Fingerprint Classification Techniques: A Review

Alaa Ahmed Abbood * **Ghazali Sulong**

Faculty of Computing, Universiti Teknologi Malaysia, 81310 Johor Bahru

Abstract

A biometric is the automatic identification of an individual that is based on physiological or behavioral characteristics. Due to its security-related applications and the current world political climate, biometric is currently the subject of intense research by both private and academic institutions. Fingerprint is emerging as the most common and trusted biometric for personal identification. The main objective of this paper is to review the extensive researches that have been done on fingerprint classification over the last four decades. In particular, it discusses the fingerprint features that are useful for distinguishing fingerprint classes and reviews the methods of classification that have been applied to the problem.

Keywords: *fingerprint classification, singular point detection, segmentation, Biometric, orientation Field Estimation*,

1. Introduction

Generally the most important stage in automatic fingerprint identification system (AFIS) is a fingerprint classification because it provides an indexing mechanism and facilities the matching process over the large databases. When a class of a query fingerprint is known, matching the fingerprint only requires that the comparison be done within the class similar to the query fingerprint. Fingerprint based recognition systems work in two modes: verification and identification. In verification mode, the systems verify the person's identity using a 1: 1 comparison between the person's fingerprints and those stored in the record. Verification process confirms whether the identity of the person with the fingerprint is the valid person. However, the process used in fingerprint identification systems is more complex than the process employed in verification especially for large database because fingerprint identification requires the input fingerprints to be compared with all the fingerprints in the database for matching. While verification uses 1:1 comparison for matching, fingerprints identification requires 1:N comparison to establish if the individual is present in the database [1].

The exact time regarding the origin of the use of fingerprints for identification is unclear. There is evidence which indicates that fingerprints were used in ancient times. However, there is no indication that anyone recognised the full potential of fingerprints as a means of personal identification[2]. Sir Francis Galton (1892) began the first rigorous study of fingerprint-based identification. Among many contributions to the field, his work contained the first system for fingerprint classification. Galton's classification was introduced as a means of indexing fingerprints in order to facilitate searching for a particular fingerprint within a collection of many prints and proposed three basic fingerprint classes: the arch, the loop, and the whorl shown in figure 1. Galton's other major contribution was the first study into the uniqueness of fingerprints. In addition to permanence, uniqueness is the other necessity for fingerprints to be a viable method of personal identification.

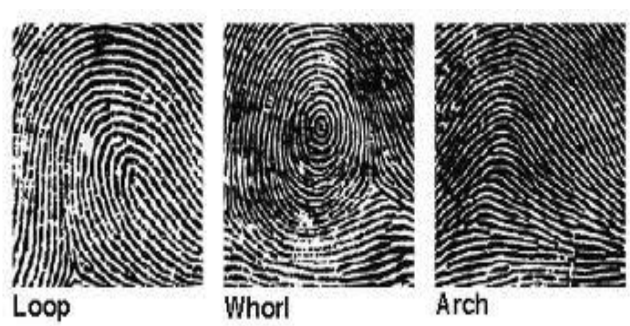

Fig. 1 examples of Galton's three classes.

Several years later Edward Henry (1900) continued Galton's work on fingerprint classification. Henry subdivided the three main classes into more specific subclasses, namely, arch, tented arch, left loop, right loop and whorl as shown in figure 2. He also introduced the concept of fingerprint ''core'' and ''delta'' points and used them as aids for fingerprint classification. Henry's classification scheme constitutes the basis for most modern classification schemes.

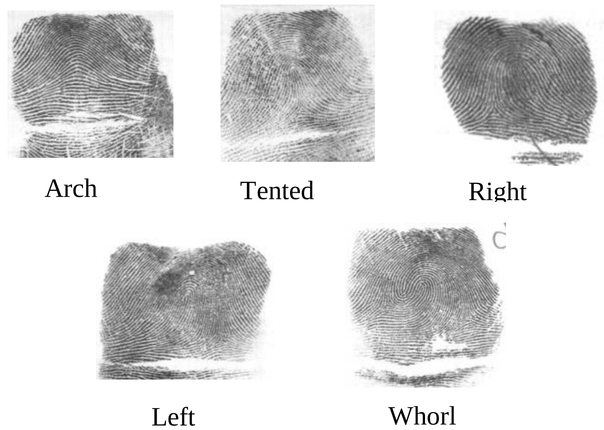

Fig.2 Example of Henry's five classes.

