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Segmentation of slap fingerprints

Derek Johnson

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Segmentation of Slap Fingerprints

Derek M. Johnson

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Chair
Dr. Roger S. Gaborski ______________________________

Reader
Dr. Peter G. Anderson ______________________________

Observer
Yuheng Wang ______________________________

Abstract

This thesis describes a novel algorithm that segments the individual fingerprints in a multi-print image. The algorithm identifies the distal phalanx portion of each finger that appears in the image and labels them as an index, middle, little or ring finger. The accuracy of this algorithm is compared with the publicly-available reference implementation, NFSEG, part of the NIST Biometric Image Software (NBIS) suite developed at National Institute of Standards and Technology (NIST). The comparison is performed over large set of fingerprint images captured from unique individuals.

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Chapter 1

Introduction

The advent of Automated Fingerprint Identification Systems (AFIS) in the late 1990s and the concurrent development of electronic fingerprint scanners has led to an explosion in the number of fingerprints captured during the last decade. The FBI now has over 66 million fingerprint records stored in their IAFIS and they are receiving an average of 162,000 new submissions every day[1]. The number of records available and the relative ease of searching against AFIS databases has led to significant growth in the use of fingerprints to conduct routine background checks for civil purposes. Fingerprint-based criminal history checks are increasingly required by local, state and federal agencies as well as private employers as a condition of employment. The US Census Bureau alone collected fingerprints from each of the more than 700,000 temporary workers that were hired for the 2010 census[12].

Fingerprints that are collected to facilitate criminal background checks are generally not retained by the FBI or state agency. Because they will only be matched against existing fingerprint sets and not against latent prints collected at a crime scene it is not necessary to capture the traditional roll prints from all ten fingers. Instead, a smaller set of fingerprints can be captured that will still provide a statistically suitable match probability against the same individual's fingerprints if they appear a criminal history database. This simpler set of fingerprints consists of only three images images: one containing the four fingers from the left hand, one containing the four fingers from the right hand and one containing both thumbs. Each fingerprint is captured as a single operation, known as a slap fingerprint image. This simpler set of fingerprints are sometimes called 4-4-2 prints because that is the number of fingers that each image is expected to contain. Figure 1.1 shows the full 4-4-2 set image set.

Because the 4-4-2 capture process of does not require any rolling motion, or messy ink and paper, the fingerprint capture can be performed by operators with minimal training. The loss of rolled images makes these types of prints unsuitable for storage in an AFIS for matching against latent prints. But it is generally not necessary, or

often even permitted by law, to retain civil applicant fingerprints in an AFIS. Because these types of prints are simpler to capture they are also likely to be of better quality than roll prints, especially if they are captured by operators with minimal experience and training. The ease of capture is also improved by modern electronic fingerprint capture devices[7], known as livescan machines. The electronic capture also facilitates the quick and reliable transmission of the fingerprint images. All of these factors have contributed to the increased use of fingerprint background checks for civil purposes.

The identification and location of each individual finger within the slap image is known as fingerprint segmentation. Segmentation in the context of fingerprints may also refer to the separation of background elements from the foreground fingerprints[10][9], itself a necessary portion of fingerprint slap segmentation. The matching algorithms used by AFISs match single fingers against other individual finger using features–or minutiae–that are extracted from the ridge detail of the finger[11]. In order to perform this matching, the fingers within the slap image must be identified and located. The AFIS systems that perform the criminal history search are sensitive to both the orientation and extraneous ridge detail of the the identified fingerprint so it is necessary to closely crop each individual fingerprint to achieve ideal matching performance. The segmentation of 4-slap images must identify the distal phalanx portion of each finger—the area of the finger from the tip to the crease below the first knuckle. Each individual fingerprint must also be identified as one of the index, middle, ring or little finger so that each print be matched against the same finger in AFIS database.

A slap fingerprint segmentation algorithm may also be employed during in the image capture software to help a livescan operator obtain the best quality fingerprints. The segmentation algorithm may be used to provide live feedback while the operator is capturing a subject's fingerprints. It can indicate that all of the fingers are found in the image and label them for the operator to observe. The segmentation algorithm can also be used to confirm that the operator is capturing the correct hand and to verify that the hand is oriented correctly on the scanner. Applying these types of checks at the capture device improve the accuracy at the AFIS because the quality of the captured slap fingerprints will be improved by preventing images that can't reliably be segmented from ever being transmitted to the AFIS.

1.1 Background

The majority of slap fingerprint segmentation algorithms are proprietary owing to the commercial value of a fast and reliable segmentation algorithm. In 2004 the National Institute of Standards and Technology (NIST) conducted an evaluation of thirteen segmentation algorithms from ten organizations[16]. The only publicly available segmentation algorithm among those evaluated was NFSEG published by NIST.

A follow-up evaluation, SlapSegII, was performed in 2008 with ten segmentation algorithms from seven organizations[17]. Unlike SlapSeg04, SlapSegII did not use NFSEG.

Despite the scarcity of information about the methods used by each of the segmentation algorithms analyzed in the SlapSeg competitions they do provide a basis for segmenter performance and comparison. Newly developed algorithms can be compared to the publicly available NFSEG implementation to judge relative performance. The NFSEG algorithm performed close to average among the segmentation algorithms analyzed in 2004 providing a useful benchmark for future development.

To date there have been no comparative studies of the techniques best suited for four finger segmentation. The baseline performance of NFSEG has been established and about half of the algorithms evaluated in SlapSeg04 performed better. Unfortunately the techniques used to achieve better-than-NFSEG results are unknown. Did the algorithms used a more sophisticated segmentation technique? Or did they simply employ tweaks to NFSEG such as more sophisticated thresholding and better optimization of various parameters? This thesis seeks to describe a technique that does measurably improve on the performance of NFSEG.

1.2 Baseline Algorithm

Histograms are a well-established method of segmenting images[14]. The peaks and valleys in a histogram that accumulates pixel density along some axis can be used to identify boundaries in an image. Histograms are used by NFSEG to segment the fingers in a 4-slap image[18]. The input grey-scale fingerprint image is first down-sampled and binarized. The 16x down-sampling used by default in NFSEG results in a 256-fold reduction in the number of pixels. Computing a linear histogram on an image requires only a single pass over the image, but the multiple histograms employed by NFSEG require multiple passes over the image. Therefore the reduction in image dimension is an important factor in achieving reasonable performance.

In NFSEG separate histograms accumulate the black pixel density and the white pixel density along parallel lines running from the top row of the image to the bottom row of the image. This histogram creation process is performed iteratively while varying the angle of the parallel lines that run from the top to bottom. The best angle is determined by a weighting system that, in essence, selects the angle which generates histograms with maximum variance.

Once the angle that results in maximum variance black and white histograms is determined, the other histograms are discarded. Four local maxima are selected from the black histogram. The local maxima from the black histogram identify the centers of each fingerprint and local maxima from the corresponding white histogram identify

the boundaries between each fingerprint.

