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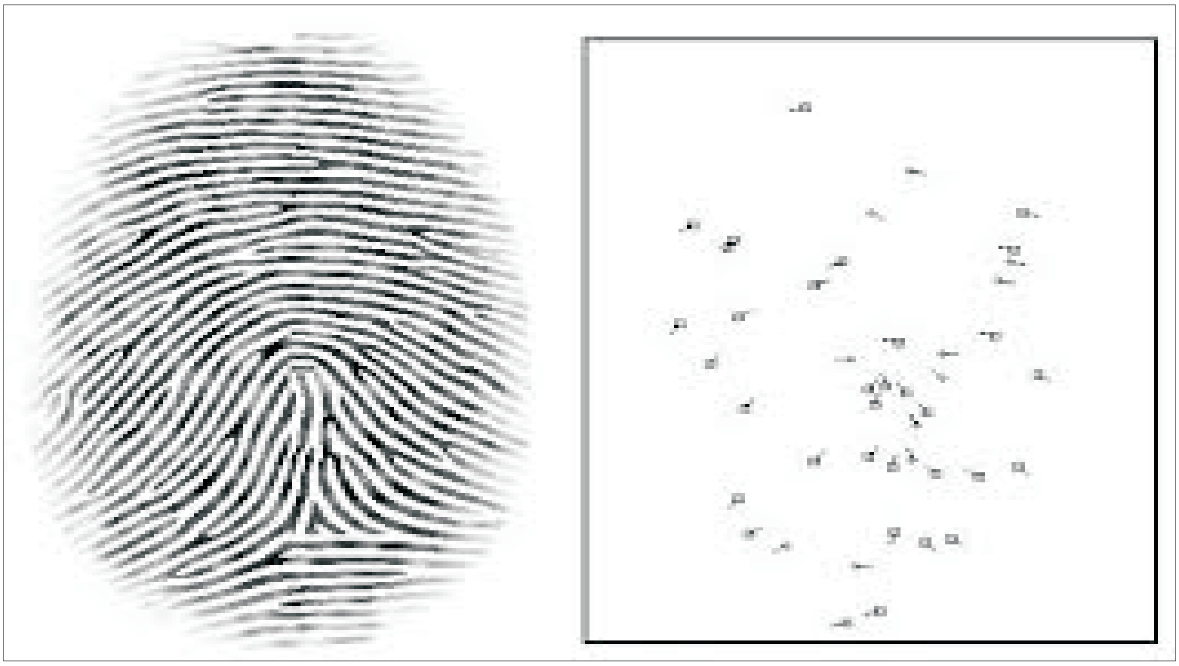
FINGERPRINT RECOGNITION USING MINUTIAES



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ABSTRACT:

The Main purposes of the recorded Fingerprints are to identify repeat offenders who often use an alias to hide their true identity andto perform background checks for employment or licensing.An important application of Fingerprints in Law Enforcement is to establish the Identity of a suspect based on partial Fngerprints (latent Fingerprints or simply Latentss) left at a crime scene. Minutiae based Recognition is used here .Minutiae based representations are extensively used in Automated Fingerprint Recognition systems, primarily due to the following reasons :Minutiae capture much of the discriminative or individuality informationin Fingerprints and Minutiae basedrepresentations are storageefficient.Minutiae Extraction is reasonably robust to various sources of degradation. Feature extraction can be challenging in poor quality fingerprints .It requires the fingerprint to be complete (i.e.,a rolled fingerprint). The pattern type ofLatents fingerprints obtained from crime scenes is considered as unknown and Latents Fingerprints are often searched against all

types of fingerprints in the database.The proposed Latents Fingerprint method outperforms the commercial matchers.

KEY WORDS: Latents Fingerprints, Minutiae ,Latents Fingerprints Matching ,Latent Fingerprint Recognition, Features, Ridges,Latents.

INTRODUCTION:

Compared to rolled and plain fingerprints ,Latents Fingerprints have poor image quality. As the size of Fingerprint Databases began to expand to the millions, the Automated Fingerprint Identification Systems (AFIS) weredeveloped in the 1970s to improve the efficiency and accuracy of fingerprint Matching. At present almost every Law Enforcement Agency worldwide relies on AFIS to match Fingerprints.Fig1.showsthe AFI Sinstall edatthe Michigan State Policefacility. Growingconcernsa bouthome landsecurity and consumer fraudha veprompted the use of Fingerprint based biometric systems in many non forensic capplications.

