Final Report
Fingerprint Based User Authentication

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1. Executive Summary

The focus of this project is to look at the problems surrounding fingerprint-based user authentication. Biometric authentication is more reliable than tradition methods because it is not knowledge- or possession- based like a password or swipe card that can be forgotten or lost, it is a part of the person being identified.

Fingerprint analysis starts with image processing which is where the fingerprint is converted into a form that can be used to classify and extract minutiae. The next step is classification which is where the fingerprint is distinguished as part of a smaller group of fingerprint types so that it is not compared to every fingerprint in the database. Finally, minutia-based fingerprint analysis involves matching the local discontinuities of the fingerprint. Discontinuities include terminations, also known as ridge endings, and the bifurcations which is where ridges fork or diverge. The authentication stage validates the identity of the individual by extracting the pattern of minutiae from the fingerprint and subjecting it to a matching algorithm in an effort to validate it against one of the templates stored in the system database.

This project puts emphasis on the image processing stage by giving detailed descriptions of each step within this segment of fingerprint authentication. It also investigates the different methods used to produce a final fingerprint skeleton and the algorithms that are required for each one. Each algorithm's effect will also be explained with a demonstration of its results. The recommended fingerprint classification method is to group the fingerprints into four types; Arch, Right Loop, Left Loop, and Whorl. This is done by calculating the Poincare index and tracing the original lines.

2. Introduction

2.1 Problem Statement

The focus of this project is to look at the issues surrounding fingerprint-based user authentication. Biometric authentication is the use of physiological characteristics such as a fingerprint, hand shape, face map, voice, or iris to determine the identification of the user [1]. This type of identification is more reliable in comparison to traditional verification methods such as possession of a key or swipe card, or the knowledge of a password or login, because the person is required to be physically present at the time of identification [2]. Reliable personal identification is important in everyday transactions ranging from ATM withdrawals to restricted building access. Biometric identification could decrease billions of dollars lost every year to credit card fraud, welfare "double-dipping", cellular bandwidth thieves, and ATM fraud by providing near irrefutable proof of identification.

2.2 Objectives

- Investigate the process of fingerprint-based user authentication.
- Create a software package that implements the pre-processing techniques suggested in the Greenberg et al article [8].
- Provide software tools and information that can be used to facilitate future research.
- Recommend a method for classification.

2.3 Constraints

- The fingerprint image must be an uncompressed Bitmap, 256 x 256 pixels.
- Fingerprint images must be previously acquired

2.4 Criteria

- Minimize the cost of the design.
- Provide usable solutions to problems for fingerprint-based authentication.
- Algorithms should be as easy to understand as possible and upgradeable.

2.5 Assumptions

- Assume that a fingerprint image is from a real person.
- Assume the supplied fingerprint has no background or noise which requires segmentation.

3. Background

3.1 Fingerprint Biometrics

Biometrics is the science of identifying a person based on physiological characteristics that distinguishes one person from another [3]. Biometric identification is more reliable than traditional verification methods because the person is required to be physically present at the time of identification [2]. These methods may include the possession of a key or swipe card or the knowledge of a password or login.

All fingerprints are believed to be unique to each person and finger; even twins do not have the same fingerprints [1]. As well, fingerprints do not change over time. These characteristics contribute to why the fingerprint is the most widely used biometric trait. Fingerprint technology is the most developed technology in biometric recognition [3], and is legitimate proof of evidence in courts of law all over the world [2].

Fingerprint recognition has been used for a significant amount of time. The "Henry System" was developed in the early 1800's by Edward Henry to classify and identify fingerprints based on the ridge configurations and was revamped by the FBI in the early

1900's [3]. The classes of fingerprints are based on the global patterns of the ridges and valleys. The human fingerprint can have many different ridge patterns but the six general classifications are: Arch, Tented Arch, Right Loop, Left Loop, Whorl and the Twin Whorl as seen in Figure 1. Loops are the most common pattern found making up nearly 65% of all fingerprints, whorls making up almost 30% of all fingerprints, and arches making up the last 5-10% [4]. There is also an accidental category but it is very rare and covers the fingerprints that do not clearly fall under any of the other categories.