The histogram approach requires relatively few passes over the image, tunable by selecting how many angles should be tested, and therefore can be performed at high speed. Each pass does involve an entire sweep of the image area, but this area is much reduced in the down-sampling step.

Unfortunately there are several scenarios where the histogram approach used by NFSEG does not provide a good result. Because it is only capable of detecting linear boundaries between the fingers and only within some narrow range of expected angles it is very sensitive to fingers that are not perfectly straight, compressed fingers that lie very close together with very little whitespace between and any substantial amount of background noise. NFSEG also does not have any provision to select fewer local maxima than the expected number of fingers in the image. That is, if four fingers are expected–such as is generally the case in a 4-slap image–but less than four fingers appear in the captured image the local maximums will not be accurately selected. This generally results in a 'split' finger image where a single fingerprint is segmented into two identified prints.

1.3 Improved Segmentation

Although the slap fingerprint segmentation algorithms evaluated in the SlapSeg competitions are proprietary there have been several algorithms described in recent literature that seek to improve on the technique used in NFSEG. In general these techniques involve a binarization and downsampling step, some variety of clustering method to identify the finger areas, a heuristic that discards non-finger tip clusters and a method to identify each finger.

[8], presumably related to the algorithm fielded by Motorola in the SlapSeg evaluations, describes a technique that that finds the edge boundaries of the candidate fingerprint areas using a connected component algorithm, followed by a splitting and joining heuristic to avoid merging text or extraneous data to the fingerprint area. A convex hull computation is performed to determine a convex outline of each candidate area. Additional splitting occurs based on the putative finger joint creases where the identified region narrows. An iterative process is used to select the 4 fingers in the image. This approach appears to have difficulty in accommodating significant degrees of rotation. Because the heuristics to identify the final finger regions is based on the leftmost or rightmost area, it is unlikely to identify the correct fingers if they are rotated more than 45 degrees, such that the left or right most finger is not the expected index or little finger.

[4] uses a typical down-sampling step, a variant of a k-means clustering technique is applied to determine locally dense clusters of grey pixels. A best-fit ellipse is deter-

mined for each of the locally dense clusters. The orientation of the ellipses as well as their size is used to prune the resulting ellipses to a set of candidate fingertip ellipses. Finally, an additional pruning step is performed by dropping fingertip candidates that fall with an expanding 'shadow' of another finger candidate. The mean orientation of the candidate ellipses is assumed to be the hand orientation and is used to determine an area below each candidate fingerprint where no other candidate fingerprint may appear.

Although the weaknesses of the approach are not discussed, it is apparent from the test dataset from only five individuals that the approach described has not been sufficiently fine-tuned to perform well on a large set of images collected from unique individuals. Also telling is that hand detection is performed by assuming that the longest finger is always the middle finger, which will either appear second from left in the case of a right hand or third from left in the case of a left hand. This heuristic will not handle a missing middle finger or if the middle finger is shorter due to some injury or defect. More importantly if the computed hand orientation is slightly off the index or ring finger may appear to be the longest finger because of the relative similarity in size between those fingers. Using the little finger as the indicating finger is likely to be a better option, it will only ever appear as the left-most or right-most finger and is generally substantially shorter than the other fingers. The only scenario where the little finger will not be able to accurately identify the hand is if the index finger has been shortened due to injury or defect such that it will appear to be shorter than the little finger.

[21] adds a more sophisticated binarization technique that takes into account local ridge detail within the putative finger region. This is likely helpful in separating a noisy background from the fingerprint regions themselves. A k-means algorithm is used to identify the finger regions, and the same ellipse fitting algorithm as the previously described algorithm is used to determine the local orientation of each candidate regions. Ridge detail is used to split the candidate regions at the distal crease using a line perpendicular to the orientation of the candidate region. The authors compared their algorithm to the previously described algorithm and claim that it has improved performance on their test image set. The use of ridge data in the segmentation algorithm does appear to be a useful addition, but obtaining the ridge data is very computationally expensive, making this algorithm unlikely to be suitable for real-time use. Additionally it appears to have some of the same flaws as the previous algorithm with regards to the optimization of the heuristics used to identify the correct portion of the finger, particularly when used on images that have missing or significantly rotated fingers.

1.4 Hypothesis

The algorithm described in the next chapter will provide a 10% or greater reduction in the number of slap images where less than the full number of fingers are accurately identified as compared to NFSEG operating on the same dataset.

Figure 1.1: Slap fingerprint set

Chapter 2

Segmentation Algorithm

This thesis develops a segmentation algorithm that uses a combination of the approaches discussed in previous chapter to obtain improved segmentation algorithm. Figure 2.1 shows the steps that the algorithm uses to segment a 4-slap. This thesis concentrates on a method to segment four finger slap images, but conceptually other slap images such as the double thumb slap are substantially similar. Some operations used in evaluating four finger slap images–such as the hand identification–are needed for thumb slaps. Once an adequately performing 4-slap segmentation algorithm is developed it is simple to make minor modifications to support segmentation of other slap fingerprint types.

2.1 Operation Steps

2.1.1 Binarization

The fingerprint ridges are captured as a dark grey pixels in the fingerprint images and the space in between is light grey to white. The distance between the peak grey levels between adjacent ridges varies within a small range within a single fingerprint image and remains relatively constant between individuals regardless of hand or finger size[6]. Therefore it is reasonable to apply a closing operation on the entire image with appropriately selected kernel size in order to merge adjacent ridges into a larger aggregate area. The resulting image will not merge adjacent fingers because the minimum spacing possible between the fingers is far greater than the spacing between ridges. Furthermore the creases between phalanges of the finger generally exceed the ridge spacing. Therefore an ideal fingerprint image with an appropriately sized dilation and erosion kernels applied will have largely solid regions for each individual phalanx.

