Machine Learning Techniques for Fingerprint Identification: A Short Review

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Abstract. Fingerprint is considered as a dominant biometric trait due to its acceptability, reliability, high security level and low cost. Due to the high demand on fingerprint identification system deployments, a lot of challenges are keep arising in each system's phase including fingerprint image enhancement, feature extraction, features matching and fingerprint classification. Machine learning techniques introduce non traditional solutions to the fingerprint identification challenges. This paper presents a short survey that emphasizes the implementations of basic machine learning notions for compensating some fingerprint problems. This survey contributes as a ground truth for developing machine learning based algorithms for fingerprint identification in the near future.

Keywords: Biometrics, Fingerprints, Machine Learning Techniques.

1 Introduction

Biometrics technology is a way of personal identification using the phycological or the behavioural characteristics. Driven from the security needs for the electronically connected world, biometrics identification compensates some weaknesses of token- and knowledge-based identification in terms of loss, duplication and theft. Biometrics traits contain iris pattern, retinal scan, fingerprints, voice and signature. Fingerprint is one of the dominant biometrics traits that keeps spreading out because its uniqueness, acceptability, and low cost [1]. According to the biometrics market and industry report [2], Fig. 1 represents the total fingerprint revenue which is around 66% compared to the other biometrics technologies.

In spite of fingerprint identification provides high security level and it has large application domains, fingerprint identification system (will be explained in Section 2.2) is attacked by many challenges that lead to system performance degradation with respect to identification time and accuracy [3]. These challenges are found in fingerprint acquisition, fingerprint preprocessing and enhancement, feature extraction, fingerprint matching and fingerprint classification [4]. However, these problems have been tackled by many researches using different techniques in order to enhance the overall identification system performance, the ideal solutions for some of these problems are still unavailable.

A. Ell Hassanien et al. (Eds.): AMLTA 2012, CCIS 322, pp. 524–531, 2012.

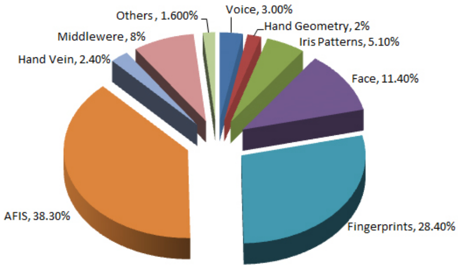

Fig. 1. Biometrics technologies deployment in 2009

Machine learning techniques such as Artificial Neural Networks (ANN), Support Vector Machine (SVM) and Genetic Algorithms (GA) [5] play an important role for presenting non traditional solutions for fingerprint identification problems. The idea behind these techniques is to build a feature vector and train (learn) the machine how to process that vector according to some particular rules. This way, machine learning techniques can process efficiently the complicated fingerprint data, and hence, contribute in solving some problems of the fingerprint identification system.

The contribution of this paper is to introduce a precise survey about some machine learning techniques that have been used in fingerprint identification. The survey can be used as ground truth for developing new machine learning based algorithms for fingerprint identification system. The methodology of this research is to consider only the most promising techniques in machine learning and their deployment in some phases of the fingerprint identification system.

The reminder part of this paper is organized as follows. Section 2 gives a preliminary information about the fingerprint identification system components staring from fingerprint acquisition phase and ending with fingerprint matching phase. Moreover, fingerprint structure has been explained as a first part of that section. Section 3 reports the research progress of deploying three machine learning techniques, namely, ANN, SVM and GA over fingerprint identification system. Finally, conclusions and future work have been reported in Section 4.

2 Fingerprint Identification

This section covers the fingerprint identification system in order to fully understand the implementations of the machine learning techniques in each phase.

2.1 Fingerprint Structure

Fingerprint is defined as the ridge and valleys formed on the fingertip [6]. It is constructed from harmonic patterns of alternating ridges and valleys. However, fingerprint ridges and valleys are parallel in most regions, several deforming features such as scars, cuts, cracks and calluses, are also present on the finger

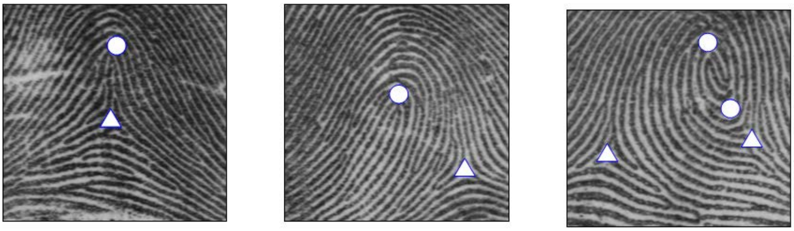

Fig. 2. Fingerprint global structure with singular points illustrations (Circles- for core points and Triangles- for delta points)

tip [7]. In common, there are three representation levels of fingerprints: (*i*) Global structure, (*ii*) Local structure, and (*iii*) Low level structure [8]. Fig.2 shows three different examples of fingerprint images with ridges and valleys representations.