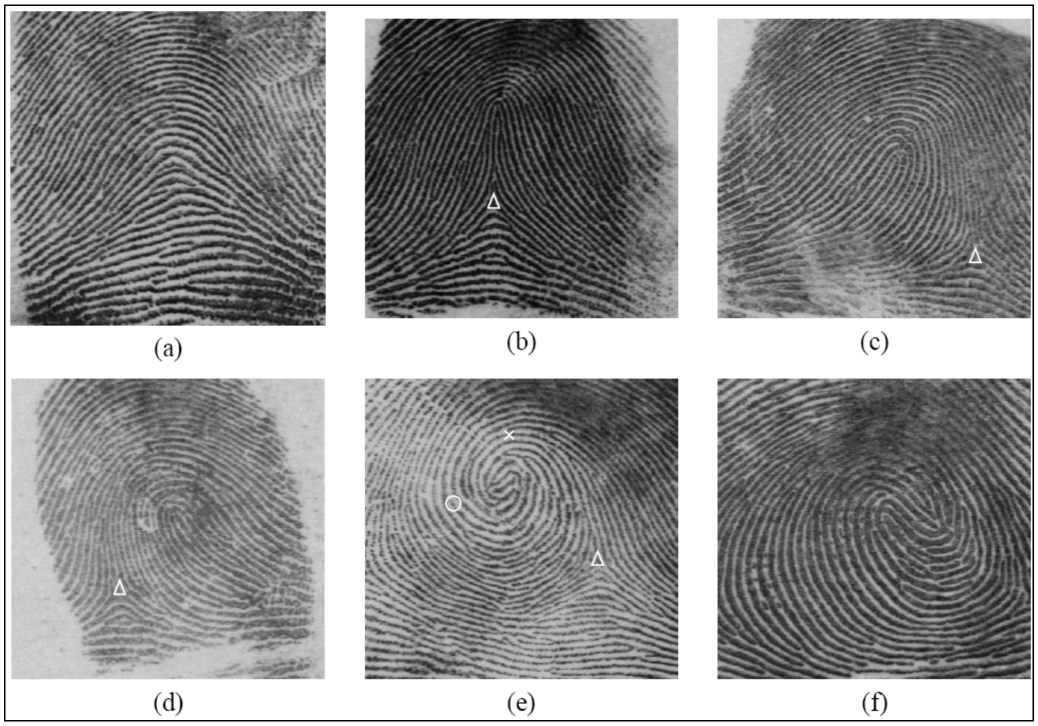

Figure 1: The six main fingerprint classes. (a) arch, (b) tented arch, (c) right loop, (d) left loop, (e) whorl and (f) twin loop [2]

3.2 Fingerprint Analysis

There are three main components to fingerprint-based user authentication: image pre-processing, classification, and authentication. Image processing is defined as the process of taking the original image and converting it into a form that can be used to extract feature points called minutiae. This includes passing the image through a series of filters to make the image clearer and more concise. The final product should be an image of the fingerprint ridges thinned to one pixel without any spurs and bridges remaining. Without this step the fingerprint cannot be analysed further. Following this is classification where the fingerprint is distinguished as part of a smaller group of fingerprint types so that it is not compared to every fingerprint in the database. By only comparing it to similar fingerprints the amount of time required for processing is drastically reduced. The authentication stage is the last step where it validates the identity of the individual by extracting the pattern of minutiae from the fingerprint and subjecting it to a matching algorithm in an effort to match it against one of the templates stored in the system database.

The minutiae-based fingerprint matching is a very popular authentication method. Minutiae-based fingerprint analysis involves matching the local discontinuities or minutiae of the fingerprint. Discontinuities in a fingerprint include terminations or ridge endings and the bifurcations where ridges fork or diverge [5]. The information for a fingerprint is then stored as a point pattern of minutiae instead of a complete image of a fingerprint [6]. It is also simpler compared to other forms of fingerprint matching such as ridge-pattern based or complete image based and is faster and has a small template [2].

4. Method

4.1 Analysis techniques:

A review of the literature on dealing with fingerprint analysis shows that there are three steps that are required to implement fingerprint authentication. The first step involves pre-processing of the fingerprint information so that information can be reliably extracted from the fingerprint data. The next step is to classify the fingerprint into one of several sub categories. By classifying fingerprints into sub categories it does not need to be compared with all the reference fingerprints but, only those in its category. The last step is then to try and reliably match the fingerprint to one of the stored reference prints. Within these main steps there is some variety in each approach but all these methods essentially attempt to produce a similar result. This result in an enhanced fingerprint that will provide valid information that allows for fingerprints to be matched to previously sampled information.

It is obvious from our literature review and early attempts to implement some of the common algorithms suggested in articles centered on fingerprint analysis that the complete task of fingerprint analysis and matching is far from trivial. For this reason, our project concentrated on the pre-processing of the grey-scale fingerprint image and to assign fingerprints to different classes. Fingerprint matching techniques will not be directly addressed.

The real first step in any fingerprint authentication system is taking a sample of the fingerprint. This is usually done through the use of a sensor but could be done with manual techniques. The important detail about sampling a fingerprint is that the information taken to represent the fingerprint must be converted to a form that can be manipulated using digital systems. This means that through whatever source that the fingerprint is taken, the end result is a matrix of pixels that represent the grey-scale ridge and valley structure of the fingerprint.

The major issue that stem from taking fingerprint samples is the quality of the information. The quality of the fingerprint will directly affect the system's ability to match fingerprint samples and this is the reason that the image needs to be processed before matching can be attempted. Most of the articles reviewed suggest a basic methodology for image pre-processing which is shown below in Figure 2.

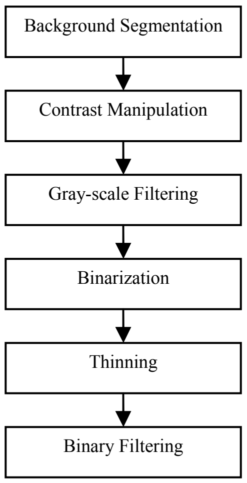

Figure 2: Flow chart for Image pre-processing.

4.2 Background Segmentation:

Fingerprint images may have background information that does not represent the fingerprint itself. The process where the background information is removed is referred to as background segmentation and may be required as the first step in the pre-processing of the fingerprint. The need for background segmentation will depend greatly on the individual methods used to create the digital representation of the fingerprint image. This process is usually done by dividing the fingerprint image into square blocks of eight or sixteen pixels. For the purpose of the document, a block will be considered to be a square sample from the image matrix. The variance in the grey-levels of the pixels in a block is then compared to the variance of the entire image. Any block that varies beyond some threshold will then be considered information that is not valid for the fingerprint. This is a fairly easy task but the problem lies in correctly choosing what threshold will be used to properly separate the background from the fingerprint image. So far trial and error has been used to determine this threshold value. Images that do not have a background or extraneous information do not need to be segmented. The images that we assume are supplied do not have ambiguous background information and therefore the segmentation function is not implemented in our final filtration process.