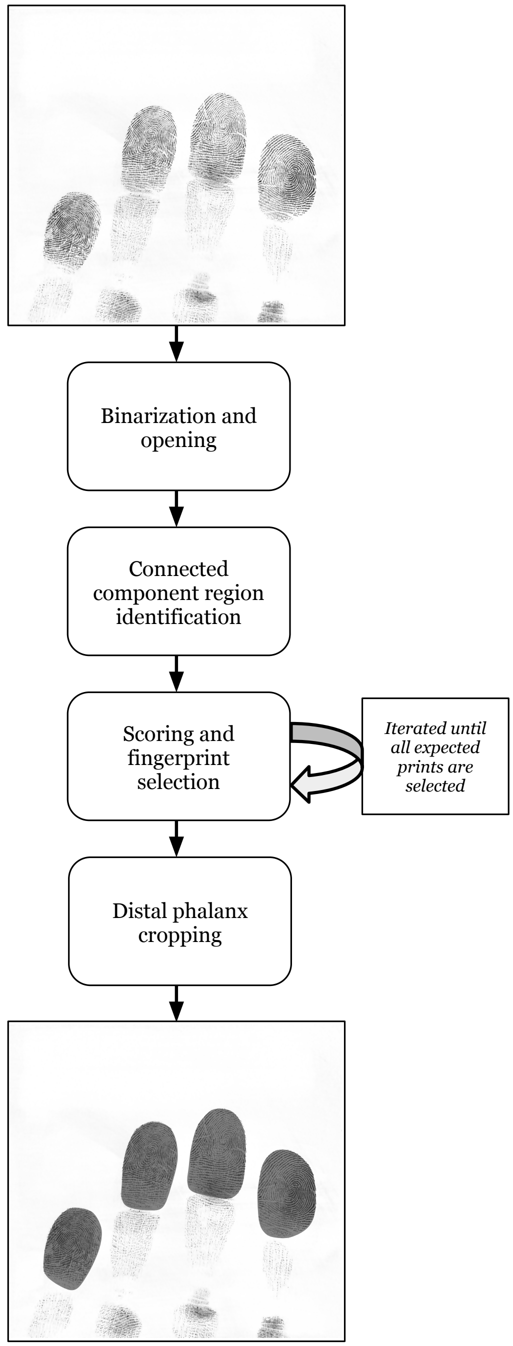

Figure 2.1: 4-slap segmentation steps

2.1.2 Clustering

After the closing operation has been applied with a binarization step regions are then labeled with a connected component algorithm. Each discrete region is labeled $R_1, R_2, \ldots, R_{n-1}, R_n$. Regions that fall below some minimum threshold total area may be removed from the candidate list. The chosen minimum threshold size is approximately the size of a pencil eraser, about $30mm^2$. The connected component algorithm will also be used to drop any enclosed white regions that appear within the candidate regions that are not filled in by the closing operation. These white areas, or holes, may appear as the result of scarring of the subject's fingers or as an artifact of the imaging method used.

The centroids of each candidate region R are computed during the connected component phase by determining the mean:

$$\bar{x}_R = \frac{\sum_{i=1}^{p} x_i}{p-1} \text{ and } \bar{y}_R = \frac{\sum_{i=1}^{p} y_i}{p-1}$$

where p is the number of pixels labeled by the connected component algorithm for the candidate region.

In addition a set of points representing the outline of each region are also determined during the connected component algorithm. Each point on the edge of a region, either the minimum or maximum x for a particular y value is retained as an outline point if the corresponding minimum or maximum edge point above and below have different x values. This creates a minimal set of m outline points, $(x_1, y_1), (x_2, y_2), \ldots, (x_{m-1}, y_{m-1}), (x_m, y_m)$ for each region.

2.1.3 Fingerprint Candidate Selection

At most there can be four final fingerprints identified in a 4-slap image. The n fingerprint candidates must be reduced to only the fingerprint candidates that encompass the distal phalanges. The fingerprint candidates, $R_1, R_2, \ldots, R_{n-1}, R_n$, may include regions from the lower portion of the finger or hand. In order to determine which candidate regions should be rejected a scoring method is used.

Finger Orientation

Each candidate region will have a dominant orientation. Although there is some variation between individuals, fingerprints are generally longer than they are wide. Within a 4-slap image all of the fingers should be generally aligned. Given the capture

area used even with small hands the angle between the left most and right most finger will be no more than 15 degrees.

The orientation of a fingerprint candidate can be determined by using principal component analysis. The covariance matrix for all of the points $(x_1, y_1), \ldots, (x_p, y_p)$ in R is:

$$C_R = \begin{bmatrix} \dfrac{\sum_{i=1}^{p}(x_i - \bar{x}_R)(y_i - \bar{y}_R)}{p-1} & \dfrac{\sum_{i=1}^{p}(x_i - \bar{x}_R)^2}{p-1} \\ \dfrac{\sum_{i=1}^{p}(y_i - \bar{y}_R)^2}{p-1} & \dfrac{\sum_{i=1}^{p}(x_i - \bar{x}_R)(y_i - \bar{y}_R)}{p-1} \end{bmatrix}$$

From the covariance matrix C_R it is straightforward to compute the eigenvalues λ_{R1} and λ_{R2} from the characteristic polynomial of C_R: $\det(C_R - \lambda I) = 0$. The larger of λ_{R1} and λ_{R2} determines the dominant eigenvector and the dominant orientation of the fingerprint. The normalized eigenvectors are also determined for later use in translation and rotation operations on the region points.

Distal Candidates

Using the orientation determined by the dominant eigenvector, the regions that are 'shadowed' by a candidate region are identified. A region is considered shadowed if the centroid $(\bar{x}_{Ri}, \bar{y}_{Ri})$ falls within a region described by lines parallel to the orientation of another region that intersect the leftmost and rightmost points in the other region where the leftmost and rightmost point are discovered with respect to the other region's orientation. The shadowed regions are necessarily not the desired distal portion of the finger but are the lower finger or hand. If the centroid of region R_i falls within the area that is between these two lines and also below the other region, again with respect to the other region's dominant orientation, then the region R_i is said to be shadowed by the other region. See Figure 2.2 for an illustration of the shadow created by a single region. In the figure, the unshaded region represents the area shadowed by the left ring finger. In this image one or more regions are likely to be identified that will fall within this shadowed area and will be removed from the candidate regions.

Uniformity

The average area, $\overline{\text{AREA}}$, and the average orientation, $\overline{\text{ORIENTATION}}$, are computed for all of the regions. If the lower portion of the finger or hand is identified as a candidate region, often it will have an orientation and area that is unlike the candidate regions that encompass the distal phalanx region of the finger.

Figure 2.2: Shadow created by the left ring finger

Candidate Score

A score is computed for each region R_i as follows, with W_A and W_O selected for optimal results on a test data set:

$$
\begin{aligned}
S_{R_i} = & \\
& W_A \times \sqrt{\text{AREA}_i - \overline{\text{AREA}}} + \\
& W_O \times \sqrt{\text{ORIENTATION}_i - \overline{\text{ORIENTATION}}}
\end{aligned}
$$

The regions with the lowest score that are also not shadowed by any other region are selected as $F_1, \ldots, F_k$ where $k \leq 4$. If $k < 4$ and $n \geq 4$ additional passes are made with the modification that the region must not be shadowed by one of the previously selected $F_1, \ldots, F_k$ instead of all of the regions. Subsequent passes are made until no additional regions are identified or $k = 4$.

2.1.4 Distal Phalanges

After the final fingerprint identification has been made it is necessary to determine if the regions need to be clipped at some lower bound to reduce the identified region to only contain the tip of the finger, the distal phalanx. The crease below the joint between the intermediate phalanx and distal phalanx is the ideal clipping point. The

set of outline points obtained during the connected component step will be used to determine the appropriate clipping location. Each outline point is translated relative to $(\bar{x}, \bar{y})$ to obtain $(x_1 - \bar{x}, y_1 - \bar{y}), (x_2 - \bar{x}, y_2 - \bar{y}), \ldots, (x_{m-1} - \bar{x}, y_{m-1} - \bar{y}), (x_m - \bar{x}, y_m - \bar{y})$. The set out outline points are then rotated about the origin using the finger orientation determined in the PCA step. The outline is also rotated vertically about the origin using the normalized eigenvector determined earlier. It is then a straightforward operation to slice the fingerprint horizontally at regular intervals to obtain the width of each slice. The rotated and translated outline points are sorted based on y values allowing simple computation of the points where the horizontal lines enter and exit the region. These computed widths are used to compute a local maximum width w that appears no more than w rows from the top of the fingerprint. Once the local maximum width is discovered, the upper and lower bounds of the interphalangeal crease search window can be determined. The local minimum width that is below the local maximum width and at least w rows from the top, but less than $2.5 \times w$ rows from the top is the interphalangeal crease where the fingerprint region should be clipped. See Figure 2.3 for an illustration of the search window. It may be that the local minimum is actually the last row of the vertically oriented fingerprint outline, in which case no clipping is required. If clipping is required, all outline points that fall below the clipping line are removed from fingerprint F and the remaining outline points are connected with a line perpendicular to the orientation of the finger.