Fig. 1 AFIS installation at Michigan State Police facility. This system was first installed in 1989; the database

Fingerprint Recognition is one of the most mature biometric technologies overa decade. Some of the challenges to apply Fingerprint Recognition to other fields are :

Capturinghighquality Fingerprintimages fromfingersun dernonidealconditions and unhabituated users is still problematic. One technology that shows promise is the acquisition of 3D fingerprints in a touchless mode. A major advantage of this modality is that it can capture rolled equivalent Fingerprint images much fasterth anthe convention alrolling process .Itmay also avoid theskindistortion introduced byrollingandother pressure variations.

The wide deployment of Fingerprint Recognition systems in various applications has also resulted in some novel methods for circumvention. It has been reported that some individuals have successfully defeated positive Recognition systems (e.g. physical access control systems) using spoof fingers and some individuals have successfully circumvented negative Recognition systems (e.g. border controlsystems) bysurgically alteringtheir Fingerprints. research isrequired toassure theintegrityo fFingerprints presented tothesensor.

Although Fingerprint Recognition is one of the earliest applications of pattern Recognition, the accuracy of state-of-the art Fingerprint Matching systems is still not comparable to human Fingerprint experts in many situations, particularlyLatentsprint Matching where imagequality tendstobepoor .State-of-the-artfingerprint identification systems require extensive manual intervention inLatents encodingand inverify in gacandidate listreturned by the system. With thein crease in Latents Matching transactions for civilian, Law Enforcement, and homeland security applications, Automated Latents Fingerprint processing and Matching is a fruitful area of Research.

Theuse of Finger print Recognition system sinlargescale Government and civilian applications hasraise dconcernsa boutthe Finger printtemplate's security and theresulting privacy of theuser.Security and privacy are of particular concern in centralized databases, which can store millions of Fingerprint templates .Privacy Enhancing technology along with cancel able biome tricsislikely to raise the privacy and security level so fsuchcritical personalin formation. More research is required to incorporate these schemes in an operational environment.

FRICTIONRIDGE PATTERN

Fingerprint Recognition methods can be Feature based or Image based. Both these methods are wide lyuse dinthe Literature to indicate the me thodsused for representing and Matching images suchas Fingerprints.

A Feature basedmethod extracts explicit Features from the image under consideration and encodes these Features into a Feature set, which is subsequently used for Matching.

An Image based method directly uses the image for Matching with out explicitly extractingany Features fromit.

Feature basedLatents Fingerprint Recognition are : Manually by a Human Expert,Semiautomatic ,Automatically by a Machine

Fundamental requirements ofLatents Fingerprint Recognition are :

The Knowledge of differentty pesof Features(The details in the Fingerprint are Level1,Level 2,Level 3 Features) thatcanbe Extracted froma Fingerprint.

The description of the histology of Friction Ridges kinandits formation inunder standing theuniqueness and permanence of Friction Ridge patterns.

FEATURES

Major Fingerprint pattern typesare Plain arch, tented arch, left loop, right loop, whorl and twinloop.

Each Ridge is only one pixel wide. The exact locations of the Ridges are recorded in level 2. The geometric and dimensional details of the Ridg esareignored.Thelocations wherea Ridgeemerges ,Ends ,Splits ,or Merges with another Ridge are called as Ridge characteristics or Minutiae.

The properties of Minutiaesare : Direction &Type.

The direction faMinutiae isalong the localRidgeorientation.There are two basicty pesof Minutiae: ending ('termination') and bifurcation .Each Minutiae can be characterized by its :Location in the image,Direction,Type. Level 2 details of a Fingerprint can be easily observed in images acquired at a resolution of 500 ppi. The number of Minutiae found in a Fingerprint varies a lot according to the acquisition method and other factors.

Example : Commercial Fingerprint Matcher extracts 136 Minutiae from the Rolled impression of a Finger and 56 Minutiae from Plain impression.But only18 Minutiaeinthe Latents by aLatent sexaminer.

A Minutiae set, consisting of all the Minutiae in a Fingerprint, is an abstract representation of the Ridge skeleton ,that the Minutiae set captures most of the discriminative in formation at Level2 and Ridgesk eleton scan beapproximately derived from the Minutiae information alone. The spatial distribution of Minutiae (Ridge ending & bifurcation are the most extensively used Ridgean omaliesin Automated Finger print Recognition systems)in a Fingerprint is required for the assessing thein dividuality of Fingerprints.