4.3 Contrast Manipulation:

The quality of fingerprints will almost never be of a consistent quality. In fact most will be fairly poor. For this reason fingerprints need to be enhanced to improve the quality of the results. To improve the quality of the fingerprint image some sort of filtering is required. To aid in filtering the grey-scale levels of the fingerprint image are usually manipulated to help enhance the effects of filtering. Two common methods of contrast manipulation are normalization and histogram equalization. Normalization standardizes the grey-level intensities of the pixels in the overall matrix of pixels that represent the fingerprint. One method used to accomplish this uses the accepted mean and variance of the pixel intensities in the image. The actual mean and variance of the fingerprint is also calculated. This information is then used to shift the actual pixel intensities proportionally to the manually specified mean and variance [7].

Another method suggested to enhance the contrast of an image is to use histogram equalization [8]. This method was implemented in our project as per the first stage presented in the article by Greenberg et al. The histogram equalization adjusts the grey-level intensity of the pixels in the local neighbourhood to produce an image that has a more balanced distribution of pixel intensities over the full range of values from 0 to 255.

$$I_{new}(i, j) = \sum_{i=0}^{w}\sum_{j=0}^{w} I(i, j) \times \frac{255}{w^2}$$

w : is the size of the local neighbourhood

The Greenberg et al article suggests that they performed the histogram equalization based on a 13x13 local neighbourhood. We created a function that will perform the histogram equalization on the input image and this function allows for the size of the local neighbourhood to be specified in the function call.

After this stage the ridge and valley structure is not changed but the variation of the grey levels or the pixels is reduced to aid with the future steps used to enhance the fingerprint.

4.4 Grey-scale Filtering:

The majority of the articles in the last ten years strongly reference the article by Hong et al which suggests fingerprint enhancement based on filtering the image using a Gabor filter. Early efforts in this project were focused towards trying to implement this suggested algorithm, shown below in Figure 3 [7].

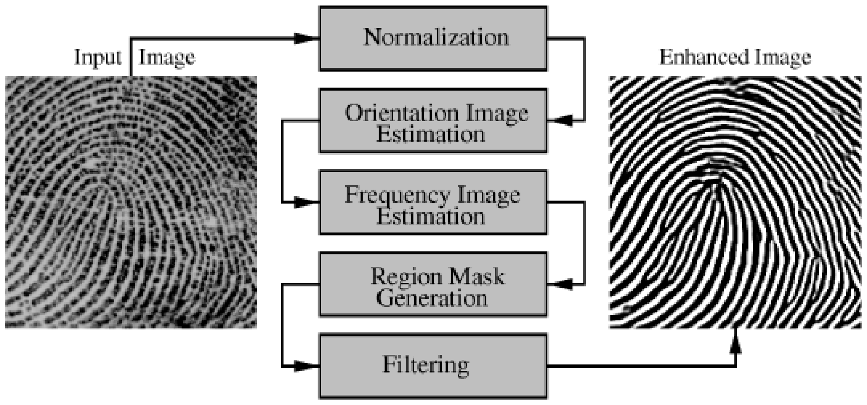

Figure 3: Flow chart for a Gabor filter [7].

The main issue with this technique is that the Gabor filter requires an estimation of the block orientation around each pixel and an estimation of each blocks frequency. This information is then used create a complicated filter mask from the Gabor 2-D symmetric filter equation. Once the mask is calculated it is then convolved with each pixel to produce a filtered image for that block. This process is then repeated for every pixel and the associated block around it. These three steps require complicated algorithms that are computationally expensive and for this reason the Gabor filter will not be pursued further.

Greenberg et al in “Fingerprint Image Enhancement using Filtering Techniques” suggests a method that does not require the use of a Gabor filter. This is the method that has been pursued with respect to the pre-processing of fingerprint images. A block diagram of the Greenberg et al process is shown below in Figure 4 [8].

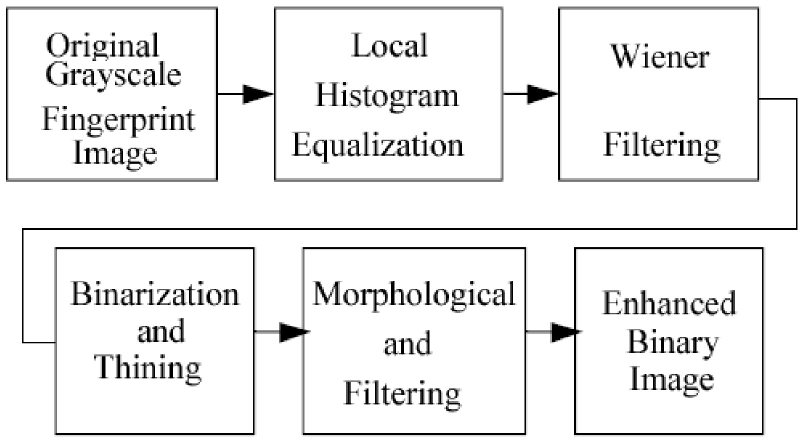
Original Grayscale Fingerprint Image
Local Histogram Equalization
Wiener Filtering
Binarization and Thining
Morphological and Filtering
Enhanced Binary Image

Figure 4: Block diagram for Wiener filtering method [8].