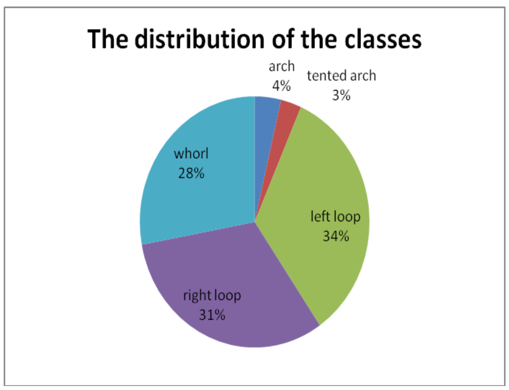

Fig.3 The distribution of Henry's five classes in nature.

The distribution of the classes in nature is not uniform. The probabilities of the classes are approximately 0.037, 0.029, 0.338, 0.317, and 0.279 for the arch, tented arch, left loop, right loop, and whorl, respectively(Jain et al. 1999; Wilson C et al., 1993) (as shown in figure 3) . Left loop, right loop and whorl are the most common, making up 93.4% of all fingerprints. Therefore, for developing and testing of a classification system, it is important to use a suitable dataset with sufficient sample size that can represent natural distribution of human fingerprint classes. However, most researchers employed NIST database 4 which provides insufficient samples (i.e. less than 10,000 prints) for testing and validating their experiments [3]–[6]. Thus, the validity of their experimental results' is disputable, and consequently the performance of their proposed classification methods is also implausible [7]. In relation to that, NIST Special Database 14 was created and becomes the de facto standard dataset for developing and testing of automatic fingerprint classification systems [7].

Unfortunately there are several complicated issues related to the fingerprint classification. These include the problem of classifying ambiguous fingerprint which cannot be classified even by human experts because this fingerprint has properties shared by more than one classes (see figure 4). From 27000 fingerprint images contained in NIST special Database 14, 3.39% are ambiguous. Under this condition, which fingerprint classes these ambiguous prints should be matched against is very uncertain [7].

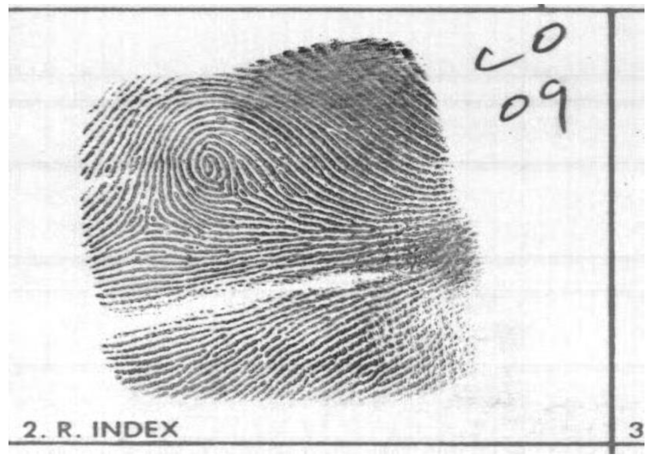

Fig. 4 shown sample image of ambiguous fingerprints.

The second difficulty which makes fingerprint classification problematic even by human expert is that the sample of fingerprint images has poor quality due to injuries or scars which result, for many applications, in the fingerprint images being rejected. Rejection would be less damaging than a wrong decision. For this reason, to improve classification accuracy, the images are first enhanced by a process of reconstruction. Rejection procedure is applied for those images which cannot be classified. In this case such images will be put under the classification "unknown" (as shown in figure 5).

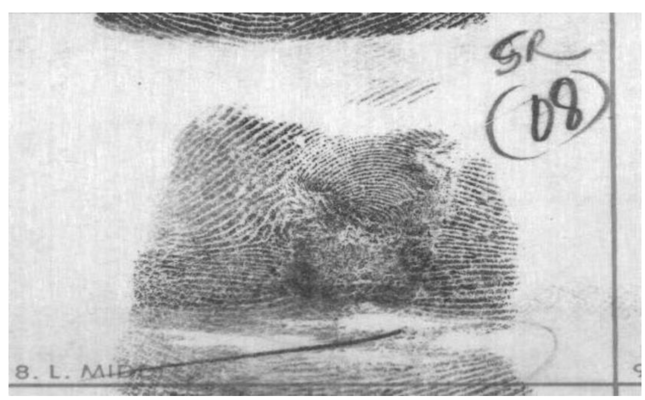

Fig 5 shown sample image of rejected fingerprint.

The noise in the fingerprint image which brings about misclassification is normally generated by ink scan and live scan. For ink scan, the noise is created by over ink or by insufficient use of ink during fingerprint imprinting process. For live scan, the noise is caused by dry and wet prints produced by the coating on the skin (from oil, water, sweat etc.). NIST Special Database 14 contains images that are often tainted by signatures and handwriting of the human expert (see figure 6). These signatures and comments are considered as noise and require manual pre-processing to remove this annotation and artefact [7]. However, the above processes are considered non-automatic because of human intervention, and should be avoided if possible. Therefore, developing a full scale automatic fingerprint classification system is considered a very challenging task.