ADDITIONAL FEATURES

Fingerprints other Featuresare :creases, cuts, and scars. These Features are not inherent to Fingerprint formation, they may become permanent depending on the severity of cuts and scars. These Features are not as universal as the three levels of Features,their utility in Fingerprint Matching is limited. These abnormalities are often the source of Matching errors.

The clarity of Ridge pattern is another important determinant of quality. Both the finger skin and the sensor have a large impact on the Ridge clarity.

In a good quality Fingerprint, Ridges continuously fiow and adjacent Ridges are well separated.

When the finger is moist the adjacent Ridges may be joined.

when it is dry, the Ridges may have many breaks and the inherent quality of some fingers is poor Fingerprint images obtained using live-scan or inked techniques are typically of better quality than Latents fingerprints

.

LATENTS FINGER PRINTMATCHING

Latent Fingerprint Recognitioni so fcritica limportance to law Enforcement Agencies in Identifyings us pect sand victims. Latents Fingerprint Matching is more challenging than rolledorplain Fingerprint Matchingdue to typically poorimage quality, small finger area, and large nonlinear distortion of most Latents Fingerprints. State-of-the-art Feature Extractors do not work well for many of the difficult Latents images. Minutiae in Latents Fingerprints are manually marked by trained Latents Fingerprint examiners in order to efficiently Extract the limited information available.

Due to the limited number of Minutiae in many Latents Fingerprints, it is not possible to accurately match Latents Fingerprints solely based on Minutiae. As an example, Latents Fngerprints in a public domainLatents Fingerprint database, NIST SD27 [19], have 21 Minutiae per Fingerprint image , on average, (the minimum and maximum number of Minutiae for Latents Fingerprints in NIST SD27 are 5 and 82 respectively) while the corresponding (mated) rolled prints on average have 106 Minutiae (the minimum and the maximum number of Minutiae in the rolled prints in NIST SD27 are 48 and 193). One way to improve the Latents Fingerprint Matching accuracy is to utilize a more complete Feature set (namely, the extended Feature set that includes Level 3 details) in Matching. While some algorithms have been proposed for Matching plainorro lledfinger prints using extended Features, Latents Matching based on extended Features is still an open problem. Amainchalleng eisho wtore liably encode and match Level3 Feature sinpoor quality Latents Fingerprints.

Evidence based on Fingerprints has been believed to be infallible and as such it has been accepted in U.S. court sof Lawforalmosta century . There liability of Fingerprint evidence is being challenged under the Daubert standard, a set of criteria regarding the admissibility of scientific testimony largely derived from a 1993 Supreme Courtcase .The Dauber stand ardhas two basicrequirements forsour ceof ForensicEvidence: the unde rlying scientific basis should be accepted widely and its errorrate should be known.It is the“knownerrorrate”criterionof the Dauber trule that has been primarily used to question the scientific value of Fngerprint Evidence. Many researchers have attempted to estimate the inherent individuality of Fingerprints, the actual problem of estimating the error rate of Latents Fingerprint Identification, which involves human factors in many stages (Latent Fingerprint development, encoding, Matching) is not yet solved. The only viable solution in the near term may be to keep improving the performance of Automated Fingerprint systems and ultimately replace human experts with Automated systems.

LITERATURE SURVEY

The discovery of many archaeological artifacts having human fingerprint impressions on them indicates that ancient civilizations were aware of the Fingerprints. This awareness did not appear to have resulted in any analysis of the Fingerprint patterns and their individuality until the late seventeenth century [34, 40]. The first scientific study of Fingerprint structures was reported in a publication by Nehemiah Grew in 1684 [34] and a detailed description of the anatomical formation of fingerprints was provided by Mayer in 1788 [40]. In 1823, Purkinje was the first to classify fingerprints into nine categories according to the Ridge configurations [40]. Readers interested in knowing more about the early history of fingerprints are referred to [11, 40, 4, 34].

