A Novel Application of the Classifier DECOC Based on Fingerprint Identification

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Abstract—**Human fingerprints are rich in details, here called "minutiae". In this paper, a fingerprint recognition system based on a novel application of the classifier DECOC to the minutiae extraction and on an optimised matching algorithm will be presented. The minutiae extraction has been performed from fingerprint skeletons. To identify the different shapes and types of minutiae, a Data-driven Error Correcting Output Coding (DECOC) has been adopted to work as a classifier. The proposed classifier has been applied throughout the fingerprint skeleton to locate various minutiae. Extracted minutiae have been used then as identification marks for an automatic fingerprint matching that is based on distance, direction and type between two minutiae.**

Key Words- Biometrics, Fingerprint, recognition, Minutiae extraction, DECOC, Matching.

I. INTRODUCTION

The modern society is challenged by the need to identify individuals. Among all the biometrics, fingerprint matching is one of the most popular, mature, and advanced technologies. In 1888 Sir Francis Galton found that fingerprints are rich in details in form of discontinuities in ridges.The uniqueness of an individual fingerprint is exclusively determined by the local ridge characteristics and their relationships. There are various types of local characteristics called minutiae in a fingerprint, but widely used fingerprint features are restricted to only two types of minutiae. The first is a ridge termination defined as the point where a ridge ends abruptly. The second is a bifurcation defined as the point where a ridge merges or splits into branch ridges. Galton also discovered that such features are permanent during lifespan [1].

Due to the varying quality of fingerprints, some preprocessing is usually required. Consequently, an enhancement algorithm is applied on gray-scale images to improve and separate fingerprints from the background. This process is denoted binarisation, the first preprocessing step (see Fig. 1). Some of the most frequent methods are directional filters [2].

The minutiae are determined only by the discontinuities in the ridges, which are totally independent of the ridges thickness.

By minimizing the data that represents minutiae without corrupting it, a more effective and faster minutiae extraction can be achieved. Thinning the ridges to only 1-pixel-wide lines preserves minutiae with a minimum data usage. This process of skeletonisation follows binarisation. It is usually an iterative method, either sequential or parallel [3].

The next step is the extraction of the minutiae from the skeletonised fingerprint, (see Fig.1). The method that handles this, simply examines the nearest neighbor pixels around a pixel that belongs to a 1-pixel-wide line [4].

Another method [5] studies the relationship between the thinned ridges and depends on the flow; it detects and extracts the various minutiae. Unfortunately binarisation and skeletonization might risk some important details of a fingerprint to be removed. Therefore there are algorithms ([6] and [7]) that extract the minutiae directly from the gray-scale image through a ridge line.

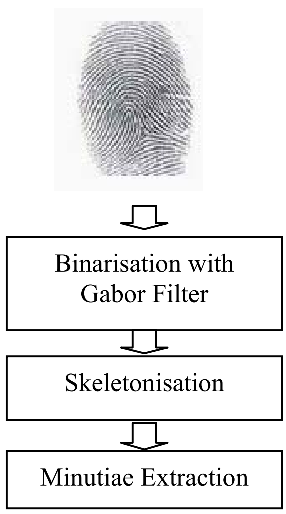

Figure 1. Minutiae extraction with the preprocessing steps.

The algorithms in [6] and [7] above have different rules or ad-hoc methods to handle the various situations that arise while extracting the minutiae. This makes it more or less difficult to cover all the possible situations.

The method proposed in this paper for minutiae extraction is based on Data-driven Error Correcting Output Coding (DECOC) to recognize the minutiae patterns in skeletonised fingerprint images. A well defined training set of patterns with a suitably chosen size proves that no additional ad-hoc rules are required. However, methods extracting the minutiae from the skeletonised fingerprints heavily depend on the preprocessing phase. Producing high-quality skeleton fingerprints relies on properly performed binarisation and skeletonization. The method used to produce skeleton fingerprints is based on the thinning process; a 3X3 pixel neighborhood of a black pixel with its 8 neighbors [3] can be considered.

Jie Zhou [8] improved that the classifier DECOC has better recognition rate than SVM in manuscript recognition and OCR. For this reasons, DECOC classifier is tried to be trained in to the fingerprint recognition.

II. MINUTIAE EXTRACTION

A. *Error Correcting Output Coding (ECOC)*

Error correcting output codes have been used in the fields of network communication and information theory for the purpose of enhancing the reliability of transmitting binary signals and maintaining information integrity. It adds the redundant parity bits to an information word. The result is called a code word, which is a binary code string. Distances between two code words are described using Hamming distance, which is the count of the different bits in the two patterns.

On the receiving end, a decoding process examines the Hamming distances between the received binary message and all the valid code words to detect and cope with errors.

