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Comparative Analysis of Fingerprint Classification Algorithms- A review

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***Abstract*—** Fingerprint classification plays an important role in automatic recognition of fingerprints from a given dataset. It significantly reduces the time taken to map a fingerprint to its nearest match by providing a broad classification of given fingerprint into its relevant class and performing the further search in that class domain only. Various rule-based, model-based and structure-based approaches have been proposed and used to perform such classification. This paper discusses the various mechanism employed to categorize fingerprints into basic classes like arch, whorl, left loop, right loop and tented arch along with the advantages and limitations of each approach. The paper aims to provide a concise study and performance based comparison of various fingerprint classification approaches and the different techniques they use to perform the classification.

***Keywords*—** Fingerprint Classification, statistical classifiers, rule-based classifiers, neural networks, structural classifiers, hybrid classifiers

I. INTRODUCTION

Fingerprints have been long recognized as a critical aid in personal identification due to their unique and permanent nature with chances of two individuals having same fingerprints being less than 1 in 64 billions[1]. Fingerprint patterns are generated in between tenth and eighteenth weeks of gestation and remain pretty much unchanged throughout the life of an individual. They constitute of a series of papillary ridges and valleys on a person's fingertips [2]. An automated fingerprint recognition system provides a one to one mapping of an input fingerprint to the images in a fingerprint database and tries to determine if the input fingerprint matches with any fingerprint present in the database. The exhaustive database search poses a challenge to restrict the time complexity of the program. Fingerprint classification involves categorizing a fingerprint database into distinct classes and searching for an input fingerprint in the relevant class [3, 4]. The classification aims to generate an index corresponding to each fingerprint and deciding on the class to which it belongs. It involves steps like pre-processing (involving image enhancement and segmentation), feature extraction (involving recognition of core and delta) and then performing minutiae based or correlation based classification. This paper provides a brief introduction to the basics of fingerprint processing in section II followed by a description of various fingerprint classification algorithms based on respective evaluation parameters in section III. Section IV contains the conclusion.

II. BASICS OF FINGERPRINT PROCESSING

A fingerprint refers to the dermal ridge pattern on fingertips of an individual. The distinctive features of a fingerprint have been broadly categorized at 3 levels [5].

The first level includes macro details used primarily for image classification. eg:- global ridge patterns, orientation fields, singular points and location of core and delta. The orientation field/map describes the local ridge flow i.e. the angle and direction at which the ridges bend. The singular points mark the location with maximum deviation in ridge orientations.

The second level includes minutiae details that are used extensively in matching and recognizing fingerprints. eg:- ridge endings and bifurcations.

The third level features include quantitative details to increase efficiency of any fingerprints recognition system. eg: ridge edge, contours, sweat pores etc. At macro level the fingerprints have been divided into three main classes – arches, loops and whorls which have been further partitioned to finer subcategories. The most commonly used classes are – plain arch, tented arch, radial/left loop, ulnar/right loop, plain whorl, central pocket whorl, double loop whorl and accidental whorl[6].

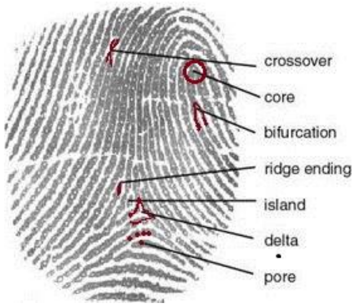

Figure1: Minutiae

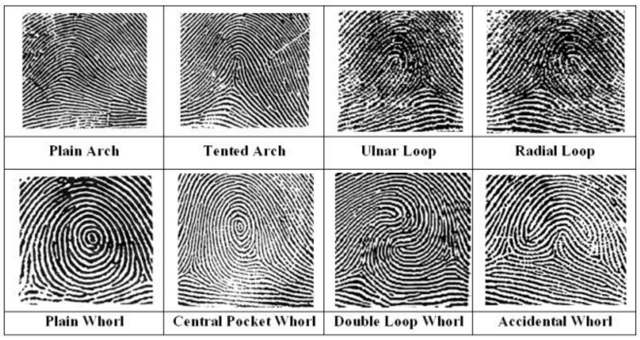

Figure 2: Fingerprint Classes

An automated fingerprint recognition system usually involves fingerprint acquisition, enhancement, classification and matching.