It was only in the late nineteenth century that the scientific community started contemplating the use of fingerprints as a tool for person identification. The foundation for modern fingerprint Recognition was laid in 1880 by Henry Faulds [12] and Sir William Herschel [24], who independently suggested the individuality of finger- prints based on empirical observations . This was quickly followed by the work of Sir Francis Galton, who extensively studied the characteristics of fingerprints [18] and introduced the Minutiae Features for Fingerprint Matching [17]. The claim of uniqueness of fingerprints did not lead to an immediate demise of the anthropometric system of identification (introduced by Bertillon), which was in use at that time. This was due to the lack of an efficient scheme to index large fingerprint databases in such a way that human experts can quickly search for similar Fingerprints and perform manual fingerprint identification. An important breakthrough was made by Edward Henry in 1899 , who established the well-known "Henry system" of finger- print classification [23].

In 1891, Argentine police officials initiated the Fingerprinting of criminals and used Fingerprints as evidence in a homicide case in 1892 [22]. This appears to be the first use of fingerprints in criminal proceedings. Soon, fingerprint Recognition came to be formally accepted as a valid personal identification method and became a standard routine in forensics [34]. Fingerprint identification agencies were set up world wide and fingerprint data bases were established by law enforcement agencies . The Federal Bureau of Investigation (FBI) in the United States set up its fingerprint identification division in 1924 with a database of 810, 000 Fingerprint cards [13].

Various Fingerprint Recognition procedures, including techniques for Latents Fingerprint acquisition [14] and standards for fingerprint Matching were developed [33].

The initial success of Fingerprint Recognition led to its rapid expansion in law enforcement and forensic applications. As a result, operational Fingerprint databases became so huge that it was infeasible to perform manual Fingerprint card searching even with the aid of "Henry system" of classification. This created a strong demand for Automated fingerprint identification systems (AFIS). One of the first publications on Automated Fingerprint Matching was authored by Mitchell Trauring in 1963 [49]. The U.S. National Bureau of Standards (NBS), which later evolved into the National Institute of Standards and Technology(NIST), started the formal testing of Automated Fingerprint identification systems in 1970 [53] and the FBI installed its first prototype AFIS in 1972.

As rightly predicted by Trauring [49], the use of Automated Fingerprint recognition has not been limited to law enforcement and forensic applications. Today, Automated fingerprint Recognition technology is being used in a number of civilian applications for physical and logical access control and by government agencies for civil registry and border crossing. This has been made possible through technological advances in the following three main areas : livescan Fingerprint sensing, fingerprint image analysis and Feature Extraction, and Fingerprint Matching techniques. While the following paragraphs present a brief review of the evolution of Automated fingerprint Recognition technologies, the reader should consult [39, 10] for a more detailed description.

A good overview of the innovations in Fingerprint sensing devices can be found in [39, 56]. The Frustrated Total Internal Refiection (FTIR) technique that is widely used for live-scan fingerprint acquisition was first proposed in 1984. While the concept of solid-state sensors was proposed in the 1980s, such sensors became commercially available only a decade later. In the last two decades, the focus has been on improving the sensing technology to reduce cost and make the sensors compact (e.g., sweep sensors), capture high resolution fingerprints, rapidly acquire impressions of all ten fingers, acquire fingerprints in a touchless manner , and detect spoof or fake fingers.

The most commonly used Features used in Automated Fingerprint Recognition are the Minutiae, which are also known as Galton details [17]. With the advent of high resolution sensors, researchers have also been examining the use of more intricate details such as sweat pores and finer Ridge structures for Automated fingerprint Recognition [28]. Several efforts have also been made to standardize the definition of Minutiae [2, 26, 27] and other extended Features in a fingerprint [3]. Attempts have also been made to quantify the uniqueness of different fingerprint Features through statistical modeling [46, 42, 58]. The possibility of reconstructing a Fingerprint from Minutiae points has been established [44, 9], thereby challenging the previously held notion that a Minutiae template does not divulge information about the actual fingerprint image.

Fingerprint image analysis and Automated Extraction of fingerprint Features has been studied extensively over the last five decades. Most of the preprocessing steps in Automated Feature Extraction such as computation of local image gradients [21],estimation of the Fingerprint orientation field [31, 43, 5] , regularization and modeling of the orientation field [45, 32, 51], estimation of the local Ridge frequency [38, 25], segmentation of the Fingerprint area from the background [43] , and enhancement of the Ridge valley structure [41, 25] have been studied in detail. Several techniques have also been proposed for Automated Extraction of singular points (core and delta) that can facilitate easy alignment of fingerprint patterns [32, 54], Minutiae detection either through binarization and thinning [43, 29] or through direct gray-scale Extraction [37] , postprocessing of Extracted Minutiae to filter out spurious ones and estimation of other Features like Ridge counts.