If a clipping operation is performed a new centroid point is computed for the fingerprint F.

2.1.5 Hand Identification

Based on the normalized eigenvectors obtained new centroids for each finger can be computed with the dominant axis as the new y-axis, $\bar{x}\prime_F, \bar{y}\prime_F$. The rotated centroids can be used to determine the relative positions of the fingerprints and therefore identify the hand that was captured. $\min(\bar{y}\prime_F)$ is the shortest finger identified and is therefore the little finger. If this is F_1 than the image was captured from the right hand, or if F_4 it is the left hand.

If the leftmost and rightmost fingers are too similar in height, relative to the tallest finger, it is possible to select the hand instead based on the tallest finger. If the tallest finger is F_2 than it is a left hand, if the tallest finger is F_3 than it is a right hand.

However, this rule does not hold true if less than four fingers are identified. If only three fingerprints are identified it is possible that one of the middle or ring finger is missing. If $(\bar{y}\prime_{F_2} - \bar{y}\prime_{F_1}) > 1.5 \times (\bar{y}\prime_{F_3} - \bar{y}\prime_{F_2})$ then the second finger from the left is assumed to be missing and if $(\bar{y}\prime_{F_3} - \bar{y}\prime_{F_2}) > 1.5 \times (\bar{y}\prime_{F_2} - \bar{y}\prime_{F_1})$ the third finger from the left is assumed to be missing. In either case the shortest finger rule will continue

Figure 2.3: Interphalangeal crease search window

to apply. If neither case applies then the hand cannot be reliably identified.

Once the hand is identified it is straightforward to assign the appropriate finger label, skipping over any identified missing finger as appropriate.

2.1.6 Upside-Down Detection

The scoring steps following the object identification steps can be performed with the coordinate system rotated 180 degrees simply by inverting all of the y-coordinate values. If the same steps are performed on the inverted data the result obtained will contain some number of identified fingerprints. The scores obtained from the fingerprints obtained from the inverted set can be compared with the regular set. If the scores of the set of fingerprints obtained from the inverted set are higher than the scores from the normal set the image will be labeled as upside down.

A small additional positive weighting factor is applied to the confidence score of fingers that are within 45° of vertical because this the expected normal orientation.

2.2 Output

The algorithm generates polygons that describe a tight boundary around the distal phalanx of each finger in the input 4-slap image. Each finger is labeled as either the

index finger, middle finger, ring finger or little finger. The numbers 2 through 5 are used to label the fingers on the right hand, index through little, and 7 through 10 are used to label the fingers of the left hand, index through little. This numbering scheme is based on the FBI 10-print card which numbers each print in this manner. The algorithm also identifies the orientation of each finger and the overall orientation of the hand. If enough fingers are found in the image the relative positions of each finger are used to determine if the slap print is from the left hand or right hand.

Figure 2.4 shows the steps of the operation on an actual fingerprint slap image. Step one shows the binarization and opening step. Step two shows the result of the connected component algorithm. The connected component algorithm removes interior holes from each region and deletes regions which fall below a fixed size threshold. Step 3 shows the result of iteratively obtaining the four regions with the highest score. Step 4 shows the distal phalanx cropping. Step 5 shows the final fingerprint locations.

