A SURVEY ON VARIOUS APPROACHES TO FINGERPRINT MATCHING FOR PERSONAL VERIFICATION AND IDENTIFICATION

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ABSTRACT

Automatic Fingerprint authentication for personal identification and verification has received considerable attention over the past decades among various biometric techniques because of the distinctiveness and persistence properties of fingerprints. Now fingerprints are set to explode in popularity as they are being used to secure smart phones and to authorize payments in online stores. The main objective of this paper is to review the extensive research work that has been done over the past decade and discuss the various approaches proposed for fingerprint matching. The proposed methods were based on 2D correlation in the spatial and frequency domains, Artificial Neural Networks, Hough transform, Fourier transform, graphs, local texture, ridge geometry etc. All these different techniques have their pros and cons. This paper also provides the performance comparison of several existing methods proposed by researchers in fingerprint matching.

KEYWORDS

Fingerprint Recognition, Correlation, Minutiae, Singular points, Pores

1. INTRODUCTION

Automated fingerprint recognition systems have been deployed in a wide variety of application domains ranging from forensics to mobile phones [36]. Designing algorithms for extracting salient features from fingerprints and matching them is still a challenging and important pattern recognition problem. This is due to the large intra-class variability and large inter-class similarity in fingerprint patterns [36]. The factors responsible for intra-class variations are a) displacement or rotation between different acquisitions; b) partial overlap, especially in sensors of small area; c) non linear distortion, due to skin plasticity and differences in pressure against the sensor; d) pressure and skin condition, due to permanent or temporary factors (cuts, dirt, humidity, etc.); e) noise in the sensor (for example, residues from previous acquisitions); and f) feature extraction errors [36].

Fingerprint identification system may be either a verification system or an identification system depending on the context of the application. A verification system authenticates a person's identity by comparing the captured fingerprint with her/his previously enrolled fingerprint reference template. An identification system recognizes an individual by searching the entire

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enrolment template database for a match. The fingerprint feature extraction and matching algorithms are usually quite similar for both fingerprint verification and identification problems. For fingerprint recognition purposes, a hierarchy of three levels of features, namely, Level 1 (pattern), Level 2 (minutiae points) and Level 3 (pores and ridge shape) are used [36].

Level 1 features (Figure 1) refer to the overall pattern shape of the unknown fingerprint—a whorl, loop or some other pattern. This level of detail cannot be used to individualize, but it can be useful for fingerprint classification and indexing [36].

Level 2 features (Figure 2)refers to specific friction ridge paths — overall flow of the friction ridges and major ridge path deviations (ridge characteristics called minutiae) like ridge endings, lakes, islands, bifurcations, scars, incipient ridges, and flexion creases. [36]

Level 3 features (Figure 3) refers to the intrinsic detail present in a developed fingerprint - pores, ridge units, edge detail, scars, etc. High resolution sensors (1000dpi) are required for extraction of Level 3 features.[36]

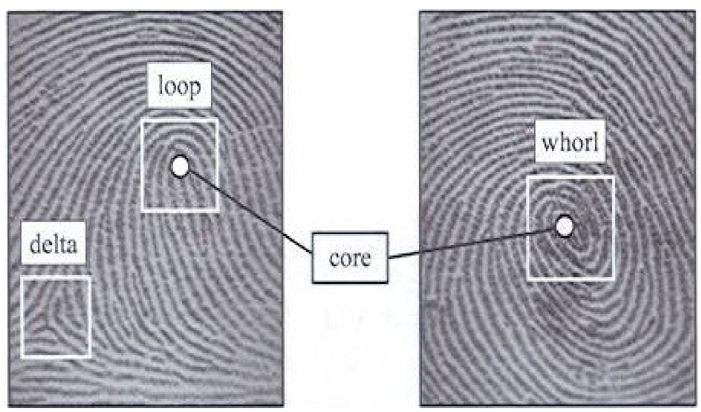

Figure 1: Singular points

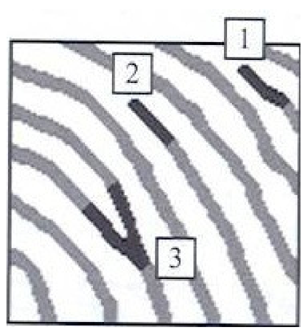

Figure 2: minutiae: ridge endings and bifurcations

Figure 3: intra-ridge details – Sweat pores

2.REVIEW

A large number of algorithms for automatic fingerprint matching have been proposed in the literature. Two given fingerprints are compared by a matching algorithm and return either a degree of similarity (also called matching score) or an acceptance/rejection decision. This work classifies the fingerprint matching approaches into correlation-based, minutiae-based approaches, and non-minutiae feature based such as ridge shape, texture information etc. The purpose of the survey is to analyze those algorithms and discuss the performance evaluation. The performance measure is presented in Table 1, 2 & 3.