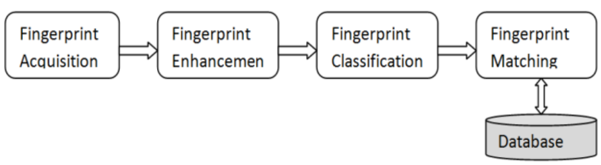

Figure 3: Steps for fingerprint recognition process

Fingerprint classification step involves extracting relevant features from a fingerprint image that may help distinguish between different classes of fingerprints and then applying some classification function to determine the class to which the fingerprint belongs.

III. Fingerprint Classification algorithms

Fingerprint classification forms an extremely significant component of an automated fingerprint identification system. Fingerprint classification performs the task of dividing a huge fingerprint database into smaller subsets differing according to the various fingerprint classes. This helps in limiting the search area for a particular fingerprint match to that part of the database which contains fingerprints of same class as the fingerprint being searched, thus immensely reducing the time complexity of such search algorithm. The classification usually involves detection of ridge orientations (orientation map), global features like core (approximate centre of a fingerprint pattern) and delta (a triangular ridge pattern) and local features (minutiae) in a fingerprint.

Fingerprint classification algorithms vary on the basis of type of classification technique used, number of classes obtained, accuracy level of classification and sensitivity towards noise and distortion. On the basis of classification technique used they can broadly be categorized as Rule based classifiers, Statistical classifiers, Neural Network based classifiers, Structural classifiers and Hybrid classifiers.

Rule based classifiers classify the entities based on a collection of if-else rules. This approach codifies the fingerprint ridge orientations and number and location of singular points into a set of rules to determine a fingerprint class.

Fingerprint Class	**Core**	**Delta**
Arch	None	None
Whorl	1 or 2	1 or 2
Loops	1	1
Tented arch	1	1

Table 1: Fingerprint Classes according to singular points

[7], used a rule based classification approach wherein the algorithm determines the ridge orientation of a fingerprint image at every pixel and extracts the global features (count and location of cores and deltas). The algorithm classifies the good quality images with high accuracy but categorizes low quality images into unknown type.

[8], used directional histograms of fingerprint image to obtain the cores and deltas. The algorithm involved conversion of input image to a directional image using a direction mask, partitioning of image into blocks and determining the direction for each block and detection of singular points followed by their classification into Lasso and Wirbel (more than one singular points) classes. [9], worked on the premise that actual fingerprints contain little information regarding deltas in a fingerprint and hence focussed on using features related to core points. The algorithm enhances and segments the input image and partitions it into 8x8 blocks of directional images. It then uses Poincare Index and k-mean grouping method on these blocks. False core points are eliminated and curvature and orientations of remaining core points are used for classification into arch (no core point or one core point with symmetric orientation), left-loop & right loop(one core point and upper curvature), whorl(two core points).

[10], used a rapid singularity searching algorithm for fingerprint classification. The input image was partitioned into 8x8 and 16x16 blocks and their local orientations were computed. Using the difference in orientations of the two block sizes Poincare index was computed and singularities were detected using its value (core – ½, delta – -½, others – 0). To remove false singularities and improve accuracy, post processing was applied which involved probability analysis of singularities, Poincare index computation with different circle curves and neighbourhood scan of singularities. At last

the delta direction and singularities information was used to classify the input image into 5 classes. [11], proposed a two step algorithm which firstly computed singularity points based on maximum variations in local orientations of a fingerprint image and then performs the classification based on the location of core and delta points. To detect the singular points input image was partitioned into non-overlapping blocks of 8x8 sizes and gradient at each pixel was calculated, followed by estimation of local orientation of each block. These orientations were converted in a range of 0-180 and smoothening of image in continuous vector field is performed using low pass filters. The portion of image having maximum variations in intensity was extracted and singularities obtained as core (for angle>60 degree) or delta (for angle<60 degree). A set of if-else rules are used to perform the classification into five classes (left loop, right loop, twin loop, whorl and arch).

[12], worked on improving accuracy of fingerprint classification in case of flat fingerprints where some singular points might be missing. This was achieved by adding a couple more rules to pre-defined set of classification rules. New rules were introduced to differentiate between right and left loop when the delta is not captured and for correctly classifying the whorl class and for distinguishing between a plain arch and any partially captured class. The resultant algorithm could predict correct classes for even those fingerprint images that missed on some singularities.