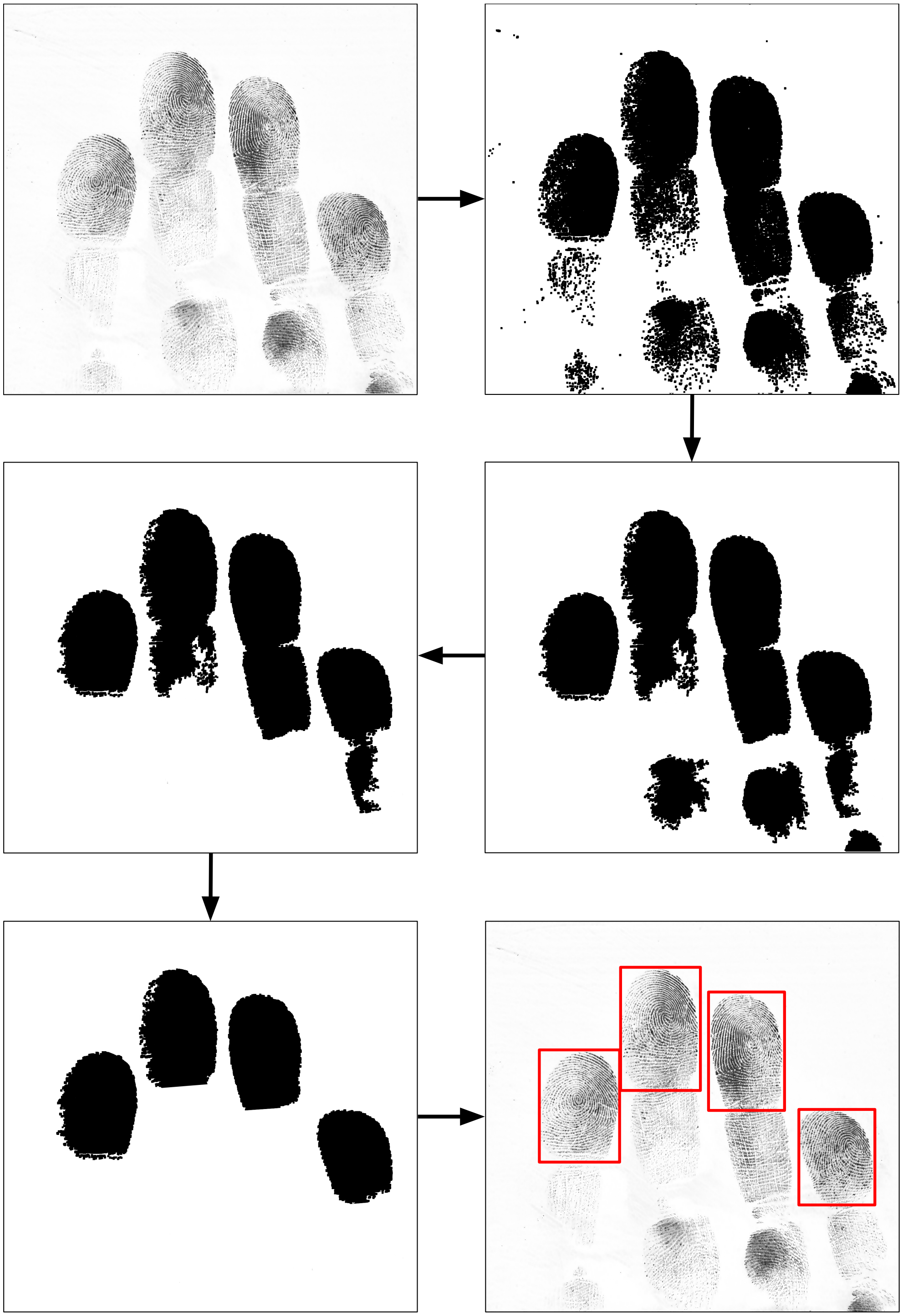

Figure 2.4: Algorithm operation

Chapter 3

Performance Evaluation

3.1 Evaluation Image Set

In order to effectively measure the accuracy of the algorithm as compared to NFSEG both algorithms need to operate on a large and diverse set of fingerprint images. Because the operator of the fingerprint capture device can have such a significant impact on the quality of the fingerprints obtained, it is important that the fingerprints used are from both a variety of individuals and are collected by a variety of operators. SlapSeg04 used a library of 29,484 pairs of slap fingerprint images and SlapSegII used a library of 24,968 right hand slaps and 24,964 left hand slaps[1] to measure the relative performance of various segmentation algorithms. Unfortunately the image libraries used by SlapSeg04 and SlapSegII are not publicly available, so it was necessary to collect a new diverse set of images for the analysis.

3.1.1 Fingerprint Sources

The data captured at more than 250 applicant fingerprint collection sites was aggregated through a 'store and forward' service for a period of approximately 18 months. The data collected on the store and forward server consisted of Electronic Biometric Transmission Specification (EBTS)[2] formatted files containing three Type-14 records as well as various personal information about the subject that was fingerprinted. Each Type-14 record in the EBTS data contains either the left hand impression containing all the fingers on the left hand, a right hand impression containing all of the fingers of the right hand, or an impression of both thumbs in a single image. Each Type-14 record also includes is additional information including rectangles

[1]SlapSeg04 used only 2-inch slap images (2 inches high by 3.2 inches wide) SlapSegII used both 2-inch and 3-inch (3 inches high by 3.2 inches wide). The number quoted for SlapSeg II refers to the number of 3-inch slap fingerprints used.

identifying the location of each finger in the image and a quality score for each finger identified. Wavelet Scalar Quantization (WSQ) compresses the Type-14 image data. WSQ is the algorithm preferred by the FBI for fingerprint images because it substantially reduces the size of fingerprint images, by approximately 15:1, without degrading the matching performance. The 500dpi 8-bit greyscale images are each 1600 pixels wide and 1500 pixels tall, or nearly 2.3 megabytes if they are uncompressed, so the space savings is substantial.

3.1.2 Fingerprint Image Preparation

The fingerprint images collected at the store and forward servers were prepared for use by extracting the image data from the EBTS file, uncompressing it using WSQ, and saving the image to a PNG file. Lossless PNG compression was used rather than the original WSQ compression because WSQ compression engines are typically not free and are generally quite slow. The PNG compression yields only a average 3:1 compression ratio on the slap fingerprint images. However, PNG compression libraries are freely available, more portable than WSQ compression libraries, and are able to decompress the image data much faster than WSQ. This was a preferable format to use for this evaluation because it allowed the analysis of large fingerprint image sets to be performed faster by avoiding a time consuming WSQ decompression on each image. The applicant data from each individual was assigned a sequentially random identifying number, and the prints extracted for that individual are assigned the same identifying number, and an 'R' or 'L' indicating the hand that the image is for. After extracting the fingerprint images and related fingerprint data the original privacy-sensitive information contained in the applicant data was discarded[2]. The fingerprint location information consists of a rectangular region within the image area and the associated finger number for each finger identified in a slap print. This information was written to a text file associated with each slap fingerprint image.

A total of 110,318 right and left hand fingerprint image pairs were collected with an additional 13 right hand and 18 left hand fingerprint images. These fingerprints were collected at more than 250 unique locations operated by at least as many different operators, and are of mostly unique individuals[3]. The operators responsible for

[2]Note, due to privacy concerns, the final fingerprint image and associated position data can no longer be associated with the individual the fingerprints were collected from, the location where the print was captured, the operator performing the capture or the time and date the capture was performed. Unfortunately, even with these precautions to remove identifiable information, the fingerprints images cannot be publish because the individuals fingerprinted did not give express permission for them to be distributed.

[3]There are a small number of duplicate slap prints in this set because some individuals had one or both of their hands reprinted if the original set was rejected due to quality or other problems.

capturing the prints in this set are generally not law enforcement professionals. The amount of training they received in operating the fingerprint capture device varies, but is generally much less than a law enforcement professional would receive. The process of capturing the 4-4-2 slap prints is much simpler than the rolled prints used in law enforcement, but the quality of the prints is still very dependent on operator competence. Therefore the fingerprints in this set have a range of image qualities, although all were good enough to have passed the basic quality checks performed by the capture software. No attempt was made to weed out low-quality images or perform any enhancement on any of the images. Some of the captured prints were subsequently rejected by the AFIS that was responsible for processing the captured fingerprints after they were forwarded from the store and forward server. Fingerprints image sets that could not be processing by the AFIS have *not* been removed from the evaluation image set.

3.1.3 Ground Truthed Image Set

Because the image locations extracted from the large data set are not guaranteed to be accurate, a smaller set of 2,000 images (1,000 right and left fingerprint image pairs) was randomly selected from the full fingerprint image set. The images in this set were carefully individually inspected and the fingerprint locations were adjusted where necessary to accurately identify only the distal phalanx portion of each finger. This set of 2,000 images is referred to as the ground truthed image set.

Two fingerprints from this image set had incorrectly identified fingers that had not been correctly adjusted by the livescan operator. An additional number of the fingerprints had inaccurate lower bounds that extended well past the interphalangeal crease. Some images had slightly larger identified fingerprint regions than necessary, generally due to some background noise or dark areas caused by condensation on surface of the capture device. None of more minor flaws were judged to be significant or likely to affect the accuracy of a match performed based on the identified area, nevertheless they were also adjusted to the ideal rectangular segmentation area.

3.1.4 Full Image Set

The full evaluation image set also contains a number of 4-slap images that were not correctly identified by the operator. Due to time constraints and the size of the image set, a less exhaustive method was used to find images that were not segmented or labeled properly before they were submitted. Instead only the images that had identified finger locations that are different from the finger locations identified by both NFSEG and the thesis segmentation method were inspected and adjusted as necessary. Most of these fingerprints were incorrectly identified by both algorithms

because of significant background noise. Of a total of 1,746 fingerprints that were identified as requiring additional inspection 390 had at least one finger that was misidentified or unidentified. These finger locations were fixed and the fingers were properly labeled. Only minor adjustments were made to the finger locations in the remaining 1,446 slap fingerprints that were subjected to additional scrutiny.