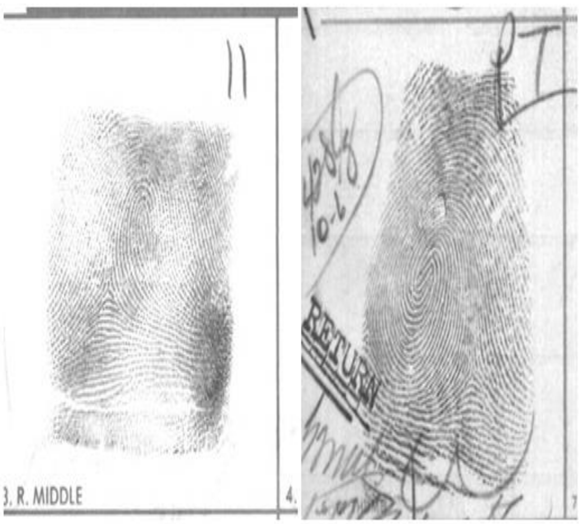

Fig. 6 shown dry image & image contain hand writing.

Most of classification schemes use five classes. Any significant similarity in the structure and shape of the human fingerprint creates difficulty in the process of distinguishing and differentiating orientation patterns of ridge structure within the same class, especially in the whorl case (see Fig. 7). This difficulty and problem are associated with large intra-class variation, where the prints of the same class have the same similarity characteristics covering a large spread, and therefore is difficult to classify[8]. This interclass problem is extremely difficult to deal with even by a human expert.

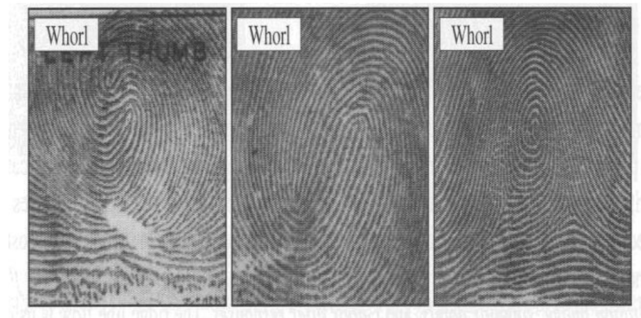

Fig. 7 Three fingerprints of the same class that have very different characteristic (large intra-class variability).

Generally a fingerprint image contains two features, viz the global feature and the local feature. The global feature of the fingerprint image is described by structure shape (ridge and valleys) and the singular point as shown in figure 8. The local feature of the fingerprint consists of the minute details of the ridges. The global feature has the global information which is considered the valid feature used in the design of automatic fingerprint identification system [3]. Therefore, it is natural to base the features directly to the fingerprint ridges. The orientation field estimation is a convenient way to represent the global ridge structure of the fingerprints. Although the orientation field estimation is the best approach to represent the ridge structure, there are still many challenges and problems with regards to classification of low quality image. Zhu [9] suggested many new creative methods to improve image quality and proposed a much improved automatic fingerprint classification system[9].

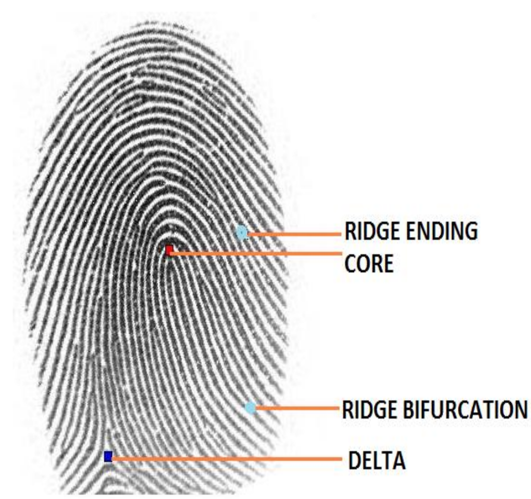

Fig. 8 Ridges and valleys structure.

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Another global feature often used by the researcher to distinguish fingerprint classes is the existence and location of singular points. The singular points of fingerprint are represented by "core" and "delta" which is singularities based patterns. The difficulties faced by singularities-based patterns are: the singular points may not appear in the image, especially if the image is poor in quality or if the image contains high noise which makes the extraction of singular point in the fingerprint unreliable when the singularity points of the image is not detected or incorrectly detected. Several methods have been proposed to locate the singular points. The most common and widely used approach is the Poincaré index, although this approach has a lot of drawbacks, is very sensitive to noise and has problems with low contrast and low quality of fingerprint images[10].