2.1.Fingerprint matching

The existing fingerprint recognition systems uses techniques based on the local and global feature representations of the fingerprint images such as minutiae, ridge shape, texture information etc.

2.1.1.Correlation-based matching

The correlation-based methods used in spatial or in the frequency domain correlate two fingerprint images to compute the similarity between them.

A novel approach to fingerprint alignment and matching was proposed by Arun Ross et.al [24]. The feature set used in this method was a ridge feature map. A set of Gabor filters pre-tuned to a specific frequency were used to captured the local ridge strengths at various orientations and extract the local ridge characteristics. The convolution was performed in the frequency domain. A standard deviation image that captured the variation in the ridge strength at various orientations was constructed using the filtered images. The ridge feature map was obtained using standard deviation image. A 2D correlation of the ridge feature maps of the query image and template was determined to generate a matching score.

Karthik Nandakumar and Anil K. Jain [23] proposed a correlation-based fingerprint matcher that utilized local correlation of regions around the minutiae to estimate the degree of similarity between two fingerprint images. Minutiae points and the associated ridge points were extracted from the template and the query fingerprint images. This method used Procrustes analysis to get a good estimate of corresponding ridge curves to align the query with the template. The two images were enhanced using a bank of Gabor filters of different orientations. The normalized cross-correlation was computed to determine the quality of the minutiae match. A database consisting of fingerprint impressions of 160 users were used to evaluate this method.

A Robust Fingerprint Matching Algorithm for Verification based on correlation was presented by Abdullah Cavusoglu et. al [25]. They used a variance based segmentation method to segment the fingerprint image. Local ridge orientation was determined using Sobel operators. The method used to find the Reference point was based on differential sum of sine values of the directions of the pixels located on a certain radius. The proposed algorithm calculated 12 different cross correlations based on certain radius values from the reference point for both the input and template images and found a total sum to determine whether the images correspond to the same fingerprint. The proposed algorithm was evaluated on a public domain database.

Koichi Ito et.al [3] proposed an efficient fingerprint recognition algorithm using the phase components in 2D Discrete Fourier Transforms of the images. They used Phase Only Correlation (POC) function and Band-Limited Phase-Only Correlation (BLPOC) function to determine the height and location of the peak from phase characteristics in Fourier space, which gave the similarity measure and the translational displacement between the images respectively. The rotation and the displacement between the registered fingerprint and the input fingerprint images was normalized using BLPOC function. The overlapped region of the two images was extracted and finally the matching score is evaluated as the sum of the highest two peaks. The performance of their algorithm was evaluated on a database consisting of 330 fingerprint images.

Jiang Li et.al [11] described a fingerprint matching algorithm that combines minutia based matching method with correlation based matching method. Minutia based matching algorithm was used to extract the list of matched minutia pairs from the two fingerprint images. Correlation of the local neighbourhood regions around each matching minutiae pair that represents the local similarity and also the correlation between edges of neighbouring minutiae that indicates the resemblance of areas in between the two corresponding minutiae pairs were computed. The product rule was used to combine the number of matched minutiae pairs, neighbourhood correlation score and edge correlation score that represented a total sum of matching areas in two fingerprints. The proposed matching algorithm distinguished between genuine matched minutiae and impostor matched minutiae thereby improving the matching accuracy.

Haiyun Xu et.al [9] presented a novel method of spectral minutiae representation for fingerprint verification. The spectral minutiae represented a minutiae set as a fixed-length feature vector and was based on the shift, scale, and rotation properties of the two-dimensional (2-D) continuous Fourier transform. The two minutiae representation methods used for minutiae matching were Location-Based Spectral Minutiae and Orientation-Based Spectral Minutiae. To attenuate the higher frequencies,a Gaussian low-pass filter was applied on the spectrum. Two matching algorithms were presented. The correlation of two spectral images (direct matching) was chosen as a similarity score. The second algorithm is the Fourier–Mellin matching, in which the magnitude of the Fourier transform of the minutiae spectrum was taken to calculate the similarity score. The proposed algorithms were evaluated on three fingerprint databases.

A simple correlation based fingerprint verification system was proposed by Asker M. Bazen et.al [16]. The proposed system directly used the richer gray-scale information of the fingerprints. Appropriate characteristic templates were selected in the primary fingerprint and their corresponding positions in the input fingerprint were determined. The template was shifted over the entire fingerprint image and the location where the distance is minimal was chosen as the corresponding position of the template in the input fingerprint. The information of all template pairs was merged to obtain the final decision. The proposed system performance was evaluated on images from four different fingerprint databases consisting of 880 fingerprints in total.