Numerous solutions have been proposed in the literature to tackle the problem of Matching Features from two fingerprint images to determine if they are from the same finger. These solutions include Minutiae-based matchers [54, 29], and matchers based on other Ridge and texture Features [30]. While Minutiae based techniques are the most popular , there are a number of variations within this approach itself depending on how the Minutiae

Features are aligned, how the Minutiae correspondences are determined, and how these correspondences are converted into similarity measures . The use of other Features in addition to Minutiae , such as orientation field [48], frequency map [50], and Ridge skeleton [15] have also been considered. The problem of automatically classifying fingerprint images based on the "Henry system" of classification has also received wide attention due to its ability to speed-up the search in large -scale fingerprint identification systems [32, 7, 8] . Other indexing schemes that facilitate rapid search in large-scale systems without relying on the traditional fingerprint classes have been proposed [20, 6].

RIDGE EXTRACTION

Minutiae are special points on Ridges, it is natural to first Extract Ridges and then detect the Minutiaeon Ridges. Since Ridge sare darkerthan valleys, astraight forward method to detect Ridge sistoclassify an ypixelasa Ridge pixeli fitsgrayvalue is lower than a threshold (for example, the mean of its local neighborhood). For most fingerprint images, this method does not work well for the following reasons: (1) pores on Ridges are brighter than the surrounding pixels; (2) Ridges can bebrokendueto cutsorcreases;(3) adjacent Ridgesma yappeartobejoineddueto moist skin orpressure.

To deal with the above problems, Fingerprint image Enhancement is used to connec tbroken Ridgesands eparatejoine dRidges .Asuccessful Fingerprint enhancement method is based on contextual filtering. This involves filtering the image with there alpartofa 2 Dcomplex Gaborfilter who seorientation and frequency are tuned to the local Ridge orientation and frequency.

The Enhancedimage can beconvert edtoabinary image by usingeitherag lobal thres hold (forexample ,usingth emeanpixelvalueoftheenhancedimage)orthresholds that are locally computed. A Morphological operation, called thinning, is used to reduce the Ridge width to one pixel. Thinning is a common technique in image processing,which in volvesiterativelyremo vingouter Ridgepixels.

MINUTIAE EXTRACTION

Once the thinned Ridge image is available, the Ridge pixels with three Ridge pixel neighbors are identified as Ridge bifurcations and those with only one Ridge pixel neighbor are identified as Ridge endings

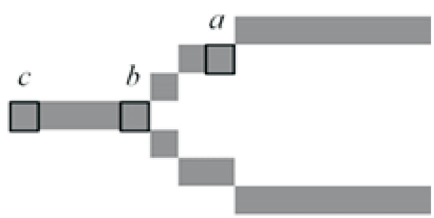
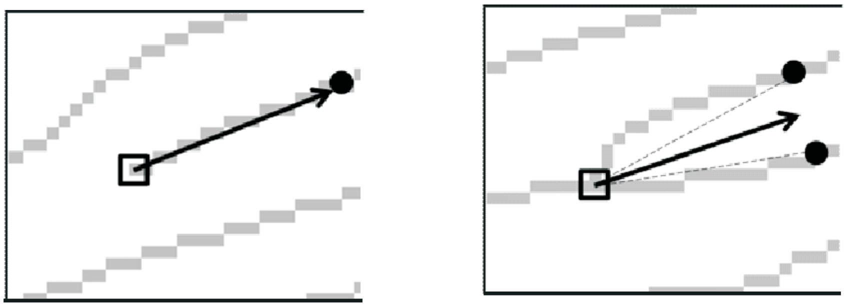


Fig. 2 .Minutiae detection. Three different types of Ridge pixels are marked: typical Ridge pixel 'a', Ridge bifurcation ' b', and Ridge ending 'c'. Either a Ridge bifurcation or a Ridge ending defines a Minutiae.



(a) (b)

Fig. 3.Direction of a Minutiae. (a) Ridge ending and (b) Ridge bifurcation.

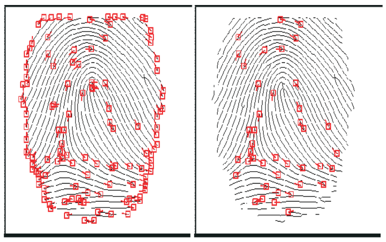


Fig. 4 .Removing spurious Minutiae. (a) Before Minutiae filtering and (b) after Minutiae filtering.