Before classification can be carried out, the fingerprint pattern has to be transformed into a format which is acceptable for classification. Many researchers had done several varied transformation processes and generally these transformation processes can be illustrated by the diagram shown in Figure 9.

Fingerprint image is initially pre-processed through consecutive techniques. The first step is the segmentation which isolates features that are of similar characteristics. The fingerprint image is split into two regions which are the foreground and the background regions. The foreground region is the area containing ridges and valleys, while the background region corresponds to the fingerprint image borders. The second step is the enhancement algorithm towards recovering the quality of fingerprint image. For the fingerprint image quality to be considered as having good intensity there must be high contrast between ridges and valleys. The final step in pre-processing is the orientation field estimation, in which involve the process to convert the fingerprint image to the vector form and improve the smoothing quality of the fingerprint ridges. Secondly, a process of singular point detection is applied on the pre-processed fingerprint image. In this process two kinds of singular points can be detected, namely core point and delta point. A core point is the turning point of an innermost ridge and delta point is a place where two ridges running side-by-side [11]. Most of the approaches proposed in the literature for singular points detection operate on the fingerprint orientation field, such as Poincaré index methods, partitioning-based methods, and methods based on local characteristics of the orientation field. Finally, fingerprints are categorized with classification process based on global features. The features are known as the global ridge structure and singularities [7]. The ridge structure characterizes the shape that describes the ridge flow, whereas the singularities are localized in small areas where the ridge flow is irregular. The scheme classifies fingerprints into five classes namely; plain arch(A), tented arch(T), left loop(L), right loop(R) and whorl(W). The entire classification scheme is depicted in Figure 9.

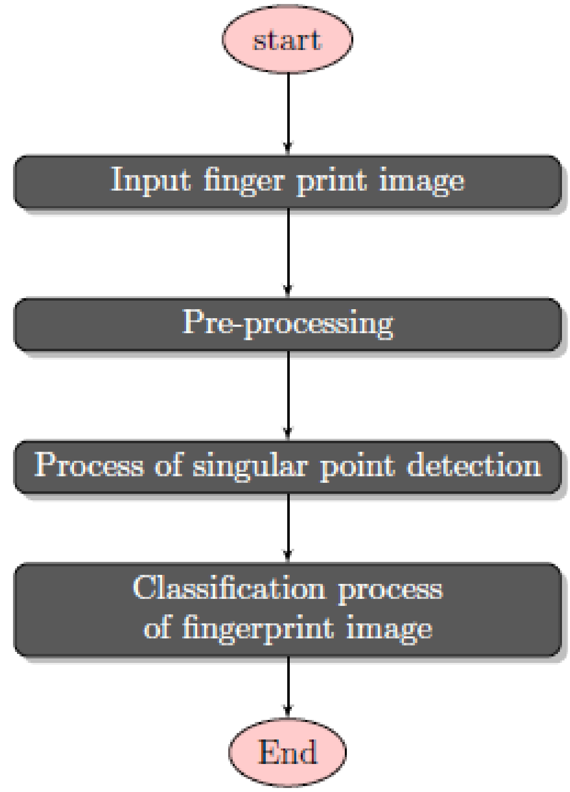

Fig. 9 Flow diagram of fingerprint classification process.

2. Pre-processing

2.1 Fingerprint Segmentation

Fingerprint segmentation isolates features that are of similar characteristics[12]. The fingerprint image is split into two regions which are the foreground and the background regions. The foreground region is the area containing ridges and valleys, while the background region corresponds to the fingerprint image borders. The background regions are located at points that can be considered to have no useful fingerprint information. According to Wu [13] and Maltoni [7], the image local intensity can be used to separate the foreground region from the background region, provided that the background regions are of uniform and lighter intensity than the

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foreground[7], [14], [15] . Generally, two steps of fingerprint segmentation. They are the block-wise and the bit-wise steps. Block wise step is employed to extract the foreground of fingerprint image from the background. The foreground of the fingerprint extracted is normally corrupted by noise[15]. Bit-wise step is used to remove noise and other unwanted interference by operating in the domains associated with image gray-scale statistical features, local directional features or coherence features[16]. Owing to the fact that the bit-wise based segmentation step is time consuming, the block-wise step is preferred especially for an automated process [12], [13], [17] (refer to Fig. 10).