As depicted in the above the block diagram, this method uses a Wiener filter instead of the Gabor filter since it is much easier and less computationally expensive to implement than the Gabor filter method.

The Greenberg et al pre-processing method used a pixel-wise Wiener filter to remove noise and improve the image quality for fingerprint samples. In the article they suggest that the filtering is accomplished using a 3x3 filter mask generated using the given equation.

$$w(n_1,n_2) = \mu + \frac{\sigma^2 + v^2}{\sigma^2}\left(I(n_1,n_2) - \mu\right)$$

μ *: is the local mean*
σ^2 *: is the local variance*
v^2 *: Estimation of the noise variance*
$I(n_1,n_2)$*: is the grey level intensity of the pixel centering the 3x3 mask*

The above equation requires an estimation of the noise variance but, does not suggest how this should be calculated. In our implementation of the Wiener filter we calculated the estimated noise variance using a method suggested by J. Immerkaer [10]. This method used a 3x3 mask that was convolved about the pixel in question to calculate the noise variance. This method was fast and fit well into the project. The mask is shown in Figure 5

$$\frac{1}{36}\begin{bmatrix} 1 & -2 & 1 \\ -2 & 4 & -2 \\ 1 & -2 & 1 \end{bmatrix}$$

Figure 5: Filter Mask for Noise Variance Estimation

The function wiener() is used perform the Wiener filtering of the image.

4.5 Binarization:

Binarization is easy to implement process that just compares each pixel to some threshold and then changes it value to either pure white (0x00) or pure black (0xFF). The threshold used is usually either the global mean or a local block mean. This has been implemented using a local block mean.

4.6 Thinning:

The Greenberg et al article mentions the characteristics of their thinning algorithm but does not actually state their algorithm. In our project we implemented two different thinning algorithms.

The first thinning algorithm was implemented from Zhou [9]. This method thins an image with two basic methods. First pixels in a 3x3 neighbourhood around the central pixel are removed if their removal does not affect the connectivity of a ridge. The second stage of the algorithm uses masks to ensure bifurcations are thinned properly.

The second thinning algorithm that was implemented was the MB2 thinning method. This method uses a series of masks that are rotated around a central pixel at even multiples of 90 degrees [10]. This method is a rotation invariant algorithm which means the resulting image is not entirely reduced to a single pixel width. This rotational invariant thinning might be useful however for a minutia matching process.

4.7 Binary Filtering:

Once again Greenberg et al do not explicitly state the binary filtering algorithm that they use but do state that this is fairly mechanical process of manually finding and removing ridge structures that probably do not belong and by filling in gaps in ridges that do not belong. We analyzed this problem and wrote a couple algorithms to solve this problem removing spurs, ladder structures, and ambiguous lines. A function has not been created which fills gaps but should be completed in future research to create an improved thinned image.

4.7.1 Ladder and Spur Removal

Although Greenberg et al. mention the added benefit of implementing a function which removes ladder structures and spurs, they do not elaborate on their method or suggest a plan of action. Ladders are usually caused by pits in the ridge detail creating a false region of lighter pixels which are then binarized incorrectly. These structures will lead to ambiguous bifurcations being detected. Spurs are also caused by ridge or image abnormalities but do not adjoin two valleys incorrectly. These will incorrectly generate ridge endings. Even after subjecting an image to a series of filters these anomalies can remain.

To solve this problem we created a function which first generates a mask which represents the number of transitions about a single pixel when traveling in a clockwise direction in relation to the image. The function then performed the following set of operations.