The direction of Ridge ending is computed in the following method :. Starting from the ending x, we trace the associated Ridge to a fixed distance (e.g.10 pixels) and reach a point, say a. The direction xais used as the Minutiae direction. For a bifurcation, there are three associated Ridges, so we obtain three points by tracing the Ridges to a fixed distance The direction of the bifurcation is defined as the mean of the two directions whose difference is the smallest among the three Ridges.

In practice , some of the Minutiae detected using the above approach may be spurious due to artifacts in image processing and noise in the fingerprint image. To remove these spurious Minutiae, a Minutiae filtering algorithm is employed, which typically consists of a number of heuristic rulesi. e Greedy method . Fore.g, Minutiae satisfying any of the following conditions are deemed to be spurious Minutiae and discarded:

1.Minutiae that do not have an adjacent Ridge on either side (mainly the endpoints of Ridges along the fingerborder);
2.Minutiae that are close in location and almost opposite in direction (namely, the difference between two Minutiae directionsis close to180◦);

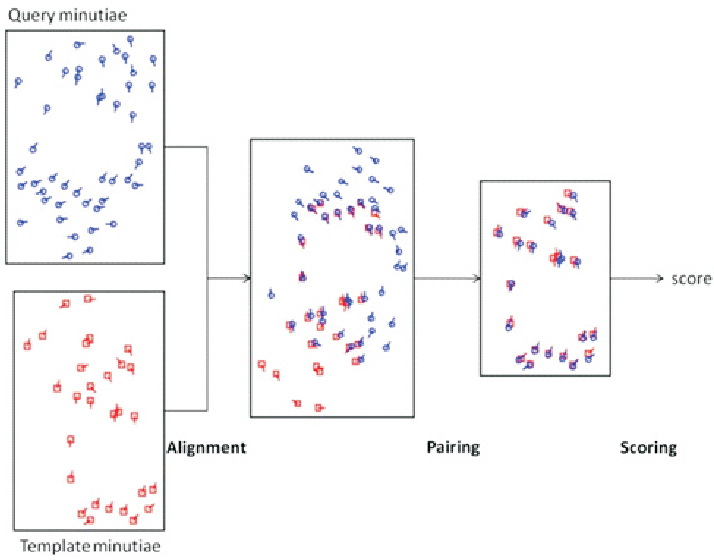
THE PROPOSED ALOGIRHM FOR FINGERPRINT MATCHING

Given the minutiae set $\{x_i^Q, y_i^Q, \theta_i^Q\}_{i=1}^{M}$ of a query fingerprint with M n
the minutiae set $\{x_j^T, y_j^T, \theta_j^T\}_{j=1}^{N}$ of a template fingerprint with N minut
describe a simple matching algorithm which consists of three steps

Alignment: Determine the geometric transformation between the two Minutiae sets so that they

are in thes amecoor dinate system.
Correspondence: Form pair so fcor responding Minutiae.
Scoregeneration: Compute the match score based on the corresponding Minutiae points.

Fig.5 .Flowchart of a Minutiae Matching algorithm



Template Minutiae - is the Reference Latents Fingerprint . Query Minutiae -Enhanced Latents Fingerprint Minutiae.

ALIGNMENT

The two impressions of the same finger taken at different instances could differ due to different placement of the finger on the sensor, an alignment process is required to transform them to the same coordinate system. This process , also known as Registration , transforms one image in such a way that it is geometrically aligned with the other. First, we need to specify a spatial transformation model. A rigid transformation is sufficient for Fingerprint Matching unless a severe nonlinear deformation is introduced during Fingerprint acquisition. Generalized Hough transform is a well known algorithm for estimating the spatial transformation between two point sets. The pseudocode of the Generalized Hough transform algorithm is given in Algorithm 1.

input : Two minutiae sets $\{x_i^T, y_i^T, \theta_i^T\}_{i=1}^M$ and $\{x_j^Q, y_j^Q, \theta_j^Q\}_{j=1}^N$
output: Transformation parameters
Initialize accumulator array A to 0
for $i = 1, 2, \cdots, M$ **do**
  for $j = 1, 2, \cdots, N$ **do**
    $\Delta\theta = \theta_i^T - \theta_j^Q$
    $\Delta x = x_i^T - x_j^Q cos(\Delta\theta) - y_j^Q sin(\Delta\theta)$
    $\Delta y = y_i^T + x_j^Q sin(\Delta\theta) - y_j^Q cos(\Delta\theta)$
    $A[\Delta\theta][\Delta x][\Delta y] = A[\Delta\theta][\Delta x][\Delta y] + 1$
  end
end
return location of peak in A

Algorithm 1: Determining transformation parameters for aligning two sets of fingerprint minutiae using the Generalized Hough Transform Algorithm.