Structural classification approach works on the most natural way to process fingerprint images by analyzing topology of the fingerprint curves. These classifiers employ methods of differential geometry for analysis of curve properties and features. Some classifiers use graphs to represent relations amongst sub patterns and implement graph matching algorithms to map a relational graph to its class prototype. [13], approached the classification problem by partitioning the directional images obtained from fingerprint topology into "homogeneous" regions that are connected to each other and give a synthetic representation that is used for classification purpose. It follows the continuous classification approach where each fingerprint is represented using a numerical vector which may exhibit a degree of similarity towards a predefined set of class prototypes. The process uses dynamic masks and an optimization criterion to perform directional image partitioning and uses different search strategies to efficiently perform fingerprint classification. The method gives high accuracy rate and exhibits robustness toward noisy data.

[14] used ridge flow patterns to classify fingerprint images. In the first step algorithm used Sobel operator and Gabor filter to extract High Ridge Curvature (HRC) region followed by tracing the ridges within the region and drawing vectors at both end points. These vectors were then used to determine the class to which the fingerprint belonged. The algorithm boasts of high speed (as detection of singular points is omitted) and accuracy of classification with whorl class being the only exception.

[15], proposed an algorithm base on ridgeline curve features and singular points to classify fingerprints. The two step classification approach works by first using total direction change and types of ridgelines to partition fingerprints into three broad classes ((a) arch class;(b) tented arch, left and right loop class;(c) whorl and double loop class) and then using singular points based classifier for further classification into six constituent classes.

[16], introduced a novel structural approach for classification that used directional images obtained from input fingerprint image. The directional images were partitioned into regions containing same direction pixels. These regions were represented with relational graphs and using them a supergraph was formed. Graph matching algorithm was applied to compare the obtained graph with model graphs corresponding to each class. Fingerprints were classified on the basis of obtained cost function.

Statistical classifiers work by extracting a feature vector of measurable properties of a fingerprint viz. Orientation fields or response to filters and apply statistical inference to estimate best class for a given input. They in turn may use logistic or probabilistic regression, support vector machines, neural networks or k–nearest neighbour classifiers.

Support Vector Machine (SVM) based classifiers use supervised learning and perform classification by determining hyper planes in a multidimensional space that can separate objects of different classes.

[17], used an algorithm that estimates orientation fields in a fingerprint image using pixel gradient and then calculates the percentages of the directional block classes. Only four directions have been used to reduce computational cost. The four dimensional feature vector generated by combining the directional percentages is fed as input for supervised training of a hierarchal SVM classifier with five steps, for distinguishing each of the six classes(whorl, arch, tented arch, twin loop, left and right loop). The method provides high classification accuracy with low time complexity. [18], proposed a nonlinear model based on singular points and orientation information of fingerprint images. A nonlinear phase portrait model was used to develop the orientation model to generate ridge orientation information. The information regarding singular points was retrieved using complex symmetrical filters. To improve the overall accuracy of feature vectors an interactive validation approach was used wherein detected singular points were verified by measuring variation in modelled orientation at singular point versus original orientation. Finally an SVM classifier was used to perform classification using the orientation and singularity features. The experiments showed a high accuracy rate of 93.5%. [19], uses a distortion detection and rectification algorithm before classifying the fingerprints using an SVM classifier to improve the classification rate of distorted fingerprints.

KNN (k–nearest neighbour) based classifiers operate by mapping an input instance to a corresponding class based on some proximity or similarity function. This type of classification basically involves finding the nearest (most similar) neighbour from stored training dataset and classifying the unknown instance with the same class label as that of the known neighbour. [20], uses an algorithm based on directional fields obtained from fingerprint image. The algorithm detects core and delta points, extracts the features and applies k-means classifier and 3- nearest neighbour to classify fingerprints into four classes namely Arch, Left and Right Loop and Whorl.

[21], uses genetic programming in combination with Bayesian classifier. The algorithm works in two phases. In the training phase, the algorithm generates primitive features obtained from orientation fields of fingerprint image. These are then fed to the genetic algorithm which in turn applies composite operators to generate feature vectors used for classification. It then computes fitness value for the composite operators based on the Bayesian classification which is used for further evolution of the algorithm. In the testing phase, the composite operators obtained in learning phase are directly used to generate primitive features from input fingerprints and classify them into Right loop, left loop, whorl, arch or tented arch.