The global fingerprint representation expresses the overall shape of the fingerprint. In global structure, a single representation is valid for the entire fingerprint image [9]. Another important feature of the global structure is the singular points (Circles and Triangles in Fig. 2) [10]. Singular points are unique for each fingerprint class, therefore, they are widely used as a feature for fingerprint coarse registration and classification [11]. The local fingerprint structure represents the ridges and valleys format at local interesting region. The most famous ridge property is ridge ending and ridge bifurcation (it is called Minutiae) [12], [13]. The local structure is mostly used in fingerprint matching because minutiae are the highest discriminant feature of fingerprint images. The low level (level-3) structure considers the sweat pores on the fingerprint skin. The low level structure is difficult to get captured as it needs properly environment with very high resolution sensor that requires high cost [8].

2.2 Fingerprint Identification System

Automatic Fingerprint Identification System (AFIS) has replaced human experts in fingerprint recognition as well as classification. It consists of two phases: (*i*) Enrollment phase and (*ii*) Identification phase. The enrollment phase is directed to register the individual identity in the database for future usage. While, the identification phase is responsible for extracting the individual identity from the database according to the user claimed identity [3].

Each phase is decomposed into the following sub-stages: (*i*) Fingerprint acquisition, (*ii*) Preprocessing, (*iii*) Feature extraction and (*iv*) Database storage. Fig. 3 shows the flowchart of fingerprint identification system. Generally speaking, fingerprint acquisition, preprocessing and feature extraction are the common stages for both enrollment and identification. However, fingerprint matching is an extra mandatory step for the identification phase to extract the claimed identity from the pre-collected database [1]. Processing time and identification accuracy are two import factors for increasing the system performance [3]. Machine

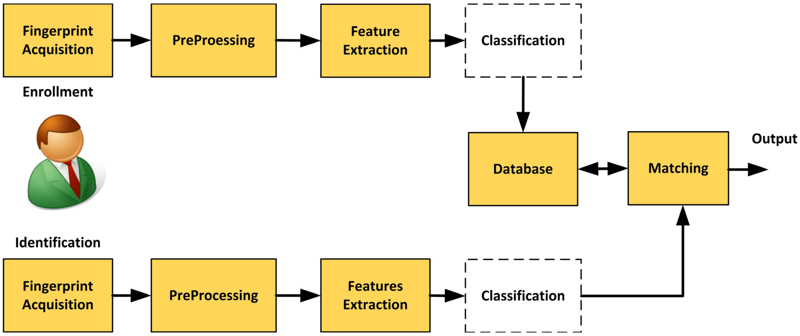

Fig. 3. A flowchart of fingerprint identification system (basic components)

learning techniques can be good contributors for enhancing the system performance as reported in Section 3.

3 Machine Learning Techniques

Machine learning systems are concerned with building fixable algorithms or techniques that their performance is automatically improved with experience (training) [14]. Machine learning system is first trained with source data, and following, it is used to perform required operations according to its acquired experience. The problem of machine learning techniques is related to their sensitivity to the training data and the training parameters as they may produce different results by changing the training data. However machine learning includes many techniques such as Artificial Neural Networks, Support Vector Machine, Genetic Algorithms, Bayesian Training and Probabilistic Models [15], we will stress only on the implementation of the first three techniques on fingerprint identification.

3.1 Artificial Neural Networks

Artificial Neural Networks is the most widely used algorithm of the machine learning system [16]. The quality assurance of the acquired fingerprint image is an important process before the feature extraction. Xie and Qi [17] designed a supervised back propagation neural network that uses the gray scale fingerprint image for continuous image quality estimation. The problems of this method are the lack of evaluation as it has been evaluated for small fingerprint images from Fingerprint Verification Competition 2002 (FVC2002)[18]. Moreover, the fingerprint image needs to be divided into blocks which is computationally expensive process before running the proposed method. Zhu et al. [19] used the neural network for quality estimation of the fingerprint images using fingerprint ridge orientation. The correct ridge orientation is estimated using the trained neural networks. Labati et al. [20] proposed the usage of neural network for image quality measurement in contactless fingerprint acquisition. They discovered a set of new features for contactless images and designed a neural network to extract the complex features for future fingerprint matching. The bottleneck of this method is the computational complexity as it needs 1.5 to 3.7 seconds for the implementation of the region of the interest needed for that method.

