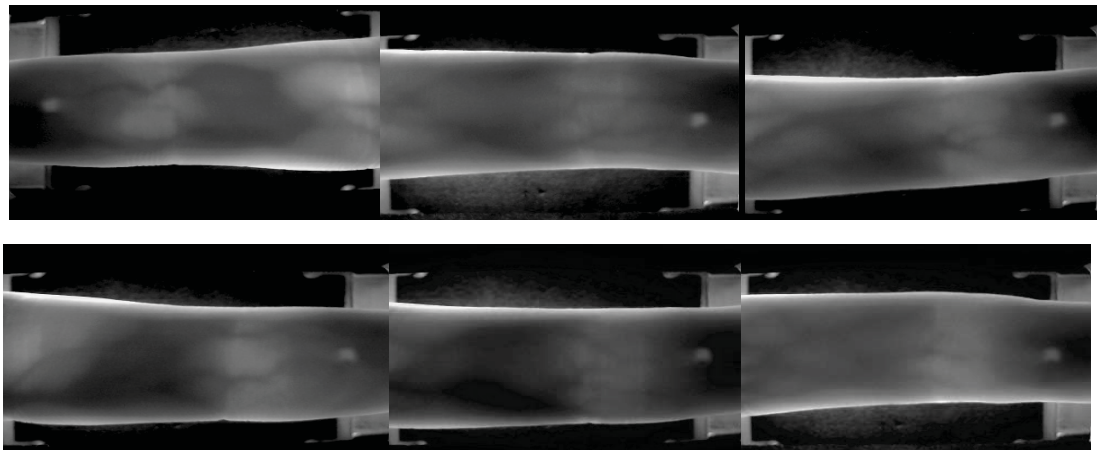

Figure 2.Sample images from the database

B. Performance evaluation

The following are used as performance metrics:

FALSE ACCEPTANCE RATE OR FALSE MATCH RATE (FAR or FMR)

FAR is the probability that the system incorrectly matches the input pattern to a non-matching template in the database. It measures the percent of invalid inputs which are incorrectly accepted.

$$FAR = \frac{No.of\ incorrectly\ accepted\ users}{No.of\ users}$$

FALSE REJECTION RATE OR FALSE NON-MATCH RATE (FRR or FNMR)

FRR is the probability that the system fails to detect a match between the input pattern and a matching template in the database. It measures the percent of valid inputs which are incorrectly rejected.

$$FRR = \frac{No.of\ incorrectly\ rejected\ users}{No.of\ users}$$

EQUAL ERROR RATE OR CROSSOVER ERROR RATE (EER or CER)

EER is the rate at which both accept and reject errors are equal. The EER is a quick way to compare the accuracy of devices. In general, the device with the lowest EER is most accurate.

$$EER = Equalizing\ FAR\ and\ FRR$$

Table 1 Experimental results – RLT

NO.OF SAMPLES	GENUINE USERS REJECTED AS IMPOSTERS(SCORES)	IMPOSTORS ACCEPTED AS GENUINE USERS (SCORES)	FAR	FRR
200	5	9	0.045	0.025
200	14	7	0.035	0.07
200	15	9	0.045	0.075
200	4	8	0.04	0.02
200	20	20	0.1	0.1

Table 2 Experimental results – DBC

NO. OF SAMPLES	GENUINE USERS REJECTED AS IMPOSTORS (SCORES)	IMPOSTORS ACCEPTED AS GENUINE USERS (SCORES)	FAR	FRR
200	6	12	0.06	0.03
200	8	5	0.025	0.04
200	3	3	0.015	0.015
200	10	10	0.05	0.05
200	5	7	0.035	0.025

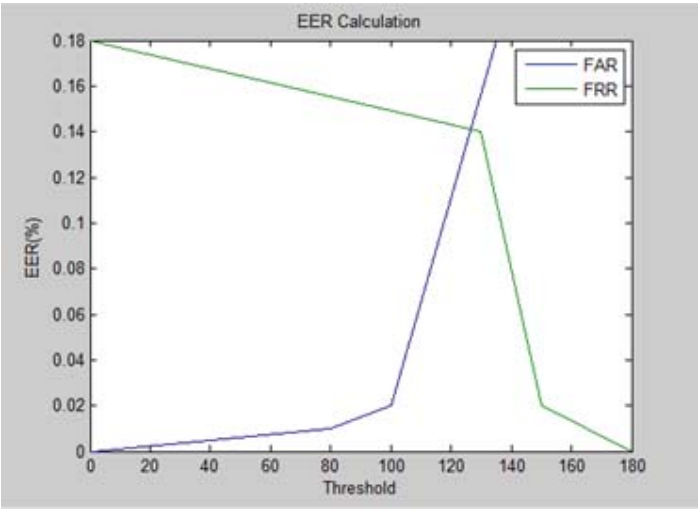

Figure 3.Performance evaluation graph using RLT

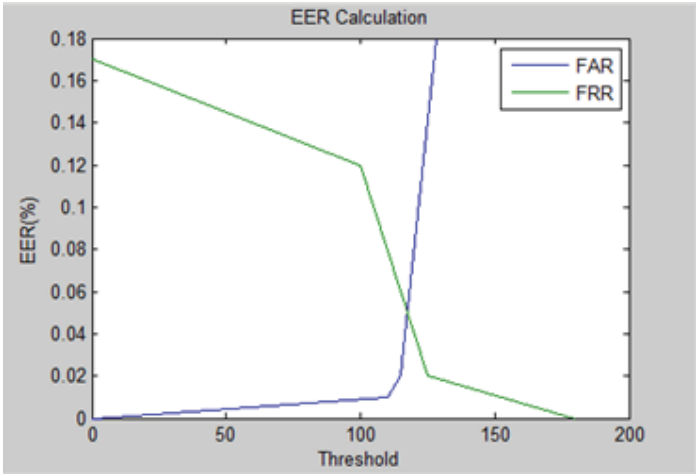

Figure 4. Performance evaluation graph using fractal model (DBC)

C. Comparison with existing method

The performance evaluation graph, Figure 3, shows that the EER for existing method (Repeated Line Tracking) is 0.14%. From Figure 4, EER of DBC method is 0.05%. Hence, the proposed system is appropriate for practical applications.

Table 3 Comparison Table

METHOD	EER(%)
Existing method- RLT	0.14
Proposed method – Fractal model using DBC	**0.05**

VI. CONCLUSION

The proposed paper is a finger vein recognition system based on differential box counting method, implemented in MATLAB platform. The complexity of pre-processing stage using vein pattern extraction method was eliminated with compatible matching performance. The experimental results showed that the EER of the recognition system using DBC method was 0.05%, significantly lower than those of other existing methods. The proposed algorithm is suitable for application in mobile devices because of its relatively low computational complexity and low time consumption. The approach can be readily extended to a three dimensional image as well.

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