[22], addresses the problem of lack of accurate classification due to smaller sized training datasets by artificially expanding it using spatial modelling technique. The resultant training set is used to train a Bayesian classifier for classification purposes. The algorithm uses an adaption of Fisher's linear discriminant for reducing dimensions of feature vector and a quadratic discriminant function to reduce estimation errors. Further an estimated mean class value is used to account for any missing feature.

Artificial neural networks are computing systems that can learn to recognize the way inputs are mapped to outputs once they have been sufficiently trained by predetermined set of data. Once we train the neural network based classifiers with fingerprint templates corresponding to each class, the network thus formed can be used to classify any input fingerprint to its corresponding class. [23], used a four layered neural network for automatic fingerprint classification. The algorithm used two step training method involving supervised learning with back propagation. It used a ridge tracing algorithm to extract the fingerprint ridge orientations. In the learning phase link weights and thresholds were adjusted to teach each subnetwork to recognize characteristics of one category using training data of 100 fingerprints for each category. Prinicpal Component Analysis of classification states represented by internal state of network was performed to check the effectiveness of the two step learning approach. It provides a classification accuracy of 86% but is restricted by the size of dataset. [24], used fuzzy neural networks for classification. The algorithm obtained singular points, their position and relative orientations using directional fields of an input image in four sub-directions by partitioning the image into 5x5 blocks and calculating the numeric gradients based on pixel intensities for each sub-direction. A feature encoder converts this information to a feature vector. Two data sets of feature vectors were used to train the neural network. The neural network component while training generated fuzzy logic rules and membership functions to be used for classification. The fuzzy logic component helps obtain correct results even for ambiguous input data.

Hybrid classifiers use a combination of more than one classification approaches. [25], performed fingerprint classification using an algorithm based on recursive neural networks (RNN) and support vector machines (SVM). RNNs were trained and used to retrieve vector representation of distributed features of relational graph of an input fingerprint. The output was fed to an SVM classifier containing error correcting code to enhance tolerance of ambiguous training data. The SVM classifier used a combination of distance measures like Hamming distance, margin weighted Euclidean distance and soft margin distance to classify the input fingerprint into arch, left and right loop, whorl and tented arch. The classification thus obtained had high accuracy rate that reaches to a maximum of 96.2% with a rejection rate of 32.5% for classification into 5 classes and to a maximum of 98.4% with a rejection rate of 32.5% for classification into 4 classes.

[26], used a combination of SVM, nearest neighbour and neural network classifiers to classify the fingerprints into arch, left loop, right loop, whorl and tented arch classes. The algorithm uses feature vectors generated from a feedback based line detector. The line detector detects ridge orientations at each point of the input image and works iteratively as a distributed dynamic network to stabilize detected lines. It then uses 3 classification strategies based on hierarchal SVM classifier; Euclidian distance based nearest neighbour classifier and feed forward neural networks with back propagation classifier for classification.

[27], performs fingerprint classification by first obtaining directional images representing ridge orientation information by using Discrete Fourier Transform and directional filters and then applying nonlinear discriminant analysis. Directional images were obtained by segmenting the fingerprint image from its background and using FFT for computing directional vectors representing dominant directions in local neighbourhood and finding the core point(around which the image is centred). Application of DFT resulted in faster pre-processing and construction of directional images while use of directional filters provided for high noise tolerance by filtering out low frequency components, resulting in directional images containing high quality discriminative information. The Kernel-based nonlinear discriminant analysis helps in dimensionality reduction of obtained feature vectors thus reducing

computational complexities. The classification was then performed using multiple classifiers viz. support vector machines (SVM), multilayer perceptron (MLP), recursive neural networks (RNN) and k-nearest neighbors (k-NN) classifiers. SVM was observed to give highest accuracy rate.