Table 1 gives an illustrative example of the ECOC code matrix of a 5-class classification problem, decomposed into 6 binary classification problems.

	BL1	BL2	BL3	BL4	BL5	BL6
Class1	1	1	0	1	1	1
Class2	0	0	0	1	0	0
Class3	0	0	1	1	1	1
Class4	1	0	1	0	1	0
Class5	1	1	1	0	1	0

Table 1. Example of an ECOC code matrix.

The code matrix is used to guide the training and testing processes of ECOC classifiers. In training, 6 binary base learners are involved. For the binary base learner fi ($i = 1,\dots, 6$), if an element bk,i ($k = 1,\dots,5$ and $i = 1,\dots,6$) in the code matrix is 1, then all samples of class k will be considered positive. The remaining samples are considered negative for fi (can be labeled as -1 or 0. Here 0 is used for analogy of binary coding). The testing process determines the class label y of a testing sample $\boldsymbol{x}$ by first applying all base learners to the unknown sample, yielding a codeword $w(\boldsymbol{x})$ (a bitstring of *1*s and *0*s). A decision on the label is then made, based on the shortest Hamming distance:

$$y = \text{argmin}_k\, H(w_k,w(x)),\ k = 1, \dots , K, \qquad (1)$$

where wk is the ideal code word for class k, that is the k^{th} row of the code matrix. $H\,(wk,\, w(x))$ is the decoding function which computes the Hamming distance between wk and $w(x)$. The class label of the closest codeword, that is, with the shortest Hamming distance, is assigned to the testing sample. In the case of the code matrix given in Table 1, the ideal code word for class 1 is [1 1 0 1 1 1] and the ideal code word for class 5 is [1 1 1 0 1 0]. If a testing sample yields a code word [1 1 0 1 1 1], it will be determined as class 1 which corresponds to the shortest Hamming distance.

Motivated by providing new solutions to the problem of multi-class decomposition and extending the applications of ECOC, we will propose a new data-driven decomposition approach. Different from current methods, it is a mechanism that adaptively designs the code matrix of ECOC based on the inherent structure of the training data. The proposed method does not limit itself to any particular base learner. There over, we will apply DECOC to two multi-class pattern recognition problems that have not been addressed yet by the ECOC approach [8].

B. *Methodology: Data-driven ECOC*

Data-driven ECOC (DECOC) is proposed to design the code matrix for ECOC by choosing the code words utilizing the intrinsic information from the training data. In a present decomposition mechanism for a K-class problem such as pairwise coupling, K*(K-1)/2 base learners are always needed, which can be a large number of base learners when K gets larger. The key idea of DECOC is to selectively include some of the binary learners into the code matrix based on a confidence score defined for a binary base learner.

This measure will help to determine how likely a learner will be included in the ensemble.

Before introducing the confidence score, it necessary to define:

- *Separability Criterion*

$$S(G)=\begin{cases} \dfrac{2}{|G|^2-|G|} \sum\limits_{j\neq k, c_j c_k \in G} d(c_j,c_k) & |G|\neq 1 \text{ and } |G|\neq K-1 \\ 0 & \end{cases} \quad (2)$$

where $d(cj,\ ck)$ is the distance between the two classes *cj* and *ck*, which is the Euclidean distance of the mean or median vectors of the two classes; G is the number of prototypes in the group of samples associated with classes; $|G|$ is the size of the set G; $2/(|G|^2 - |G|)$ is the normalization factor. If there is only one class or there are *K-1* classes in *G*, *S (G)* is set to 0 since both situations correspond to the 1vo partition of classes, which is a particular case to be considered separately. *S(G)* also indirectly describes the inherent homogeneity of a group of samples: the smaller *S(G)* is, the more homogeneous the group of samples is. It is worth noting that sample groups associated with *G* are drawn from the training samples.

- *Confidence Score*

$$C(f)=\begin{cases} \dfrac{S(G_{+/-}(f))}{S(G_+(f))+S(G_-(f))}; |G_+|\neq 1 \text{ and } |G_+|\neq K-1 \end{cases} \quad (3)$$

where G+(f) is the set of prototypes whose samples are considered as positive by the base learner f, G-(f) is the set of the remaining prototypes whose samples are considered negative. For example, for the base learner 4 in Table 1, classes 1, 2 and 3 among the 5 classes are considered as positive, so G+(f) = {1, 2, 3} and S(G+(f)) = 2/(32-3)*Σd(cj,ck) {1,2,3}. S(G+/-(f)) denotes the separability by viewing the data set as two groups of positive and negative samples separated by the base learner f. S(G+/-(f)) equals the distance between the two groups: S(G+/-(f)) = 2/(22-2)*d(c+, c-)= d(c+, c-), where c+ represents the group of all the samples considered as positive by the base learner f, and c- represents the group of all the samples considered as negative by f.