Table 1. Analysis of Correlation-based fingerprint matching

Sl. No	**Author**	**Year**	**Method**	**Accuracy /Performance**	**Benefits and Restrictions**
1	Haiyun Xu et.al [9]	2009	Location and orientation based Spectral minutiae (SML &SMO), Direct Matching, Fourier–Mellin	EER Direct matching SML – 0.47% SMO – 0.42% Fourier-Mellin SML – 6.56% SMO – 3.29%	SMO is robust against noise/ SML exhibits better results only for good quality fingerprints and reliable minutiae extractor.
2	Abdullah Cavusoglu et. al [25]	2007	Sobel operators, Reference point, cross correlation	Execution time : 0.709 sec, 0.4 threshold FAR is ~.34%	Lesser storage space for template images with minimum pre processing
3	Jiang Li et.al [11]	2007	neighborhood correlation (NC), edge correlation(EC),	Combining Minutiae score, NC and EC scores : FAR 0.04%, FRR	Scores from minutiae and correlation matchers have to

			product rule	0.01%	be combined for matching more effectively low quality images
4	Koichi Ito et.al [3]	2005	Phase-Only Correlation (POC) , BLPOC (Band-Limited Phase-Only Correlation)	EER – 1.90%	Robust for low-quality fingerprint images/effective use only for verification units
5	Karthik Nandakumar and Anil K. Jain [23]	2004	Local correlation, Procrustes analysis, Gabor filters, cross correlation	EER 5.1%	Enhances the degree of match between two fingerprint images / computationally intensive
6	Arun Ross et. al [24]	2002	Gabor filters, ridge feature map, 2D correlation	1% false acceptance rate (FAR) the genuine acceptance rate (GAR) observed is ~ 70%	obviates the need for extracting minutiae points or the core point /better performance is observed when combined with a minutiae matcher
7	Asker M. Bazen et.al [16]	2000	Correlation Template selection	EER 7.98% Average matching time -2 secs	Simple and robust for low quality image, direct gray scale matching /not invariant to rotation

2.1.2.Minutiae-based matching

Minutiae are extracted from the two fingerprints and stored as sets of points in the two dimensional plane. Minutia-based matching consists of finding the alignment between the template and the input minutiae feature sets, that results in the maximum number of minutiae pairs.

Weiguo Sheng et.al [1] proposed a memetic fingerprint matching algorithm that aimed to identify optimal global matching between two sets of minutiae. The minutiae local feature representation called the minutiae descriptor that had information about the orientation field sampled in a circular pattern around the minutiae was used by them in the first stage. In the second stage, a genetic algorithm(GA) with a local improvement operator was used to effectively design a memetic algorithm for the minutiae point pattern matching problem. The local improvement operator utilized the nearest neighbor relationship to assign a binary correspondence at each step. Matching function based on the product rule was used for fitness computation. Experimental results over four fingerprint databases confirmed that the memetic fingerprint matching algorithm (MFMA) was reliable.

A penalized quadratic model to deal with the non-linear distortion in fingerprint matching was presented by Kai Cao et al [4]. A fingerprint was represented using minutiae and points sampled at a constant interval on each valid ridge. Similarity between minutiae was estimated by the minutia orientation descriptor based on its neighbouring ridge sampling points. Greedy matching algorithm was adopted to establish initial correspondences between minutiae pairs. The proposed algorithm used these correspondences to select landmarks or points to calculate the quadratic model parameters. The input fingerprint is warped according to the quadratic model, and compared with the template to obtain the final similarity score. The algorithm was evaluated on a fingerprint database consisting of 800 fingerprint images.

Peng Shi et.al [13] proposed a novel fingerprint matching algorithm based on minutiae sets combined with the global statistical features. The two global statistical features of fingerprint image used in their algorithm were mean ridge width and the normalized quality estimation of the whole image. The fingerprint image was enhanced based on the orientation field map. The mean ridge width and the quality estimation of the whole image were got during the enhancement process. Minutiae were extracted on the thinned ridge map to form the minutiae set of the input fingerprint. The algorithm used to estimate the mean ridge width of fingerprint, was based on the block-level on non-overlap windows in fingerprint image. Four databases were used to compute the matching performance of the algorithm.

A novel graph based fingerprint matching algorithm was proposed by Sharat Chikkerur et.al.[17]. The local neighborhood of each minutiae was defined by a representation called K-plet that is invariant under translation and rotation. The local structural relationship of the K-plet was encoded in the form of a graph wherein each minutiae was represented by a vertex and each neighboring minutiae by a directed graph. Dynamic programming algorithm was used to match the local neighborhood. A Coupled Breadth First Search algorithm was proposed to consolidate all the local matches between the two fingerprints. The performance of the matching algorithm was evaluated on a database consisting of 800 images.

Jin Qi and Yangsheng Wang [20] proposed a minutia-based fingerprint matching method. They defined a novel minutiae feature vector that integrated the minutiae details of the fingerprint with the orientation field information that was invariant to rotation and translation. It captured information on ridge-flow pattern. A triangular match method that was robust to non-linear deformation was used. The orientation field and minutiae were combined to determine the matching score. They evaluated the performance of their algorithm on a public domain collection of 800 fingerprint images.