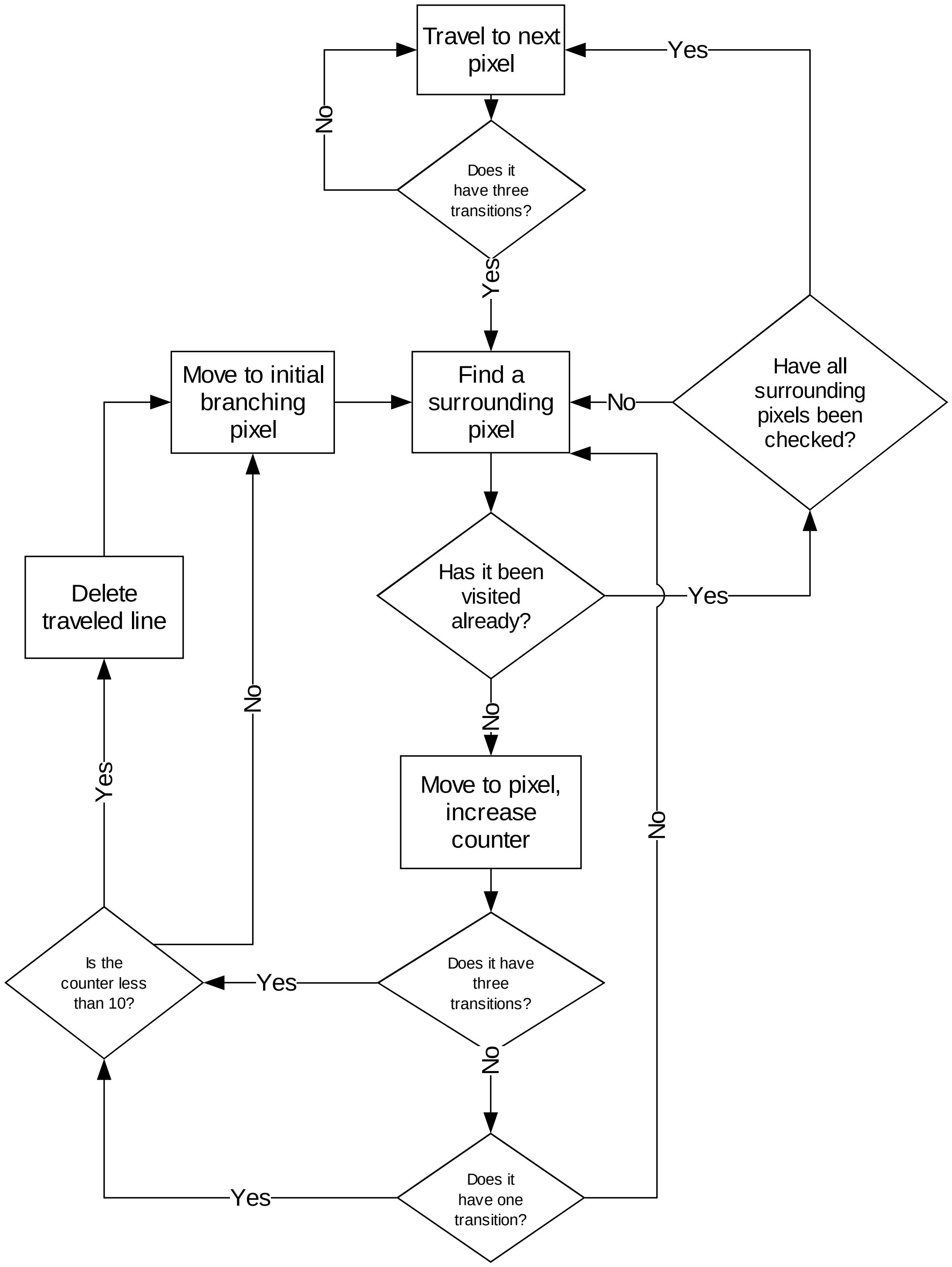
Travel to next pixel
Yes
No
Does it have three transitions?
Yes
Move to initial branching pixel
Find a surrounding pixel
No
Have all surrounding pixels been checked?
Delete traveled line
Has it been visited already?
Yes
No
No
Yes
Move to pixel, increase counter
No
Is the counter less than 10?
Yes
Does it have three transitions?
No
Yes
Does it have one transition?

Figure 6 - Flow chart depicting ladder and spur removal logic.

This function adequately removed the aforementioned structures resulting in a much cleaner image. By running this function the number of false minutiae points are drastically reduced.

4.7.2 De-Line Function

This function exhaustively inspects each line by following its path within the fingerprint. If the line is less than 10 pixels long we assume that the line can be deleted. It accomplishes this by systematically examining each pixel. When it comes to a pixel which is an end point it continues along the path until another end point has been reached using the same method outlined in the flow chart above. Any ambiguous lines remaining in a final image contribute to the frequency of ridge endings when extracting minutiae. By removing these lines the number of points which must be analyzed drastically decreases.

4.8 Other Functions

We have created some other functions that are either used to display information about the fingerprint image or were created during the early stages of the project but may be useful in future work in this area. A brief description of their utility is listed below.

4.8.1 Image Smoothing

The Greenberg et al pre-processing method started by performing a histogram equalization of the fingerprint image. We started our pre-processing by first passing the image through a smoothing filter.

$$\frac{1}{8}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Figure 1: Smoothing Filter Mask

This filter averages the value of a pixel with its local 3x3 neighbourhood and is meant to help remove spots or holes in the original image. The smoothing operation has been biased to white side of grey-scale by dividing the convolution sum by 8 as shown instead of the typical averaging value of 9.

4.8.2 Histogram Graphing

The graph of the histogram() function is used to create a 256x256 bitmap image that displays a histogram graph of a given images pixel intensities. This function was used to provide visual results of the histogramBox() function to ensure it was working correctly.

4.8.3 Orientation Estimation

Many fingerprint pre-processing methods, such as those that use Gabor filters, require information pertaining to the orientation of the ridges in the fingerprint image[#]. The gradient() function calculates an estimation of orientation for 8x8 blocks of the fingerprint image. This function uses two Sorbel masks that are used to calculate an estimation of the gradients of changing pixel intensities in the X and Y directions.

$$\begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$$

Figure 7: Sorbel Mask for X-direction Gradient Estimation

$$\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

Figure 8: Sorbel Mask for Y-direction Gradient Estimation

Using these masks the X and Y gradients are found using the following equations.

$$V_x(i,j) = \sum_{u=i-\frac{W}{2}}^{i+\frac{W}{2}} \sum_{v=j-\frac{W}{2}}^{j+\frac{W}{2}} 2\partial_x(u,v)\partial_y(u,v)$$

Figure 9: X-gradient Convolution Calculation

$$V_y(i,j) = \sum_{u=i-\frac{W}{2}}^{i+\frac{W}{2}} \sum_{v=j-\frac{W}{2}}^{j+\frac{W}{2}} \partial_x^2(u,v)\partial_y^2(u,v)$$

Figure 10: Y-gradient Convolution Calculation

Once the actual gradients are found the orientation estimation is calculated using.

$$\theta(i,j) = \tfrac{1}{2}\tan^{-1}\frac{V_y(i,j)}{V_x(i,j)}$$

Figure 11: Calculation for the Orientation Estimation in Radians

We wrote the code to perform the orientation estimation but, because we never actually used it this function has not been fully tested. This function does not check the consistency of the orientation as some articles suggests.