PAIRING MINUTIAE

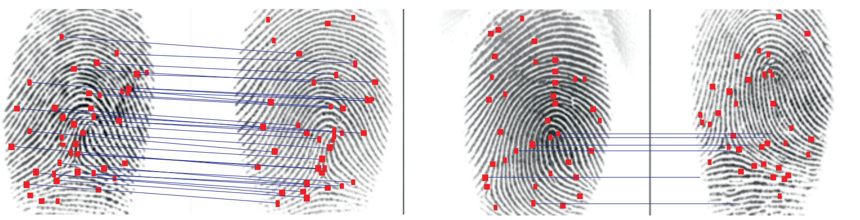
After the two Minutiae sets are aligned, the corresponding Minutiae are paired. A Minutiae a in the template (reference) Minutiae set is said to be in correspondence with Minutiae b in the query Minutiae set if and only if their distance is within a predefined distance threshold (e.g15 pixels) and the angle between their directions is within another predefined angle threshold (e.g 20 degrees). One Minutiae in the template Fingerprint is allowed to match to at most one Minutiae in the query Finger print and vice versa. The pseudocode of a Minutiae pairing algorithm is given inAlgorithm 2.

input : Two Minutiae sets $\{x_i^T, y_i^T, \theta_i^T\}_{i=1}^M$ and $\{x_j^Q, y_j^Q, \theta_j^Q\}_{j=1}^N$;
Transformation parameters $(\otimes\theta, \otimes x, \otimes y)$
output: List of paired Minutiae
Initialize: set flag arrays f^T, f^Q, and *count* as 0; *list* as empty
for $i = 1, 2, \cdots, M$ **do**
  for $j = 1, 2, \cdots, N$ **do**
    if $f^T[i] == 0$ & $f^Q[j] == 0$ & *distance between Minutiae i and j* $< t_d$ & *rotation between them* $< t_r$ **then**
      $f^T[i] = 1$
      $f^Q[j] = 1$
      $count = count + 1$
      $list[count] = \{i, j\}$
    end
  end
end
return *list*

Algorithm 2: Minutiae Pairing Algorithm.

MATCH SCOREGENERATION

In this final step, we need to compute a match score which is then compared to a predefined threshold to classify the two Fingerprints as a genuine match (they come from the same finger) or an impostor match (they come from two different fingers). This problem can be viewed as a two class



classification problem with genuine match as class-1 and impostor match as class-2. For this classification problem, several potential Features for distinguishing genuine matches from impostor matches can be examined. The first Feature is the number of paired Minutiae. It is intuitive that genuine matches should have more paired Minutiae than the impostor matches. The second useful Feature is the percentage of matched Minutiae in the overlapped area between the two fingerprints. Again, it is intuitive that this percentage be larger for genuine matches than for impostor matches . Given a set of Minutiae, the Fingerprint area can be approximated by the convex hull of its Minutiae points.

Match score=614 Match score =7
Fig. 6 Fingerprint Matching by a commercial matcher. (a) A genuine pair of fingerprints with 31

matched Minutiae, and (b) an imposter pair with 6 matched Minutiae. Corresponding Minutiae between the two image sareconnected by lines .The match score is compute dassome function of the number of matched Minutiae and some other param etersthat are proprietary to the commercial matcher.

The proposed Minutiae based Latents Fingerprint Recognition method gives satisfactory results when compared to the Commercial Matchers.

CONCLUSION AND FUTURE WORK

The partial capture of a Fingerprint is one of the main sources of Matching errors .Experiments are conducted on two Latents Databasese :using NIST SD27 and WVU DB (West Virginia University) . The proposed Latents Fingerprint Recognition method outperforms the Commercial matchers .This Latents Fingerprint Recognition method can be speed up by using texture – based descriptor to improve matching accuracy.

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