Another method for fingerprint identification and verification by minutiae feature extraction was proposed by Atanu Chatterjee et.al[21]. Minutiae were extracted from the thinned ridges from the fingerprint images and these feature matrices were applied as input data set to the Artificial Neural Network. Post processing was done to remove false minutia. Back propagation algorithm was used to train the network. Extracted features of the input fingerprint were verified with stored trained weights and threshold values. Experiments were conducted on 160 fingerprint images and the proposed system exhibited an accuracy of 95%.

A flow network-based fingerprint matching technique for partial fingerprints was introduced by Tsai Yang Jea et.al[22]. For each minutiae along with its two nearest neighbors, a feature vector was generated which was used for the matching process. Minimum cost flow (MCF) problem algorithm was used to find the one-to-one correspondence between the feature vectors and the list of possibly matched features was obtained. A two hidden layer fully connected Neural Network was proposed to calculate the similarity score. Their experiments on two fingerprint databases showed that using neural networks for generating similarity scores improved accuracy.

Marius Tico et.al [26] proposed a method of fingerprint matching based on a novel representation for the minutiae. The proposed minutiae representation incorporated ridge orientation information in a circular region, describing the appearance of the fingerprint pattern around the minutiae. Average Fingerprint Ridge period was evaluated to select the sampling points around the minutiae. Matching algorithm was based on point pattern matching. To recover the geometric transformation between the two fingerprint impressions, a registration stage was included. The Greedy algorithm was used to construct a set of corresponding minutiae. Experiments were conducted on two public domain collections of fingerprint images and were found to achieve good performance.

A minutiae matching method using a local and global matching stage was presented by Asker M. Bazen et. al [27]. Their elastic matching algorithm estimated the non-linear transformation model in two stages. The local matching algorithm compared each minutia neighborhood in the test fingerprint to each minutia neighborhood in the template fingerprints. Least square algorithm was used to align the two structures to obtain a list of corresponding minutia pairs. Global transformation was done to optimally register the two fingerprints that represented the elastic deformations by a thin-plate spline (TPS) model. The TPS model describes the transformed coordinates independently as a function of the original coordinates. Local and global alignments were used to determine the matching score.

Abinandhan Chandrasekaran and Bhavani Thuraisingham [30] presented a fingerprint matching algorithm based on tree comparison. Short Time Fourier Transform (STFT) was used to enhance the overall clarity of the fingerprint image. The common minutiae points from the template and input fingerprint images was obtained by using ratios of relative distance as the comparing function. A tree like structure was drawn connecting the common minutiae points from bottom up. The matching algorithm separated the common minutiae points into confirmed and spurious lists and then generated a matching score. Matching score was obtained by comparing the similarity of the two tree structures based on a threshold value. Experiments were conducted and performance was evaluated on two fingerprint image databases.

A new fingerprint matching algorithm based on radial structure of minutiae was proposed by Kyung Deok Yu et.al [31]. Voronoi diagram was constructed for the radial structure consisting of center minutiae and its neighbors in a fingerprint image. Fortune's algorithm was used to generate the Vironoi diagram. The proposed matching algorithm compared the radial structures of a query and template fingerprint image. If the number of similar radial structures was less than a preset threshold, transformation parameters were estimated using the three radial structures having the highest score in the first stage. Similarity was decided by translating and rotating the query along the extracting parameters. Their approach was robust to false minutiae.

A novel alignment free minimum distance graph (MDG) based fingerprint hashing algorithm for recognition was proposed by Priyanka Das et.al [32]. Core and minutiae points were used as features in their algorithm. Core point was detected using the orientation field and crossing number concept [CN] was used to detect minutiae points. In their hashing algorithm they had constructed the MDG graph comprising of the inter-minutiae minimum distance vectors originating from the core point. Correspondence search algorithm was used to search for the correspondences between the template and query images using their distance vectors. Matching was decided based on the total number of similar pairs. The proposed algorithm was evaluated on two public domain databases.

Xiang Fu et al[33] proposed a new minutia tensor strategy for fingerprint matching. This approach proposed a minutia tensor matrix (MTM) that described the first order and second order features of a matching pair. First-order tensor pair described similarities of each minutiae pair and second-order tensor matrix described compatibilities between each two minutiae pairs. Correct minutiae pairs established both large similarities and compatibilities that formed a dense sub-block. Minutia matching was formulated as recovering the dense sub-block in the MTM. Spectral matching method was used to extract the dense sub-block. Two kinds of MTMs were constructed to show both local rigidity and global non linearity for local matching and global matching respectively. Experiments conducted on two fingerprint databases demonstrated the effectiveness and efficiency of the proposed algorithm.