4.8.4 Median Filter

The function median() will perform a median filter for the given image. This filter functionally replaces the given pixels intensity with the median pixel intensity of a local 5x5 block.

5. Results

5.1 Fingerprint Image Pre-Processing

Throughout the course of this investigation several methods for each stage of the image pre-processing have been implemented and compared. For each case an assessment was made to the final thinned image. In addition to the proposed methods of Greenberg et al. additional modifications to the process were injected with beneficial results. Following the flow diagram depicted in Figure 2, the benefits of each stage are outlined. The final software package contains a program which follows these steps to produce a final thinned image. Figure 12 shows the original image and how the thinned image would appear if nothing else was done to it.

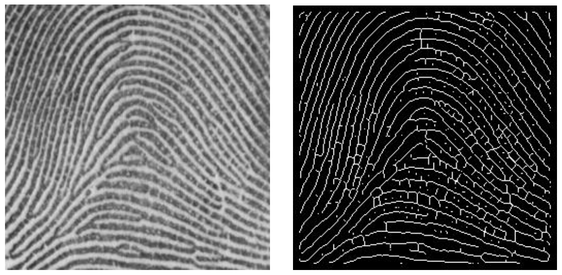

Figure 12: Original image and its binarization and thinning.

5.2 Mean Filtering

Many original images contain lighter regions within the ridges known as pits. During the binarization process these pit are often mistaken for breaks which in turn generate false ridge endings or bifurcations. The article by Greenberg et al does not address this problem within their approach but through trials we found this to be a major contributor of noise in the final thinned image. In order to alleviate this problem we applied a biased mean filter which drastically reduced the number of these false structures. This was slightly biased in the lighter direction, but affected the entire image. Note in Figure 13 the number small anomalies and structures that have been removed simply by applying this filter. One problem this did generate was a tendency to cause dark regions of the image to become darker causing a loss of ridge detail in the final thinned image. This was corrected by further filters.

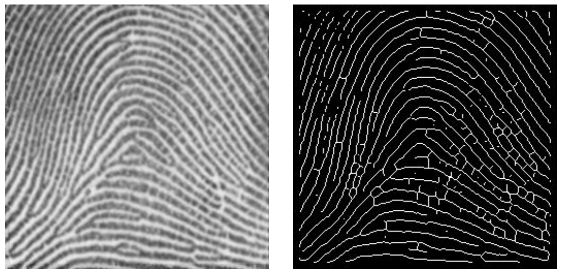
Figure 13: Mean filtered image and its result on the final thinned image.

5.3 Histogram Equalization

Histogram equalization increases the contrast of an image by remapping the frequency of pixel intensities to a larger breadth. For example, on an intensity scale from 0 to 255, most images have values concentrated in the center of the range with two peaks; one representing ridges, the other representing valleys. Figure 14 shows the original image's histogram and the histogram after applying the equalization. The reason that the post-processed histogram isn't an expansion of the original is because the equalization is applied over 13 pixel square blocks of the image. The block size of 13 is suggested in the article by Greenberg et al. [9] and proves to yield the best results after trials of many different sizes ranging from 4 to 256.

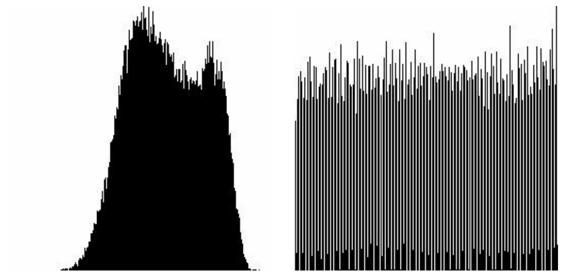
Figure 14: Original image's histogram and its histogram after applying the equalization.

Figure 15 shows the image to this point after applying the histogram equalization and the effect it has on the final thinned image. The actual function of applying this function is to prepare the image for application of the Wiener filter. It does however help to more clearly define the regions of ridge and valley detail partially lost by applying the mean filter.

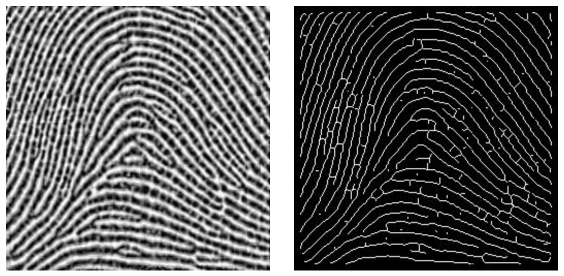
Figure 15: Image after applying histogram equalization and its effect on the final thinned image.

5.4 Wiener Filter

Examining Figure 16 it can be observed that the Wiener filter helps to increase the regional contrast further by making certain points lighter or darker depending on the requirements. At this point the most drastic impact can be seen on the final thinned image requiring only minor morphological alterations.

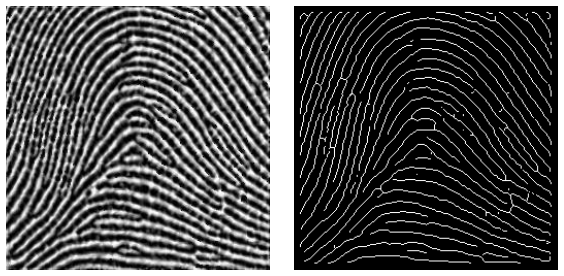
Figure 16: Image after passing it through the Wiener filter and the effect on the final thinned image.