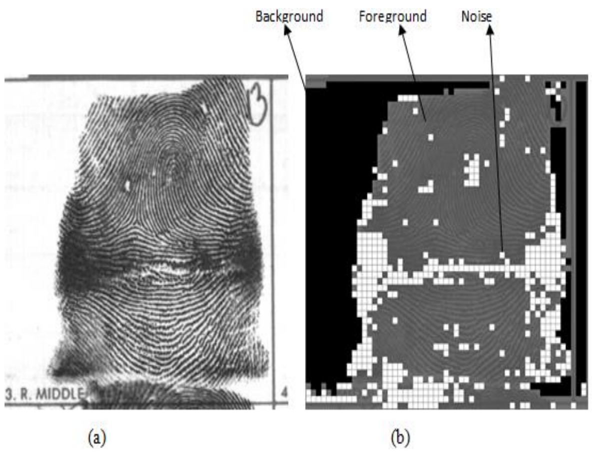

Fig. 10 (a) Fingerprint image, (b) Highlight background regions, foreground regions, and noise regions in the fingerprint image.

2.2 Fingerprint Image Enhancement

Applying enhancement algorithms to fingerprint images are necessary steps towards recovering the quality of fingerprint image[18]–[20]. For the fingerprint image quality to be considered as having good intensity there must be high contrast between ridges and valleys. There must also be clear continuity in the ridge structures. An example of a high quality fingerprint image can be seen in Fig. 11 (a) while the low quality fingerprint image is shown in Fig. 11 (b)-(f). Referring to the Figure 11 (b)-(f), low quality image can be characterized by low contrast, by the presence of high level of noise and by having big distortions[21][19]; these combined effects are known as spurious effects. Image enhancement employed by Hong et al. [22], operated as three enhancement stages which were; processing on well-defined region, processing on recoverable corrupted region, and processing on unrecoverable corrupted region[23].

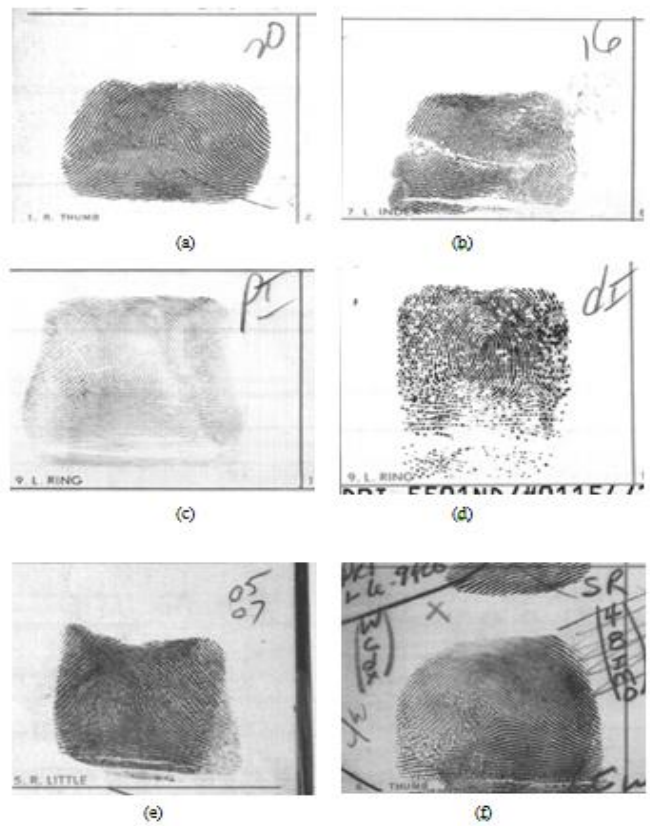

Fig. 11 Quality of fingerprint image (a) Good, (b) Broken/cut, (c) Low contrast, (d) Dry, (e) Wet, and (f) Stain.

3. Intermediate process

3.1 orientation Field Estimation

The process of estimating local ridge direction for fingerprint images can be termed orientation field estimation[24][25]. Fingerprint image are often viewed as oriented textures by assuming local ridge flow. The accuracy of fingerprint orientation field estimation consider as most important step to detect the singular point as well as to get high accuracy in fingerprint classification system. However, false orientations are inevitable because of distortions, such as impression conditions and skin conditions etc[26]. Low-quality regions pose a great threat to both feature extraction and fingerprint classification as their positions and sizes are unpredictable, so, their effects on the fingerprint related systems are unpredictable as well. Therefore, it is very important to improve the orientation field accuracy, thus facilitating the procedures followed as image enhancement and feature extraction for recognition and verification[27]. In reality, a fingerprint expert can identify the fingerprint ridges and valleys using various clues including local ridge orientation, ridge continuity and ridge tendency etc. In fact, fingerprint images do show slowly varying flow directions with some singularities. As long as the ridge and valley structures are not corrupted completely, it is possible to develop an algorithm to improve orientation estimation accuracy, thus, to increase the efficiency and the robustness of fingerprint related systems. Therefore, the problem becomes how to accommodate the unpredictability of the unreliable regions using existing information while still reserving the real ridge flow.