3.2 Computation

Both NFSEG and the algorithm developed in this thesis were used to segment all of the 220,667 images.

NBIS[13] release 3.3.0 was compiled using GCC[3], version 4.2.1. Minor modifications were made to the build scripts to make them operate on the target platform and to incorporate the use of libpng[15].

The results obtained from NFSEG are vertically oriented rectangles, as are the finger segmentation obtained from the EBTS data. A bash shell script was used to execute NFSEG on each individual 4-slap image. The computation took approximately 6 hours on a modern dual-core notebook, the operation is a single process and is only able to make sure of one core.

The algorithm described in Chapter 2 was written in C++ and also compiled using GCC, version 4.2.1. The same build of libpng was included in the executable form of the algorithm.

As with NFSEG, a bash script was used to iteratively segment each 4-slap image and. The operation took about 11 hours on the same machine used to run NFSEG. No attempt has been made to optimize the algorithm, beyond turning on basic compiler optimizations. It is likely that adding even a 2x down-sampling operation to the binarization and dilation in section 2.1.1 would substantially reduce the amount of time required to process a 4-slap image.

3.3 Segmentation Success Criteria

SlapSeg04 used matching results as its success criteria. The identified fingerprint regions from each segmentation algorithm were supplied to a matching algorithm. The segmentation success of a particular algorithm was determined based on whether the match was successfully made based on the image extracted from the identified image area. If a match was successfully made using the output of at least one of the segmenters in the comparison, than the segmentation of the particular finger would be considered successful if the segmentation algorithm being tested yielded a fingerprint image that could also be matched.

The data set obtained from the EBTS data is not as suitable for this kind of analysis because the data does not include individual fingerprint images that are captured separately. The only matches that can be performed are on images extracted from different segmentation results of the same image. This makes the matching operation superfluous. Instead it is only necessary to compare the segmentation areas to see if they are reasonably similar in size and overlap the same region. This is the method that is used in SlapSegII to compare segmentation results.

Notably, NFSEG obtains more generous fingerprint areas than necessary. This is due to the 16x down-sampling and binarization step. Therefore the outer bounds of the segmented area are between 0 and 15 pixels outside of the fingerprint area, and always fall on values that are divisible by 16. It is conceivable that this overly generous boundary may cause problems with tightly spaced fingerprints. Some of a neighboring print may be captured within a given area, which may reduce the match suitability. However, this drawback is not tested for in this analysis.

Although the algorithm described in this thesis is capable of generating a non-convex polygon that tightly circumscribe the distal phalanx portion of a finger, the vertically oriented rectangle that the polygon is inscribed within is used for simplicity of comparison. The same metric can then be used to compare these results with NFSEG results.

The success of a match is determined by an overlap of more than 50% of the area of the known fingerprint region identified in the EBTS data and the segmentation result. The lower bound is ignored when determining match success because the lower bound has much greater variability, many of the fingers have lower bounds that encompass much of the lower portion of the finger and may include all or part of the intermediate and proximal phalanges of the finger.

3.4 Results

Using the criteria described in the previous section the results obtained from each algorithm operating on the ground truthed fingerprint image set as well as the full image set.

Notably only 13 of the ground truthed image set had fingers misidentified by both NFSEG and this algorithm. This represents a 99.35% accuracy rate if both algorithms could be accurately combined to create a single result. 3,056 slap fingerprints from the full data set had one or more fingers misidentified by both NFSEG and this algorithm. This represents a 98.6% combined accuracy rate.

Clearly it is not reasonable to expect that a perfect selector could be invented that would always select the correct result from the two different algorithms. But it does suggest that there is some substantial improvement that could be made.

	Total misidentified fingers	Prints with one or more misidentified finger	Correctly segmented percentage
NFSEG	115	88	95.6%
Thesis	148	88	95.6%

Table 3.1: Segmentation of the ground truthed image set

	Total misidentified fingers	Prints with one or more misidentified finger	Correctly segmented percentage
NFSEG	16,281	13,016	94.1%
Thesis	19,824	10,722	95.1%

Table 3.2: Segmentation of the full image set

Furthermore, many of the remaining images are probably unusable due to quality issues, so segmentation of those types of images is of limited utility.

3.4.1 Reasons for Unsuccessful Segmentation

A survey of the images that could not be successfully segmented is very revealing. Each of the 88 slap prints from the ground truthed data set that could not be accurately segmented by the algorithm presented in this thesis and the 88 slap prints from the same data set that could not be accurately segmented by NFSEG were reviewed by hand. The probable cause for the failed segmentation of each slap fingerprint was identified. Figure 3.1 shows the results of this survey.

Analysis of the segmentation failure survey results for the algorithm developed in this thesis indicates that there is an issue with scoring that results in a lower portion of a finger being selected over the distal phalanx. Over 70% of the segmentation failures in the ground truthed data set were caused by this problem. Generally this occurs on only a single finger within the slap and the rest of the fingers are selected accurately. This flaw should be correctable by optimizing the candidate selection scoring such that the appropriate region is dropped from consideration. By correcting this flaw the error rate of the algorithm could easily drop as much as 50% or more.

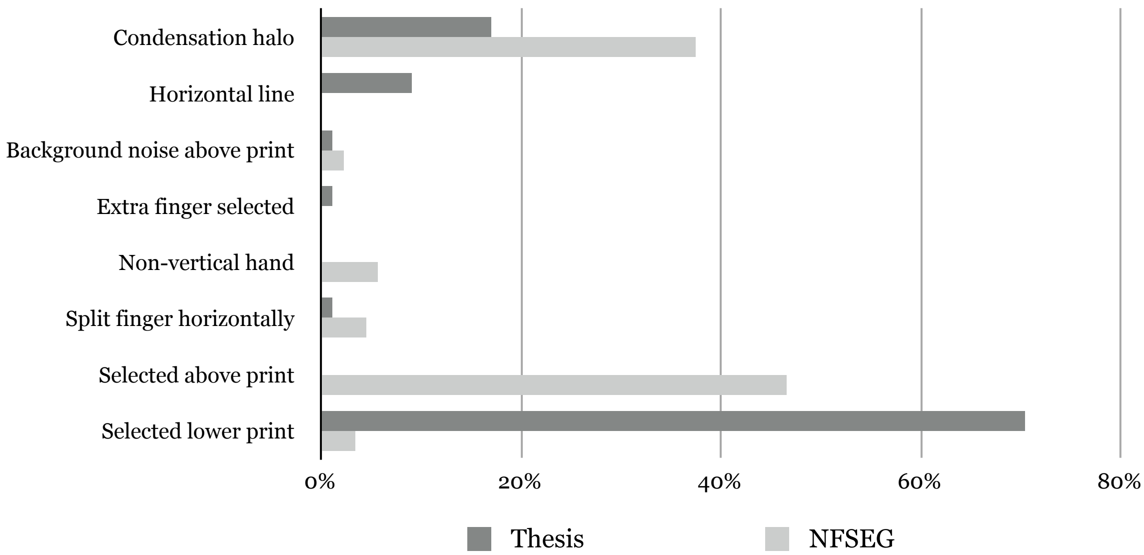

Figure 3.1: Causes of segmentation failure on the ground truthed data set

The next most common reason for unsuccessful segmentation is because one or more fingerprints are merged together into a single region and then identified as a single finger. This occurs when background noise is not accurately thresholded out of the image. This background noise is commonly caused by condensation on the glass capture surface and is referred to as haloing.