Figure 2 describes the flow of calculating the confidence scores and selecting the base learners, which is the core of the DECOC algorithm. This clear then, that DECOC is a data-driven approach of designing code matrix: instead of having a preset matrix, DECOC adaptively generates the code matrix based on the structure of the given training data.

The training data is divided into three different pattern classes: termination, bifurcation and non-minutiae. While the 3 × 3 pixel window does not represent much information, the 7×7 pixel window shows too much information.

Therefore the training data size is chosen to a 5 × 5 pixel window. The size of the window is deliberately an odd number so as to have a single pixel in the centre.

A total of 136 different patterns have been gathered. The different classes have 32 termination patterns and 104 bifurcation patterns. Such patterns have been carefully selected so that the detection would occur in the centre of the minutia. The patterns with minutiae off the centre are classified as non minutiae to avoid overlapping detection. Figure 3 illustrates some used patterns for each class: Termination (a) and Bifurcation (b).

III. THE MATCHING METHOD

There are many reasons for fingerprint template variations such as the fingers displacement, rotation, nonlinear distortion, pressure, skin condition and feature extraction errors, etc [1]. So it is hard to work with the coordinates of each minutia.

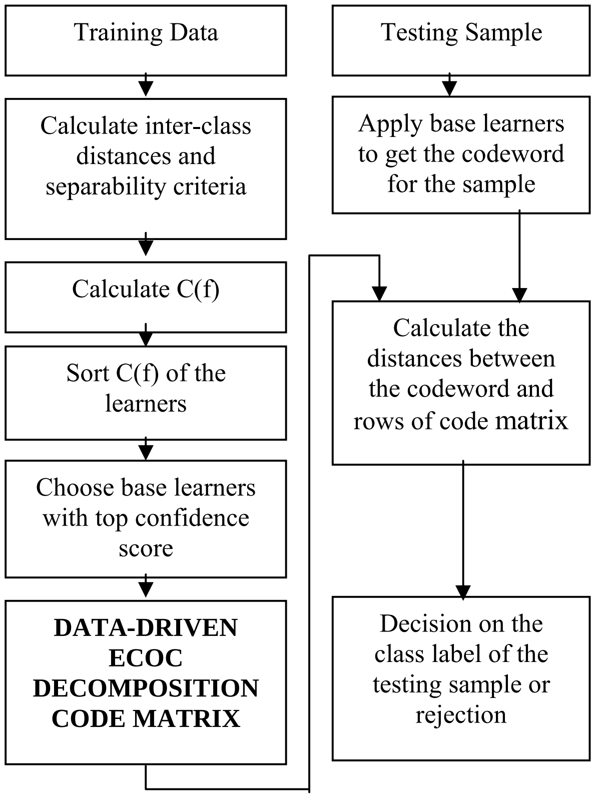

Figure 2. The flow of the training and testing algorithms for DECOC

In this section a matching method that is performed by calculating the Normalized Euclidean Distance between every two minutiae by vertical scanning is proposed, (see figure 4). This distance is calculated by squaring the difference between the corresponding elements of the feature vector.

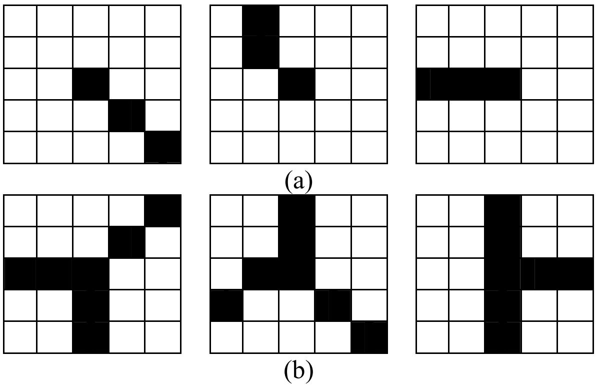

Figure 3. Sample of different patterns.

This method is optimised by adding direction between the two minutiae and types (Ending, Bifurcation). So the signature of the two minutiae is: S= (Distance, Type, Direction). So, the comparison is made by all the distances of input fingerprint and the distances of all fingerprints. When we find a distance that is inferior to ε=0.01 we verify the types between the corresponding minutiae. A minutia is accepted when the distance and types are accepted.

$$\text{Distance}_{(M1,M2)} = \sqrt{(x_2 - x_1)^2 - (y_2 - y_1)^2} \qquad (4)$$

$$\text{Direction}_{(M1,M2)} = \frac{y_2 - y_1}{x_2 - x_1} \qquad (5)$$

$$Type_{(M1,M2)} = \begin{cases} 11 & Bifurcation - Bifurcation \\ 10 & Bifurcation - Ending \\ 01 & Ending - Bifurcation \\ 00 & Ending - Ending \end{cases}$$

where M1(x1,y1) and M2(x2,y2)