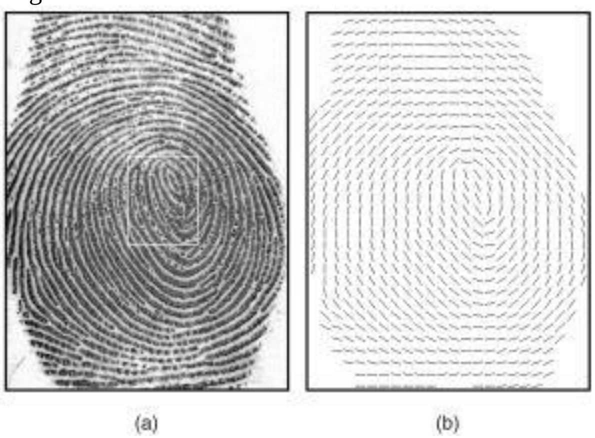

Fig 12 : (a) Grayscale image (b) extracted feature (orientation field)

Over the years, many methods such as gradient method, polynomial model method, normal vector method, gabor filterbank method, multiscale directional operator method, and line sensor method have been applied to estimate orientation field of fingerprint patterns. The most frequently adopted method to estimate orientation field of fingerprints is the gradient-based approach [9], [28]–[33] utilized a polynomial model to develop a novel algorithm to carry out orientation field estimation. The polynomial model was applied in order to approximate the global orientation field at the same time a point-charge model was used to improve the accuracy at each singular point on the fingerprint image[34].

Other methods that have been utilized include the neural network method, which Zhu [35] implemented for the design of a systematic scheme that estimated the fingerprint ridge orientation. The estimated ridge orientation was obtained by means of evaluating the correctness of ridge orientation. The purpose for the neural network was to learn the correctness of the estimated orientation for the gradient-based method.

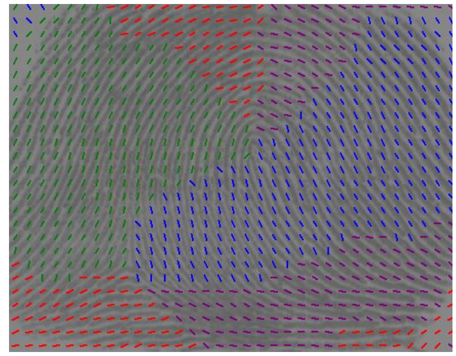

Fig 13 : orientation Field Estimation divide in four group of orientation .

3.1 Singular Points Detection

In the fingerprint image, two kinds of singular points can be detected, namely core point and delta point. A core point is the turning point of an innermost ridge and delta point is a place where two ridges running side-by-side [11]. Most of the approaches proposed in the literature for singular points detection operate on the fingerprint orientation field, such as Poincaré index methods (as shown in figure 14), partitioning-based methods, and methods based on local characteristics of the orientation field[36]–[40].

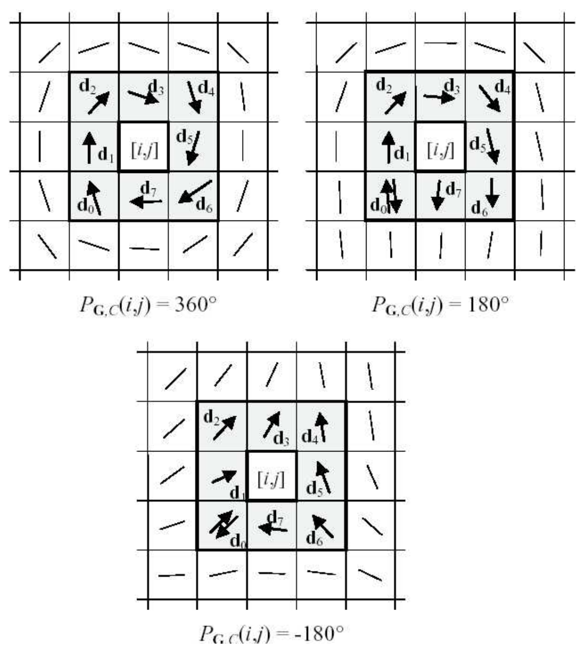

Fig 14: Computation of the Poincare index in the eight-neighbourhood of pixel (i, j)

$$PG,C = \sum_{K=1}^{7} angle(d_k, d_{((k+1) \bmod 8)}) \qquad (1)$$

Where dk is the neighboring elements as shown in Figure 3.

$$P_{G,C} = \begin{cases} 0 \text{ deg. if (i,j) does not belong to any SR} \\ 360 \text{ deg. if (i,j) belongs to a whorl type SR} \\ 180 \text{ deg. if (i,j) belongs to a loop type SR} \\ -180 \text{ deg. if (i,j) belongs to a delta type SR} \end{cases} \quad (2)$$

As mentioned, the core point is the most northern loop. We assume that the fingerprints are captured with the finger in an approximately normal position, but tolerate a rotation of up to 45 degrees either clockwise or counter clockwise. The core point is used as reference point in the extraction of classification features methods (as shown in figure 15).