A Graphics Processing Unit(GPU) fingerprint matching system based on Minutia Cylinder Code(MCC) representation was presented by Pablo David Gutiérrez et.al [34]. The proposed algorithm used GPUs to introduce parallelism in the fingerprint matching process. The neighborhood characteristics associated to each minutia was represented by a 3-dimensional structure, called cylinder. The fingerprint to be compared to the fingerprint database was represented in cylinders representing minutiae discretized into cells. For fingerprint matching, a similarity value is computed for each cylinder pair of referenced and input fingerprint. GPU computed the matching score of the input fingerprint with different fingerprints of the database simultaneously. The evaluation of the proposed algorithm was performed on different hardware devices and on different kinds of databases in order to test the robustness and effectiveness of the system.

Rodrigues R.M et.al[35] proposed a fingerprint identification system based on a new characteristic vector model for fingerprint representation. Planar graph and triangulation algorithms were used for generating characteristic vector. Delaunay triangulation was initially calculated using the extracted minutiae set. Sub-graphs resulting from Delaunay triangulation associated with each minutia were identified. All the sub-graphs represented in the system coordinates were codified in polar coordinate system so that the characteristic vector was not dependent on rotation and small distortions. A similarity coefficient was computed by comparing the characteristic vectors of the two fingerprints. The proposed algorithm was validated using a fingerprint database and was found to show a better performance.

Table 2 : Performance Analysis of minutiae-based fingerprint matching

Sl.No	**Author**	**Year**	**Method Used**	**Accuracy/ Performance**	**Benefits and Restrictions**
1	Xiang Fu et al.[33]	2015	Minutia tensor matrix (MTM), Spectral matching.	EER – 2.47% Average matching time - 1.02 (ms)	Stronger description ability and better robustness to non-linear deformation and noise/matching true minutiae pairs that exhibit low similarities and compatibilities remain unsolved.
2	Rodrigues R.M et.al [35]	2015	Planar graph, Delaunay triangulation, Characteristic vector model	EER – 1.14%	Efficient representation of fingerprints,Invariant to rotation and small distortions, Simplifies the computational complexity
3	Pablo David Gutiérrez et.al[34]	2014	Minutia Cylinder Code(MCC), Graphics	EER – 0.62%	Reduction in matching time for large databases due to parallel

			Processing Unit(GPU)		processing, hence suitable for real time applications/computational requirements not very feasible
4	Priyanka Das et.al [32]	2012	Minimum Distance graph, Correspondence Search algorithm	EER – 2.27%	Pre-alignment phase not required, Invariant to distortions such as rotation and translation, Low computational complexity
5	Atanu Chatterjee et.al[21]	2010	Artificial Neural Networks, Back propagation algorithm	95% accuracy	Reduce time complexity while working with large databases
6	Kai Cao et al [4]	2009	Minutiae, greedy algorithm, quadratic model	EER – 7.05%, time - 0.599 s	Robust to non-linear distortions and can dynamically estimate the similarities / improvement in matching time required for this model
7	Weiguo Sheng et.al[1]	2007	Minutiae local feature, genetic algorithm(GA), local improvement operator, Memetic algorithm(MFMA)	EER – 0.9 Matching time – 3.59s	More reliable matching operation but more computational time required for matching.
8	Peng Shi et.al [13]	2007	minutiae sets, global statistical features, mean ridge width, quality Estimation	EER on 4.43% lower than without global statistical features	Improve the accuracy of similarity measure without increasing time and memory consumption / Depends on the accuracy of estimating mean ridge width.
9	Abinandhan Chandrasekaran and Bhavani Thuraisingham [30]	2007	Short time Fourier transform(STFT) for enhancement, common minutiae points, tree structure	GAR – 96.25%	No pre-alignment needed and robust to distortions caused by spurious minutiae points, algorithm is sensor independent.
10	Sharat Chikkerur et.al [17]	2005	K-plet representation, dynamic programming, Coupled BFS	EER – 1.5%, FMR100 – 1.65%	Robust to non-linear distortion, solved ambiguities in minutiae pairing, explicit alignment not required

11	Jin Qi and Yangsheng Wang [20]	2005	Minutiae and orientation field, triangular matching	EER - 4.97%, average enrolment time : 0.81, match time : 0.03	Robust to non linear deformation.
12	Tsai Yang Jea et.al[22]	2005	Minimum cost flow(MCF), Artificial Neural network	EER - 1.71%	Handle spatial distortions, generate accurate similarity score for partial fingerprints.
13	Kyung Deok Yu et.al [31]	2005	Radial structure, Voronoi diagram	Matching rate – 91.78%	Robust to false minutiae /combined radial structure is needed to achieve higher matching accuracy.
14	Marius Tico et.al [26]	2003	Minutiae and orientation descriptor, Greedy algorithm, point pattern matching	EER – 2.3%	Low complexity algorithm, reliable similarity measure
15	Asker M. Bazen et. al [27]	2003	Minutiae neighborhood, thin-plate spline , least square algorithm	EER – 2.5%	Deals with elastic distortions of fingerprints and achieved high matching scores for deformed fingerprints.