5.5 Binarization

After the image has been filtered sufficiently, it must be binarized to either black or white before thinning. This is accomplished by comparing a pixel to a threshold value and changing the pixel to black or white appropriately.

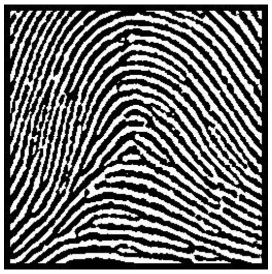
Figure 17: Binarized filtered image.

5.6 Thinning and Morphological Filtering

The final stage in fingerprint image pre-processing is to thin the image to a single pixel width. This allows minutia points to be easily identified thus increasing the speed of the feature extraction. Figure 18 shows the image after thinning it, where Figure 19 and Figure 20 show the results of applying our created point mask filter and short line removal functions.

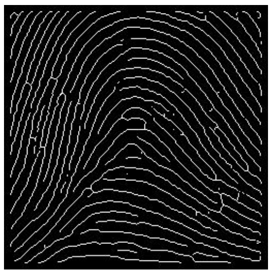
Figure 18: Thinned image after filtering and binarization.

As described above in section 4.7 we created a function which removes ladder and spur structures as well as another which removes small lines. This helps to remove false minutiae from the image increasing the over efficiency of an end product which would implement this software set.

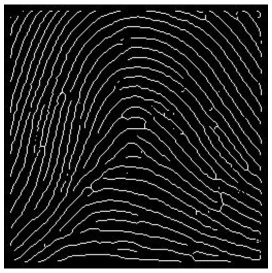

Figure 19: Thinned image passed through the point mask filter.

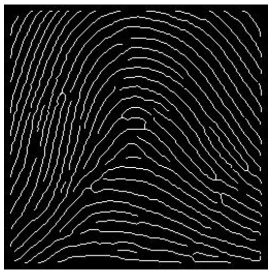

Figure 20: Final image after passing through the de-lining function.

Figure 20 shows the final product after applying the aforementioned filters. This image is significantly less noisy and of better quality than the original thinned image.

5.7 Fingerprint classification

Fingerprint classification is an important part of fingerprint authentication. By putting each fingerprint into a classification group the need to match a fingerprint to the entire database is eliminated and therefore significantly reduces the amount of computation required [2] during the matching process. After looking at multiple journals the first step most commonly used in fingerprint classification is detecting the singular points using the Poincare index. Singular points are cores and deltas. Cores are the top most point on the inner most ridge and deltas are where three flows meet [12]. These are highly stable and rotational and scale invariant [12]. To find the Poincare index the orientation needs to have been determined. This was done as part of "other functions" in image processing. The Poincare index finds the number of cores (N_C) and deltas (N_D) in a fingerprint by reading the direction of the vectors along the curve surrounding the spot in focus see Figure 21.

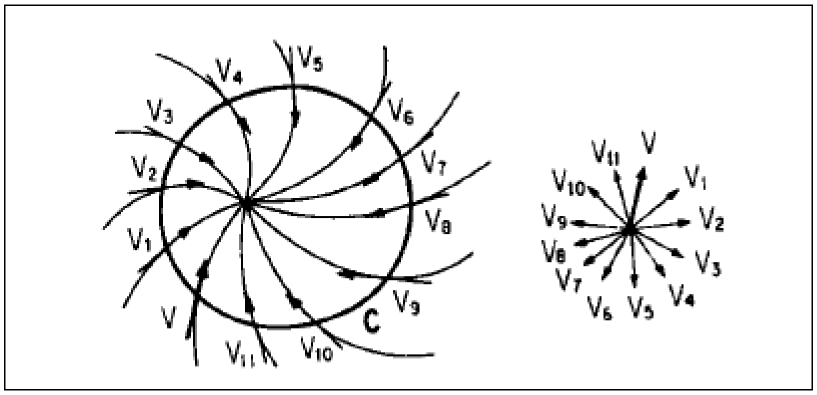

Figure 21: Poincare index, the rotation of the vector V along the curve Ψ [14].

The equations for Poincare index are:

$$Poincare(i,j) = \frac{1}{2\pi}\sum_{k=0}^{N_\Psi} \Delta(k)$$

Where
$$\Delta(k) = \begin{cases} \delta(k), & if\,|\delta(k)| \lhd \pi/2, \\ \pi + \delta(k), & if\,\delta(k) \le -\pi/2 \\ \pi - \delta(k), & otherwise, \end{cases}$$

$$\delta(k) = O'(\Psi_x(k')\Psi_y(k')) - O'(\Psi_x(k'),\Psi_y(k')),$$

$$k' = (k+1) \bmod N_\Psi,$$

O' is the orientation field or ridge map, and Ψ_x(k) and Ψ_y(k) are the coordinates for the kth point on the digital closed curve Ψ, that can encircle a large area or just one pixel. If the Poincare index value is 1 then it is a double core or whorl, ½ is a core, -½ is a delta and 0 is normal [14]. See Figure 22 for visual description of each Poincare index.