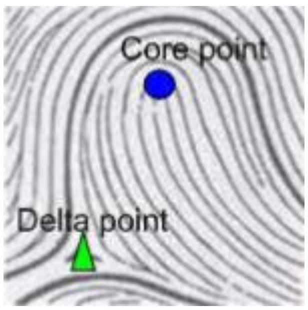

Fig 15: **Singular Points Detection**

3. Classification process

4.1Model-based Approaches

The model-based fingerprint classification technique uses the number and the locations of singular points to classify a fingerprint. Henry (1900), first proposed the model based approach to carry out fingerprint classification which was created to mimic human expert knowledge using a system of heuristic rules. The heuristic rules are used to detect the singularities in fingerprint images. The number and location of singularities are needed to ensure that fingerprints' are accurately classified. Maltoni [7] and Karu [41] referred the model-based approach as the rule-based approach. [41] proposed an algorithm, which was executed based on the following: (i) compute the ridge directions using 9×9 mask, (ii) find the singularities in the directional image using Poincaré index, and (iii) classify fingerprint based on the detected number and location of singular points[42]. The method used to determine singular points were based on heuristics. Their method was observed to be affected by noise, particularly within the singular point regions. The noise made it difficult to identify the cores and deltas, and adversely influence their positions[43][44]. Because of this, several methods under the rule-based approaches were proposed. Chong [45] proposed a rule-based approach that did not search for any singularity but was based on the geometrical shape of the ridge lines. Based on the same concept, Hong [3] used ridge details to improve the orientation field information. However, their method was not tested on low quality fingerprint images where the orientation field could be very noisy. Noise can also degrade fingerprint structural information, especially if the fingerprints have been impaired by finger cuts or by certain skin conditions [3]. Zhang and Yang [46] [47] and Wang and Dai [48] used a pseudo-ridge tracing algorithm that classified fingerprints when one singular point (a loop or a delta) is detected. Singular point detection have several weaknesses and have been challenged because fingerprints scanned from cards often are unable to capture delta points of the fingerprint image. Due to the problem of missing delta points, the work by Cho [49] aimed at disregarding the delta point. Their method makes use of the loop to classify fingerprints by the curvature and orientation fields of the regions near the loop. Jain and Minut [50] also proposed the rule-based approach that does not search for singularity but classifies fingerprint images in terms of the ridge lines geometrical shape. A fingerprint kernel models the structural shape of fingerprints according to a particular class. The information from the kernel are then used to classify the fingerprint image based on the kernel that best fits the orientation image of the given fingerprint[4]. Wang and Xie [51] proposed the use of singular points and the information from the analysis of fingerprint structures. In their work, the orientation fields are divided into non-overlapping fields for a synthetic representation. The singular points they employed were extracted using Poincaré index. Their method was said to be invariant to rotation, translation and small amounts of scale changes. Li [52] proposed interactive validation algorithm of singular points and constrained non-linear phase portrait orientation-field model for fingerprint classification. Their combined orientation and singularity features were used to classify fingerprints using the SVM classifier[53]. Wei [54] used Poincaré index to detect singular points, while Conti [55] utilized pseudo-singularity points.

4.2 Structure-based Approach

In structure-based approach, images are classified using estimated orientation fields. The local ridge of the orientation field represents the ridge flow of the fingerprint structure. The structure-based approaches are known to partition the fingerprint orientation field into "homogeneous" orientation regions and the regions governed by relational graphs [56]. Maio and Maltoni [57] adopted the concept of the orientation field partitioning. They partitioned the orientation field into regions by minimizing a cost function that takes into account the variance of the element orientations within each region[57], [58]. In the system proposed by Neuhaus and Bunke [59],

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regions that were used were extracted from the fingerprint orientation image[60]. Through the directional variance filter that selected potential singular points the regions required are characterized by vertical orientations. The characterized image structures were then converted into attribute graphs, which were based on distance algorithms. This attribute graph was then used to classify fingerprint images[59].