2.1.3.Non-Minutiae feature based matching

For extreme low-quality fingerprint images minutiae extraction is difficult. The fingerprint structure consists of periodical repetitions of a pattern of ridges and valleys that can be characterized by its local orientation and frequency, ridge shape, texture information etc. The approaches belonging to this family compare fingerprints in term of features extracted from the ridge pattern.

Aparecido Nilceu Marana and Anil K. Jain [2] proposed a new fingerprint matching technique based on **ridge features**. The ridges of the query and the template fingerprints were detected on the thinned image. The Hough transform was applied on each ridge separately to detect only the straight lines which match each ridge. A threshold was used to detect the peaks of the Hough space for each ridge which were used to estimate the rigid transformation parameters between the query and the template fingerprint images for alignment. Finally, the matching score proportional to the number of matching ridges were calculated. The proposed methodology was evaluated on a database consisting of fingerprint impressions of 160 users. Ridge features combined with minutia features lead to more accurate fingerprint matching.

Anil K. Jain and Jianjiang Feng [5] developed a fingerprint matcher for matching latent fingerprints against rolled/plain fingerprints. The proposed algorithm had used extended features that included singularity, ridge quality map, ridge flow map, ridge wavelength map, and skeleton in addition to minutiae**.** Poincare index method was used to detect singular points in ridge flow map. Local minutiae matching were performed by determining the similarity between each minutia of input and template fingerprints based on the neighborhood of a minutia defined by a circular region. The similarity between minutiae was computed using the composite minutiae descriptor based on neighboring minutiae, ridge flow, and wavelength features. The proposed fingerprint matching algorithm was evaluated on 258 latent fingerprints against a background database of 29,257 rolled fingerprints.

Another method for fingerprint representation and matching scheme was proposed by Unsang Park et.al [6] using Scale Invariant Feature Transformation (SIFT). A scale space is constructed by applying a variable scale Gaussian operator on an input image. A set of Gaussian-smoothed images and Difference of Gaussian (DOG) images were obtained. Local minima and maxima were detected by observing each image point in DOG space and a histogram of gradient orientation around each local extremum was determined to obtain feature points. Preprocessing was performed to adjust the gray level distribution, and to remove noisy SIFT feature points. Point wise matching was done to compare each feature point based on the descriptor using Euclidean distance metric. The fusion of SIFT with a minutiae based matcher showed significant performance improvement on two public domain databases.

A hierarchical matching system that utilizes features at three different levels namely, Level 1 (pattern), Level 2 (minutia points), and Level 3 (pores and ridge contours) was proposed by Anil K. Jain and Yi Chen [7]. Gabor filters and wavelet transform was used to enhance the ridges and extract pores and ridge contours. In the hierarchical matching, if the matcher was able to establish a correspondence between the two images using the orientation field and minutiae it further proceeds to examine Level 3 features. Pores and Ridge contours in the neighborhood of the matched minutiae was compared and matched using Iterative Closest Point algorithm. Their hierarchical matching system was experimented using a database consisting of 1,640 fingerprint images and was found to show significant performance gain.

Mayank Vatsa et.al [8] proposed a **quality-augmented match score fusion algorithm** which fuses match scores obtained from matching level-2 and level-3 features of fingerprint images. The proposed method assessed the image quality by using redundant discrete wavelet transform and a quality score was computed. The fingerprint minutiae were detected by tracing the gray level ridge. Gabor filtering, binarization, morphological filtering and tracing were used to extract pores. A match score was obtained each for Minutia-based fingerprint verification algorithm and pore-based verification algorithm as they are used as the primary classifiers. The quality-augmented match scores of the above matching algorithms were fused using **Dezert–Smarandache (DSm)** theory. The proposed algorithm was validated experimentally using a fingerprint database containing rolled, and partial fingerprints.

A fast fingerprint verification algorithm using level-2 minutiae and level-3 pore and ridge features was proposed by Mayank Vatsa et.al [10]. The proposed algorithm used a two-stage process to register fingerprint images using minutiae features. Taylor series based image transformation was used to perform coarse registration in the first stage and thin plate spline transformation was used for fine registration in the second stage. The Mumford-Shah functional curve evolution was used in the algorithm to efficiently segment contours and extract pores. Delaunay triangulation based fusion algorithm was proposed to combine level-2 and level-3 information and a feature supervector is generated. Support Vector Machine was used for fingerprint matching. The performance of the proposed algorithm was evaluated and was found to improve the verification accuracy.