NFSEG also had a flaw that appears to be easily fixable. An area above the finger tip was selected instead of the fingertip in a large number of images. It is not clear without reviewing the code what the source of this problem is, but it occurs on more than 40% of the images in the ground truthed data set.

The algorithm developed in this thesis does perform better than NFSEG on images that have background condensation halos, angled fingerprints and is less likely to split fingers into two distinct regions. If improvements can be made to the areas identified, this algorithm will significantly outperform NFSEG even if he major flaw in NFSEG were also corrected.

3.4.2 Difficult Slap Fingerprints

Figure 3.2 shows slap fingerprints with backgrounds that make segmentation difficult and Figure 3.3 shows other types of slap fingerprints that are troublesome. All of these images had some problems being processed by this algorithm and NFSEG.

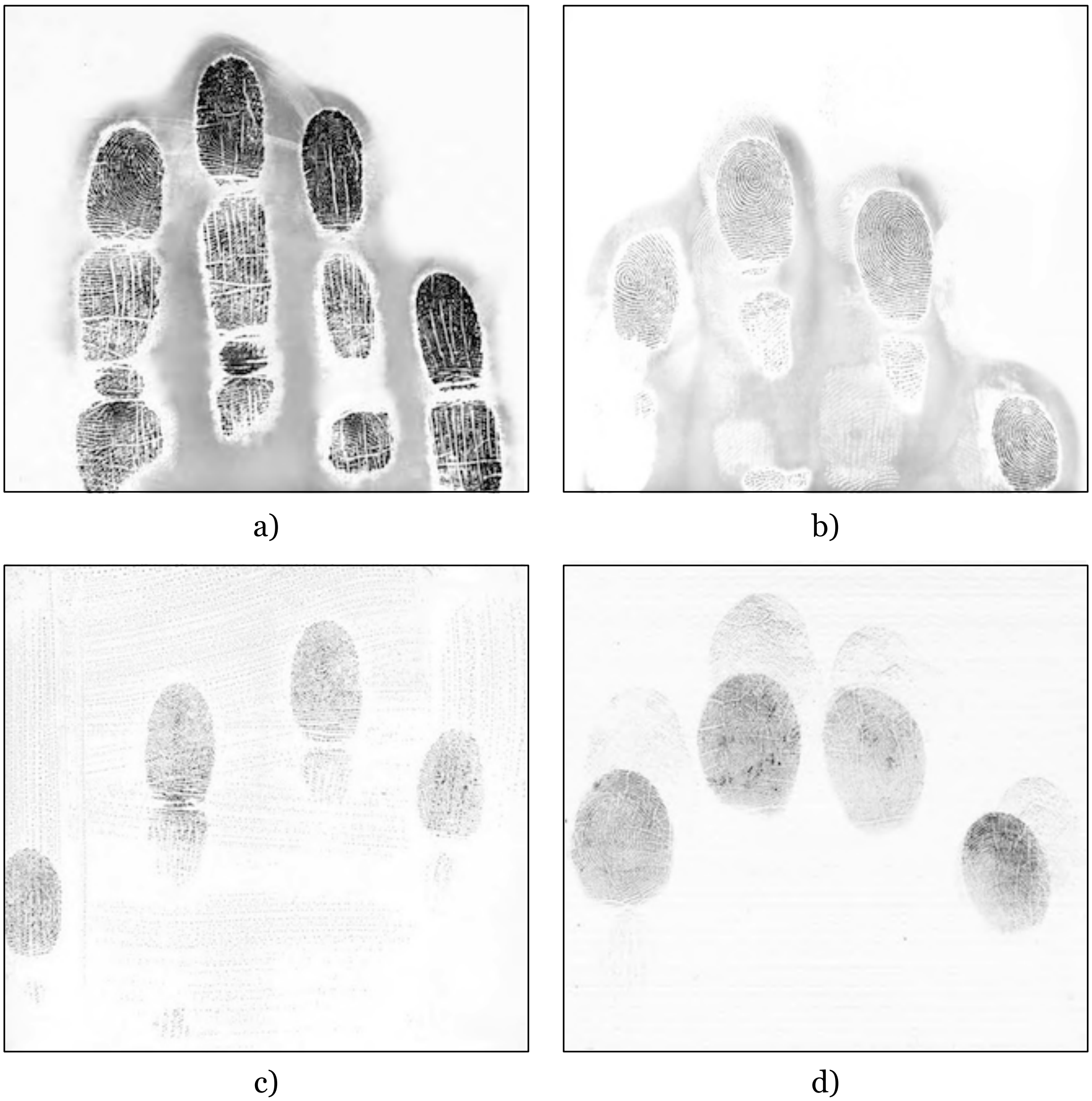

Figure 3.2: Problematic fingerprints with difficult backgrounds

a) Minimal distance between finger and large condensation halo b) Condensation halo with latent finger residue and faint prints c) Cleaning product residue in background d) Latent fingerprint residue