4.3 Combined Approaches

Complementary information about the patterns to be classified may be exploited to improve the performance of a classifier. Several studies on pattern classification indicated that the sets of patterns misclassified by different classifiers do not necessarily overlap [1]. There have been interests to combine many different approaches for the fingerprint classification task to achieve better results and better system performances. This has motivated the design of Pattern-level Classification Automation System (PCASYS) which has revolutionized fingerprint classification by coupling auxiliary ridge-tracing module, which is specifically designed to detect whorl fingerprints [61]. Jain [3] adopted a two-stage classification strategy in which two most likely classes from a fingerprint code feature vector are identified using a K-nearest-neighbor classifier. The final decision is obtained with the help of a specific neural network which has been trained to distinguish between the two classes. A total of 10 neural networks are trained to distinguish between each possible pair of classes[62][44]. Three classifiers were proposed by Senior [63]. They were the hidden Markov Model classifier, PCASYS classifier and decision trees ridge shape features classifier. Wei [54] improved the accuracy of PCASYS classifier by using a feedback genetic algorithm based process to automatically select the best input parameters of the system[64]. Cappelli and Maio [65] proposed a combination of six classifiers based on the MKL (Math Kernel Library) transform trained on different data sets.

4.4 Neural Network Approaches

Several neural network approaches have been proposed in the literature: Most are based on multilayer perceptron and use the elements of the directional image as input features [66]. Bowen (1992) proposed a pyramidal architecture by arranging several multilayer perceptron trained to recognize different classes of fingerprints. This pyramidal architecture trains the neural networks by using the position of the singularities, the relationship between them and 20×20 directional map. The outputs from this network are passed on to a third network[67], which produces the final classification. Hugo [68] suggested a feed-forward neural network which was trained to classify fingerprints on the basis of their discrete wavelet transforms. In the transformation process, Neto [68] assembled the feature vector using the 64 coefficients of the sub bands 0, 1, 2, and 3 of the transform [68][69]. [70] working on a simple neural network and later Maio & Nanni [71] who worked on self-organizing neural networks, reduced the complexity (and thus the training time) of the network by applying a dimensionality-reduction technique to the feature vectors. The neural networks operated in the following manner. First, a 28×30 directional image was calculated and aligned with respect to the core position[64]; then the dimensionality of the directional image (considered as a single vector of 1680 elements) was reduced to 64 elements by using the principal component analysis. Finally, a multilayer perceptron was used for assigning each 64-element vector to a fingerprint class [71].

4.5 Continuous Classification

To complete the survey on fingerprint classification, it is necessary to mention the fingerprint retrieval techniques which are not based on exclusive classification schemes. In continuous classification [72]; each fingerprint is associated with a point in a multidimensional space through a similarity-preserving transformation, such that similar fingerprints should correspond to points within a small cluster of points[73]. In the retrieval process, only fingerprints whose transformations correspond to points within a given radius from the query fingerprint are considered. This ensures that the problems associated with ambiguous fingerprints are avoided[64]. Trade-offs between accuracy and efficiency adjusted according to the application requirements (by changing the search radius) are taken into account in the retrieval process. These approaches do not work with existing systems based on Henry's classes[74]. However, if the aim is only to minimize the number of comparisons during fingerprint retrieval process in a large database, continuous classification seems promising [7].

4.6 Fingerprint sub-classification

Fingerprints sub-classification has been created to cater for manual fingerprint searching in forensic applications where search procedures follow steps defined by FBI (Federal Bureau of Investigation, 1984) manual on sub-classification procedures for loop and whorl fingerprints using ridge counting of right and left loop fingerprints. The number of ridges between the core and delta singularities decides which of the two sub-classes the fingerprint belongs to[8][75]. For whorl fingerprints, the ridges are counted just below the leftmost delta until the position closest to the rightmost delta and also between that core point and the rightmost delta. Depending on the number of ridges and the position of traced ridges in relation to the rightmost delta in whorl class the following three sub-classes, which are the right whorl, the left whorl and the plant whorl can be defined manually. Actually, the rules are quite complicated because the sub-classification criteria vary according to the finger (thumb, index, middle,)[76][67]. Implementing a reliable automated fingerprint sub-classification is much more difficult than realizing a first-level classification into the five classes. Therefore, it is not surprising that only a very limited number of algorithms have been proposed in the literature to address this problem[62] [7][77].

5. Conclusion

Automated fingerprint classification is an inherently difficult problem that has yet to be adequately solved. A number of approaches and various feature extraction strategies have been proposed to solve this problem. A Parameter based flow diagram has been generated which will provide a base for the user to understand the approach used for building the algorithm for fingerprint classification. Various approaches of fingerprint classification like rule based, neural network based, genetic algorithm based, ridge flow based reveals that neural network based classification provides better results compared to other techniques. Neural Network using back-propagation algorithm gives good results as it learns complex relationship but it consumes a lot of time for training. Further exploration is still necessary, in particular, to investigate orientation modeling with ability to preserve singularity and to develop advanced methods for local structure inference using global information.

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