Xinjian Chen et.al [12] proposed a novel fuzzy feature match (FFM) based on a local triangle feature set to match the deformed fingerprints which was **represented by the fuzzy feature set**. The similarity between fingerprints is characterized by using the similarity between the fuzzy feature set. The FFM method maps a similarity vector pair to a normalized quantity which quantifies the overall image to image similarity. The proposed algorithm was evaluated with two fingerprint databases. Experimental results confirmed that the proposed algorithm worked well with the nonlinear distortions.

Qijun Zhaowe et.al [14] proposed a new approach to align high resolution partial fingerprints using pores. Difference of Gaussian filtering approach was used to first extract Pores from the fingerprint images. A novel descriptor, namely pore–valley descriptor (PVD) was proposed to describe pores based on the neighboring valley structures and ridge orientation field. A PVD-based coarse-to-fine pore matching algorithm was used to locate pore correspondences. Once the corresponding pores were determined, two different approaches were employed for matching. The first approach was a minutia and pore based matcher and the second was an image-based matcher called GLBP matcher based on Gabor and local binary patterns. The proposed fingerprint alignment method was evaluated on a set of high resolution partial fingerprint images by using a custom-built fingerprint scanner of approximate 1200 dpi and was found to achieve significant improvements over the minutia-based method.

Liu Wei-Chao and Guo Hong-tao [15] proposed a recognition algorithm based on association features and multi-subset matching. Gabor filtering is used to remove noise and enhance the fingerprint image. The proposed algorithm used One Pass Thinning Algorithm to refine the fingerprint image. The whole image was evenly divided into N sub-images, and the non-directional characteristic like statistical correlation characteristics, the bifurcation point and end points of each sub-image were extracted to generate the feature subsets. 8-neighbor method was used to extract branch points and ends points of the fingerprint ridges. Matching method based on multi-subsets was to determine the valid subset in the input image and respectively by-matched with all subsets of the registered image. The performance of the algorithm was validated using complete and occluded fingerprints data sets.

Anil K. Jain et. al [18] have used a technique to match fingerprints based on texture information. A bank of Gabor filters was used to capture local and global details in a fingerprint as a compact fixed length FingerCode. The fingerprint area of interest is tessellated with respect to the core point. Each fingerprint image is filtered in a number of directions and a fixed-length feature vector called the FingerCode is extracted. The proposed method used a 640 fixed-size FingerCode to represent each fingerprint. Matching was based on the Euclidean distance between the FingerCodes.

Loris Nanni and Alessandra Lumini [19] presented a novel hybrid fingerprint matcher system based on local binary patterns. The two fingerprints were first pre-aligned based on the sets of minutiae extracted. The images were decomposed into several overlapping blocks and each block was convolved with a bank of Gabor filters at different scales and orientations to obtain more detailed information about the local orientation and scales of the ridge lines. The Local Binary Pattern(LBP) features computed as the difference between the gray value of a central pixel and the average gray value over its circular neighborhood was extracted from the convolved image. The similarity between the two LBP histograms was evaluated by their Euclidean distance.

Weiwei Zhang and Yangsheng Wang [28] presented a new core-based structure fingerprint matching algorithm. Core point was detected in two stages. The low resolution direction field was used to localize a singular area that included the core point. Then a high resolution direction field of singular point was used to precisely localize the core point. Minutiae points near the core point of the fingerprint were used to construct a local structure. Global matching was done using the correspondent point pair selected from local structure matching. The proposed method was evaluated on a fingerprint image database that included various type quality images.

Another novel fingerprint matching algorithm using both minutiae and ridge features was proposed by Heeseung Choi et.al [29]. Gabor filter was applied to enhance the image. To extract ridge features between two minutiae, a ridge-based coordinate system had been defined in a skeletonized image. The proposed algorithm extracted ridge features composed of ridge count, ridge length, ridge curvature direction and ridge type. Graph matching method was adopted in fingerprint matching. Ridge feature vectors between the minutiae were expressed as a directional graph with minutiae as nodes and ridge feature vectors as edges. Dynamic programming using Breadth First Search (BFS) was used to detect the matched minutiae pairs. Similarity score computed was based on Bayesian decision rule. Experimental results of the proposed algorithm showed higher matching scores than conventional minutiae-based methods.

Table 3 : Performance Analysis of Non minutiae feature-based fingerprint matching