Feature extraction is another application of neural networks in fingerprint identification. Liu et al. [21] used back propagation neural network for singular point detection from the gray scale fingerprint images. The problem of this method is the image division process as the image needs to be divided into small blocks (35×35 pixels) which is time consuming operation, and the location of the detected singular point is not accurate. Bartunek et al. [22] used the back propagation natural networks for extracting minutiae points (ridge termination and bifurcation) from thinned fingerprint images. A sliding (5×5 pixels) window has been used to access the whole fingerprint image searching for minutia points. The problem with this method is the huge processing time to get the thinned image. Yang et al. [23] used the fuzzy neural networks for minutiae extraction from the gray scale image with high invariant to rotation and gray level changes.

Fingerprint classification is an important process for reducing the identification time. Sarbadhikari et al. [24] proposed two-stage fingerprint classifier. In the second stage, Multi-Layer Perceptron (MLP) feed forward neural network was used to classify the directional Fourier image. The achieved classification accuracy was around 84%. Mohamed and Nyongesa [25] proposed the usage of fuzzy neural networks as a classification mechanism due to its ability to work as an adaptive filter in order to produce reliable results. They constructed a feature vector using five different parameters including number of core points, number of delta points, directional image, core point direction, and the position of delta point. The algorithm achieved 85.0% for classifying the Left Loop class, and 98.35% for classifying the Whorl class. Kumar and Vikram [26] used multi-dimentional ANN (MDANN) for fingerprint matching using minutiae points. The algorithm achieved a maximum recognition rate as 97.37%.

Kristensen et al. [27] presented a comparative study on different neural networks and support vector machine. They implemented four types of neural networks including Multi-Layer Perceptron (MLP), Bidirectional Associative Memory (BAM), Hopfield and Kohonen neural networks, as well as the support vector machine. They concluded that MLP neural network achieved the best performance with an overall accuracy as 88.8% for the $5 - class$ problem. Support vector machine came in the second rank with classification rate about 87.0%, but both classifiers failed to classify most of Tented Arches class. In general, the other three classifiers could not perform well compared to multi-layer perceptron and support vector machine.

3.2 Support Vector Machine

Support Vector Machine is a training algorithm for linear classification, regression, principal component analysis and for non-linear classifications. The idea behind the support vector machine is to maximizing the margin between the training patterns and the decision boundary [16].

Liu et al. [28] used the support vector machine technique with five features vector length to determine the fingerprint image qulaity. fingerprint has been classified into high, medium and low quality images with the accuracy of 96.03%. The problem with Liu's method is the long processing time of the feature extraction step. Zhao et al. [29] implemented support vector machine for fingerprint image segmentation as it is an important step before feature extraction. They divided the image into (12×12 pixels) blocks, and five features have been used to construct the feature vector. These features are gray mean, gray variance, contrast, coherence and the main energy ratio. The proposed method is consider as robust for small scale evaluation. From the other side, Li et al. [30] used the support vector machine for fingerprint classification into $5 - classes$ with total achieved accuracy 93.5% with a combination of singular points and orientation image. However, using the orientation coefficients only produced 87.4%, and using singular point only produced 88.3% at maximum.

3.3 Genetic Algorithms

Genetic Algorithms are promising machine learning techniques for solving fingerprint related problems. Mao et al. [31] succeeded to use genetic algorithm for singular point extraction. They presented a new definition for core point location and orientation which is used as fitness function for the genetic algorithm. The challenge of this method is processing time is become higher with increased accuracy (1×1 pixels with $10°$ accuracy). Tan et al. [32] implemented genetic algorithm for fingerprint matching process using optimized minutiae transformation. However the genetic algorithm achieves promising matching results, the required times are 15 and 8 seconds for genuine and imposter matching, respectively. Therefore, an optimization process is become a crucial need.

Tan et al. [33] developed a classification algorithm based on some new learned features. In the proposed approach, they tried to find unconventional primitives from the orientation images using the Genetic Programming (GP) technique. The learned features might never be imagining by humans experts. Then, a Bayesian classifier was used for conducting the actual classification process. The proposed method was evaluated over the NIST-4 database [34]. The first 2000 images were used for the training process, and the second 2000 were used for the evaluation purposes. The total Percentage of Correct Classification (PCC) was about 93.3% and 91.6% for the $4 - class$ and the $5 - class$ classification problems, respectively.

4 Conclusions and Future Work

This paper introduced a precise survey on the usage of machine learning techniques for solving some fingerprint identification problems. The paper has focused on three important techniques which are Artificial Neural Networks, Support Vector Machine and Genetic Algorithms, and their implementations on image quality measurements, feature extraction and fingerprint classification. The review confirms the superiority of using machine learning for tackling different fingerprint identification problems. The future work will be targeted toward developing one of machine learning technique for tackling some pending fingerprint challenges such as processing time reduction and identification accuracy enhancement. Moreover, another biometrics traits like palmprints and iris patterns will be considered as an applications of machine learning techniques.

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