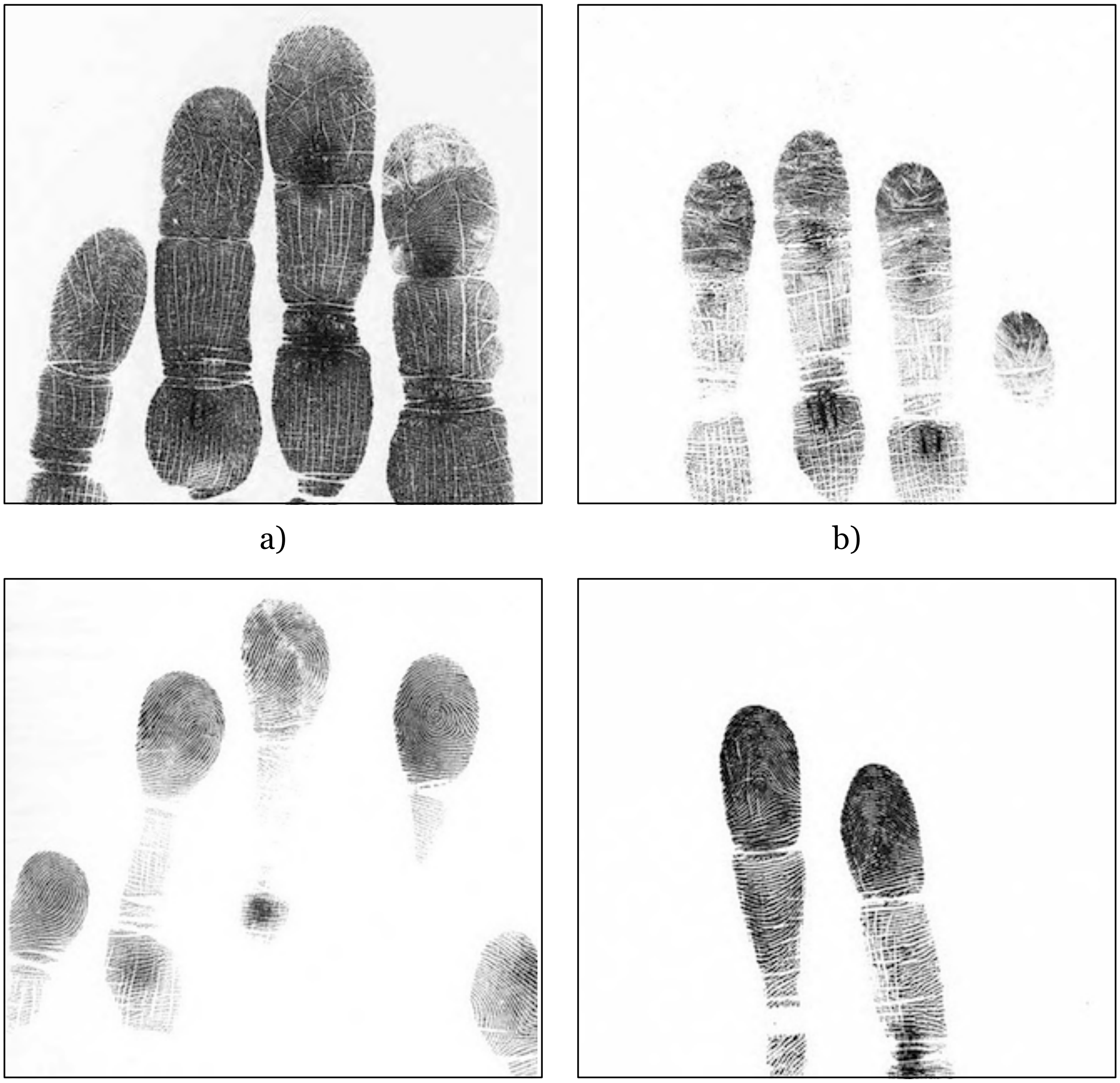
a) b) c) d)

Figure 3.3: Problematic fingerprints

a) Straight-sided fingers make it difficult to find the interphalangeal crease b) Straight-sided with unusual ridge detail c) Thumb print captured, should not be identified by the segmenter d) Amputated fingers

Chapter 4

Conclusion

It was shown in section 3.4 that the algorithm developed in this thesis performs as well as or slightly better than NFSEG in correctly segmenting 4-slap images. Using a more sophisticated clustering approach does provide better results than the histogram approach used in NFSEG. With additional optimizations and improvements, the technique can be made to perform even better. The analysis using the large evaluation data set is particularly valuable because it provides a baseline for future performance improvements.

4.1 Potential Improvements

4.1.1 Optimization of Scoring Weights

The primary cause of inaccurate segmentation was because something other than the distal phalanx was selected. Sometimes this occurred when the lower portion of a finger was selected and the distal phalanx was not, and sometimes two areas of the same finger were selected, the distal phalanx and some other portion. In both cases the selection of an incorrect area of the finger led to a failed segmentation result. The selection of a sub-ideal region occurs because scoring criteria did not yield the best four candidates. These types of errors could likely be reduced by an improved scoring criteria, even if the features remain the same.

Clearly one of the potential uses of the large image set obtained as part of this work is the possibility of using the data set to optimize algorithm parameters. The weighting parameters described in section 2.1.3 seem to be an ideal target for such optimization. The values used for the weights in this evaluation were simply guesses. Furthermore it is also possible to create a non-linear weighting of the various input features. This problem may be suitable for something like a multi-layer perceptron that could be trained on the large dataset.

4.1.2 Thresholding

The next most significant cause of failed segmentation after the non-optimal selection is haloing caused by condensation. This occurs regularly on optical scanners if the glass optical surface is cold (perhaps after being moved from a colder environment) or if the subject being fingerprinted has especially moist or warm fingers. Because the moisture has a very similar index of refraction as the subject's finger the optical sensor is likely to register the condensation as a dark area. One of the predicates that this algorithm is based on is that the ridge distance is less than the distance between a fingerprint and a halo caused by condensation. Early experimentation during the development of the algorithm seemed to indicate that there was always a significant distance between where the halo would form and the finger due to local heating of the glass surface preventing condensation from abutting the finger. Unfortunately it appears that the finger to condensation halo distance is substantially lower than expected in a number of cases. This minimal spacing causes the binarization and dilation thresholding described in section 2.1.1 to merge fingerprint areas with the surrounding condensation halo. If the halo is small and localized this does not cause a major problem, but if the halo is large and encompasses multiple fingerprints, the algorithm is likely to merge these together into a single mass and the segmentation result will be incorrect.

There are several potential approaches to address the condensation halo problem. NFSEG appears to have a far more effective adaptive threshold that is much better at separating darker fingerprint areas from the mid grey condensation halo. However NFSEG also fails on some of these images as well so a simple adaptive threshold is not sufficient to deal with all of these problematic images.

Another potential approach is to better distinguish between the mostly uniform gray condensation halo and the fingerprint. A thresholding method that takes into account the local variance of pixel intensity should be better able to enhance the foreground ridges and threshold out the uniform background, even if the local mean pixel intensity is of similar value[20].

An even more advanced method could use ridge direction mapping to distinguish the foreground ridges from the background[5]. This method is likely to be much more computationally intensive than the other approaches, although it may be increasingly realistic on modern computer equipment. The ridge mapping may also be helpful for the interphalangeal crease identification described in the following section.

4.1.3 Interphalangeal Crease Identification

The technique described in section 2.1.3 generally works adequately in most situations, but if the sides of the finger are straight or nearly so, this method does not work.

The ridge direction is also a useful indicator of the crease. Typically the ridge direction transitions to perpendicular to the overall finger orientation as it approaches the crease. A simple method to supplement the interphalangeal crease detection might simply count the number of black/white transitions and accumulate the transitions in a histogram. The black white transitions would be counted and accumulated along parallel lines that run perpendicular to the finger orientation. The local minimum of the histogram that appears within the search window described in section 2.1.3 is likely to be the interphalangeal crease. A combination of the technique used in this algorithm and the transition counting might yield the best result.

A more sophisticated method to find the interphalangeal crease involves actually mapping the ridge direction for the entire candidate finger area and looking for areas that are perpendicular to the overall orientation[19]. This method is particularly computationally expensive, so the simple perpendicular ridge counting method should be attempted first.

4.2 Final Thoughts

This thesis provides a valuable starting point for future work in 4-slap fingerprint segmentation. When developing software to address a problem that has a commercial application, rarely is the opportunity afforded to scientifically review the performance and accuracy of the solution. Yet the kind of analysis provided in this thesis is precisely what is needed to make the next level of improvements.

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