Sl.No	Author	Year	Method Used	Accuracy /Performance	Benefits and Restrictions
1	Liu Wei-Chao and Guo Hong-tao [15]	2014	Gabor filter, multi association matching features (RA-MAMF) algorithm	For 25% Occluded degree, 95.6% accuracy	Improved accuracy for Occluded fingerprint / binarization and thinning required
2	Anil K. Jain and Jianjiang Feng [5]	2011	Poincare index method, extended features, neighboring minutiae-based descriptor	82.9% accuracy	Improvement in the matching accuracy for low quality latent fingerprints, robust to noise /accurate estimation of extended features is required.
3	Heeseung Choi et.al [29]	2011	Ridge-based coordinate system, graph matching, Breadth First Search,	EER – 1.8%	Robust against non-linear deformation/improvement in matching is needed for low quality images
4	Qijun Zhaowe et.al [14]]	2010	Pores, Difference of Gaussian filtering, pore–valley descriptor	98% Accuracy	Partial fingerprints can be aligned/ suitable for high resolution fingerprints.
5	Mayank Vatsa et.al [10]	2009	Fingerprint registration, Delaunay triangulation, Support Vector Machine,	Improves the verification accuracy by 4.96% over other methods	Tolerates minor deformation of features and non-linearity in the fingerprint information/ used two-stage registration process
6	Unsang Park et.al [6]	2008	Scale Invariant Feature Transformation, Scale Space Construction,	(SIFT + minutiae) EER – 0.99%	High matching speed/ Improvement in matching can be achieved only by combining with other texture or minutiae based

			Point wise Matching		operations.
7	Mayank Vatsa et.al [8]	2008	Redundant discrete wavelet transform, Dezert–Smarandache theory	Accuracy - 97.98%	Handles inconsistent, and incomplete fingerprint information
8	Loris Nanni and Alessandra Lumini [19]	2008	Gabor filters, Local Binary patterns	EER – 6.2%	Robust to noise and skin distortions/ computationally expensive
9	Anil K. Jain et.al [7]	2007	Gabor filter, wavelet transform, Pores and Ridge contours, Iterative Closest Point	Performance gain of 20% in terms of EER over the Level 2 matcher.	Consistent performance gains observed in both high and low quality images/ high resolution sensors required for feature extraction.
10	Xinjian Chen et.al [12]	2006	local triangle feature set fuzzy feature set, genuine distorted pattern parameter space	The EER on NIST 24 - 3.11%. DB1 and DB3 of FVC2004 - 4.06% and 1.35%, respectively	Worked well with the nonlinear distortions/ overlapping area between the template and input image should be large for genuine matching
11	Aparecido Nilceu Marana and Anil K. Jain [2]	2005	Ridge features, Hough transform	(Minutiae-Ridge combination) EER – 3.03%	More accurate matching for images of poor-quality/ higher processing time.
12	Weiwei Zhang and Yangsheng Wang [28]	2002	Core point, local and global matching	When FAR is 5.0%, FRR is 0.08%	Less time for matching, suitable for on-line applications
13	Anil K. Jain et.al. [18]	2000	Fingercode, Gabor filters	For threshold 30 – FAR 0.10%, FRR 19.32%	Computationally attractive matching indexing ability/ not well suited to handle non-linear distortions.

2.2.Performance Evaluation

There are several performance evaluations to estimate the algorithm for fingerprint matching Most of the approaches quoted here used False Non Match Rate (FNMR) often referred to as False Rejection Rate (FRR), False Match Rate (FMR) often referred to as False Acceptance Rate (FAR), Equal Error Rate (EER), Zero FNMR, and Zero FMR. The performance metrics are as follows:

2.2.1.False Rejection Rate

The rate at which a registered user is falsely rejected by the system compared to the total number of trials.

2.2.2.False Acceptance Rate

The False Acceptance rate / False match rate is the probability that the system incorrectly authorizes a non-authorized person, due to incorrectly matching the biometric input with a template.

2.2.3.Equal Error Rate

The common value of FAR and FRR, when the FAR equals the FRR. A low EER value indicates a high accuracy of the system.

2.2.4.Zero FNMR

Zero FNMR is defined as the lowest FMR at which no false non-matches occur.

2.2.5.Zero FMR

Zero FMR is defined as the lowest FNMR at which no false matches occur

3.CONCLUSIONS

A large number of techniques for fingerprint matching for the purpose of authentication proposed in the literature have been reviewed. In the last two decades, most of the fingerprint matching algorithms presented are minutiae based. Non-minutiae methods based on local texture, ridge geometry, ridge spatial relationship and pores have also been proposed in conjunction with minutiae matching. This paper provides a broad study of the various algorithms used in fingerprint matching based on the various fingerprint representations and features extracted from the fingerprints images. A performance comparison table of different techniques proposed earlier for fingerprint matching, evaluated on the various parameters explained in section 2.2 is also presented. The benefits and restrictions of these approaches have been highlighted.

According to the survey, the techniques for fingerprint matching based on non-minutiae features integrated with minutiae approaches are receiving substantial interest. The matching approach proposed by Jain, Chen and Demirkus [7] showed that there is a relative reduction of 20% in the EER when matchers using level 3 features and level 2 features were combined to obtain the final score. The performance gain was consistently observed for various quality fingerprint images [7]. As fingerprint systems are being deployed world-wide on a large scale, it demands accuracy and highly interoperable algorithms. In this context, our future work mainly concentrates on integration of approaches based on global features and local structures that reduces computational complexity and adverse effects of noise and distortion, thereby significantly improve the speed and accuracy of the matching process.

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