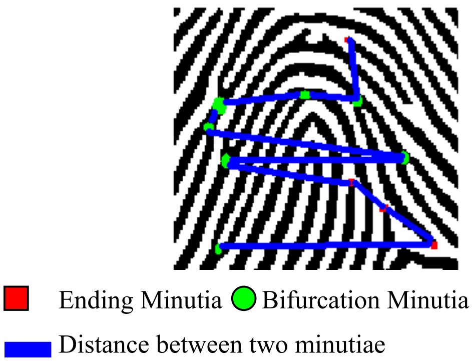

Figure 4. The matching method.

IV. EXPERIMENTAL RESULTS

This section is divided into two parts. The experimental results from the minutiae extraction are going to be shown in the first part and those from the total identification system (Extraction + Matching) are going to be presented in the second one.

The method of extracting minutiae from skeletonised fingerprints presented in the paper at hand has been evaluated by implementing it into the whole fingerprint recognition system. A database has been assembled from pre-stored fingerprints in FVC2004 Db3. This database has been chosen randomly with different qualities. Figure 5 shows a very good finger quality as well as a very bad one with size of 300x300 pixels. The proposed system extracts minutiae from the skeletonised images.

(a) (b)

Figure 5. Different quality of fingerprint image
(a) good quality (b) bad quality

The following definitions are needed for the purpose of comparing the experimental results.

True minutia: A minutia point detected by an expert, $\mathbf{m_t}$.

False minutia: A minutia $\mathbf{m_a}$ which does not coincide with $\mathbf{m_t}$ is said to be a false minutia.

Dropped minutia: When a minutia $\mathbf{m_t}$ is not detected in $\mathbf{m_a}$, $\mathbf{m_t}$ is said to be a dropped minutia.

Exchanged minutia: A minutia $\mathbf{m_a}$ that corresponds to $\mathbf{m_t}$ with their types exchanged.

Thus, True Minutiae Ratio (TMR), False Minutiae Ratio (FMR), Dropped Minutiae Ratio (DMR), Exchanged Minutiae Ratio (EMR) and Average Computation Time have been defined so far. Table 2 gives a comparison of performance and computational time between Hwang methods [9], Jain's method [10], Ray's method [10] and the proposed novel method. Indeed, it should be mentioned that the Dropped Minutia Rate is the highest although it is proved that even 12 minutiae are sufficient to identify the fingerprint. Consequently, this rate is less important than TMR, FMR and EMR.

As for the results of the matching method, six samples of fingerprint have been selected randomly as a training set and two others have been used for a testing one. A fingerprint is accepted only when the recognition rate is at its highest value which is superior to 60%. Thus, we have been obtained 88.88% as Recognition Rate (**RR**).

Factors	TMR %	FMR %	DMR %	EMR %	Average classification Time (ms)
Hwang without skeletonization	75.32	22.5	10.18	14.5	35.9
Hwang with skeletonization	79.20	48.60	6.20	14.60	105
Jain’s	74.10	22.20	Not indicated		
Ray’s	63.40	20.40	Not indicated		
DECOC	**78.23**	**15.07**	15.23	**3.08**	**93.75**

Table 2. Comparison of performance and computational time.

A comparison between the different methods and our method is presented in table 3.

	FAR	FRR
HAO GUO method [11]	4.18%	9.93%
OMER SAEED method [12]	1,12%	Not indicated
Ying HAO method [13]	1%	2.5%
Jiong Zang method [14]	0.04%	1.31%
The novel method	**0%**	**0.02%**

Table 3. Comparison of the FAR and the FRR with the other matching methods.

The results above prove that the advocated method could effectively avoid the adverse effects caused not only by some linear deformations such as rotation and translation but also by some degrees of nonlinear deformation in the process of fingerprint matching.

V. CONCLUSIONS

A novel method for reliable and fast feature extraction based on the classifier DECOC from skeleton fingerprint images has been proposed. This method classifies a bloc of 5x5 pixels into bifurcation and termination. The experimental results show that the proposed method provides an acceptable TMR, the best EMR and a good average classification time.

The optimised matching method shows a good result for fingerprint recognition. The aim of this method is to identify the fingerprint without the intrinsic coordinates. So, the distance matching solves the problem of rotation, displacement and the core region identification emerging when the matching method is based on intrinsic coordinates.

The identification takes about 5 seconds on a 2 GB RAM, 1.66 GHz Intel Core 2 Duo processor with Windows XP operating system. This speed may be increased by hardware implementation.

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