Type of Classifier	Author	Features Used	Classes Obtained	Accuracy	Advantages	Disadvantages
Rule based Classifier	Karu and Jain(1996)	Cores and delta	5	91.40%	High accuracy	Can't classify poor quality images
	Ballan(1998)	Singular point from directional histogram	2(Lasso & Wirbel)	73.30%	Simple and fast	Only two classes, lower accuracy, time complexity sensitive to image size
	Cho et al.(2000)	Core points	4(arch, left-loop, right-loop, whorl)	91.60%	Less dependence on delta detection, high accuracy	Sensitive to noise
	Afsar et al.(2004)	Singular points	5	95%	-	High time complexity, false acceptance& rejections
	Wei (2008)	Ridge orientation through Poincare index, Singular points	5	95.60%	-	High time complexity, similar classes have low distinction rate
	Suralkar et al.(2009)	Singular points and ridge orientation field	6,5	89.7%, 91.5%	Fast, low complexity, high noise tolerance	Poor distinction rate amongst left & right loops versus arch
	Webb et al.(2014)	Singular points	5	91.5%	Gives much better accuracy on flat fingerprints than other algorithms	-
Statistical Classifier	Wang et al(2002)	Core and delta, Directional fields, kmeans and 3 nearest neighbour	4	79.50%	Tolerance for low quality images	Reduced accuracy for fingerprints missing delta region, can't distinguish between whorl and twin loop
	Tan et al.(2005)	features obtained from primitive image processing operations and composite operators	4,5	93.2% and 91.2%	high accuracy rate	Slow training rate, higher complexity
	Ji et al.(2007)	Ridge orientations and directional percentage of orientation fields	5	95.17%	High accuracy, low time complexity	Lower distinction rate amongst similar classes
	Li et al. (2007)	Singular points and orientation fields	5	93.50%	High accuracy,	Sensitive to noise
	Leung et al.(2011)	Gabor filter responses	5	Upto 59% error reduction in comparison to other Bayseian classifiers	Works well even for limited training datsets	needs to generate artificial training sets before actual classification
	Sie et al.(2015)	Ridge orientation map, period map	2	Works in conjunction with a SVM classifier to give better retrieval	Can work with distorted fingerprints	Low efficiency, Needs more accurate fingerprint registration algorithm

				accuracy for distorted fingerprints		
Neural Network classifier	Kamijo(1993)	Singular points, ridge orientation	5	86%(for first candidate), 99%(for the second candidate)	High accuracy	Effective for small databases only
	Jain et al. (1999)	PCA, ridge lines, singular points	5	90 – 96%(for 5 classes with varying rejection rate) 94.8 – 97.8%(for 4 classes with varying rejection rate)	High accuracy	High time complexity
	Mohamed and Nyongesa(2002)	K-NN and neural network	5	92.4%(average for all classes)	Simple and flexible	Misclassification error, low accuracy for arches and loops
	Balti et al.(2013)	Singular points, position and direction of core and delta	5	92.5%(average for all classes)	effective identification of singular-point	Variable classification accuracy for different classes
Structural Classifier	Cappeli et al.(1999)	Directional vectors	5	92.20%	Fast and accurate	Can't perform exact Fingerprint labeling
	Nain et al. (2008)	Ridge orientations	4	98.75%	High accuracy, no need to detect singularities	Whorl class detection has lower accuracy rate, tested on small dataset
	Wei et al.(2008)	Singular points, Ridgeline types	6	95.60%	Accurately determines fingerprint class with an exception of tented arch	High time complexity for sampling ridge lines
	Tarjoman et al.(2008)	Directional ridge information	9	81.50%	Lower accuracy	Finer classification
Hybrid classifier	Yao et al(2001)	Finger code features and structural representations SVM &RNN	5	97.60%	High accuracy, ability to identify difficult test images, tolerance to ambiguous training data	High time complexity
	Shah and Sastry(2004)	SVM, Nearest neighbour and neural network	5	>90% (variable for different classes and classifiers)	High accuracy	High time complexity, requires larger training set for higher accuracy
	Park and Park(2005)	Feature vectors obtained from FFT SVM, MLP, KN, RNN	5	94.0 - 97.9%	Higher accuracy , low complexity, can work with noisy images	-

Table 2: Summary of Fingerprint Classification Algorithms

IV. CONCLUSION

Fingerprint classification provides a coarse level matching of a fingerprint image to one of its relevant class, resulting in a reduced search space and hence improved recognition rate in any automated recognition system. A wide array of algorithms have been used to perform this task, each with their unique set of advantages and loopholes. It has been observed that most of the algorithms can classify the fingerprints into five constituent classes and find it difficult to differentiate between classes with similar orientation vectors eg. Double loops and whorls, loops and tented arch. Finer classification into more number of classes introduces higher error rate. Presence of noise and distortions in fingerprints further reduce the classification accuracy. Although algorithms have been developed to rectify these problems, they accomplish the same at an increased computation cost and complexity. Availability of larger and more accurate training datasets and improved machine learning algorithms can tremendously improve the efficiency of these algorithms.

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