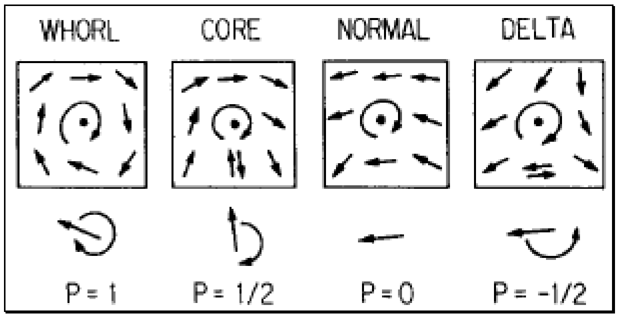

Figure 22: The Poincare index for each type of singular point [13].

To classify using the Poincare index the orientation of the singular points to each other can be used to distinguish between right loops and left loops. Classification of a fingerprint can be determined using Poincare index based on the number of cores and deltas and the orientation of the cores and deltas to each other.

Table 1: Classification based on singular points [12].

Pattern Class	Core	Delta
Arch	0	0
Tented Arch	1	1 (middle)
Left Loop	1	1 (right)
Right Loop	1	1 (left)
Whorl	2	2

After the Poincare indices have been found the way the rest of the classification method proceeds is different for every journal. There is pseudoridge tracing [12], ridge structure [handbook], neural network classifier [13], two-stage classifier [13], and nearest k-neighbour [13]. For the most part the difficulty level of 5 different methods is the same. Based on accuracy for a 4 – class classification the pseudoridge method would be the best approach. The accuracy of classification increases when the number of classification groups is decreased from 5 groups to 4 groups. The problem that rises from having 5 groups is the similarities between the arch and tented arch [12]. This then leads to the tented arch being classified as an arch [12]. When these two groups are combined into one the accuracy increases from 84% to 95.3% [12] as seen in Table 2.

Table 2: Comparison between different classification methods.

Classification	5 – Class Accuracy %	4 – Class Accuracy %
Pseudoridge tracing	84	95.3
Neural Network	90	94.8
Ridge Structure	87.5	92.3
Two-Stage Classifier	86.4	92.1
Nearest K-neighbour	85.4	91.5

6. Discussion

Image Pre-Processing:

The image pre-processing that has been implemented is very successful producing the final skeleton as depicted in **Figure 23**. This shows a dramatic improvement from the original and is in a form that can then be used to extract minutiae for authentication.

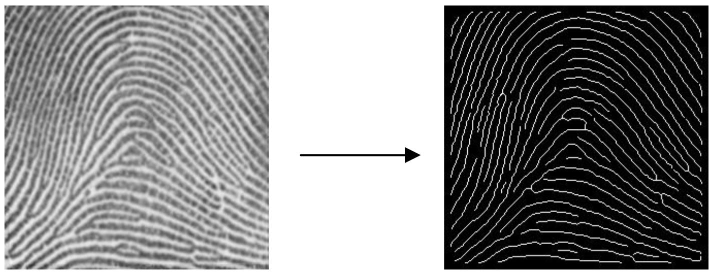

Figure 23 - Best case final skeleton

The fingerprint is now in a state where it can be classified and be used in a feature extraction process. These results however, were obtained from an image that is fairly consistent and that has minimal amounts of noise. When the process is used on an image that contains a more significant amount of noise, the results are not as good. The image in **Figure 24** is an example that shows the limitations of this method.

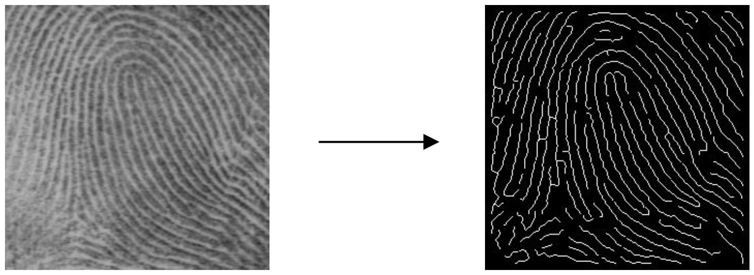

Figure 24 - A noisy final skeleton

The resulting thinned image in **Figure 24** is definitely improved using the software created but, this thinned image is probably not of sufficient quality to produce reliable authentication. For this reason another filtering technique, such as a Gabor or anisotropic filter, should be investigated.

The software that performs this image pre-processing was created by following the techniques suggested in the greyscale filtering portion of the Greenberg et al article [8]. Functions have been created to implement all of the techniques suggested in the article with the exception of morphologically filling false ridge gaps. The only other small discrepancy in our software is in regards to the removal of false bridges. The article suggests that only bridges that are approximately 90 degrees to the ridge direction and less then 13 pixels long should be removed. We did not implement the 90 degree check. Even with these slight limitations, the software that was created performs very well and will provide a useful tool for future work in this area. The results as produced will provide a good measuring stick for other implementations of pre-processing techniques. The software also provides results that that will enable classification and authentication software development and testing to begin while any attempt to improve the pre-processing results are being examined.

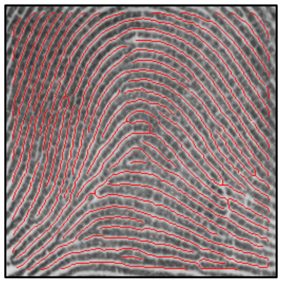

Figure 25 - Best final image with skeleton overlay

Fingerprint Classification:

When is comes to classification of fingerprints there many different approaches to take. The approach that is recommended for the next step in this project would be to get a working Poincare index and pseudo ridge tracing program that classifies a fingerprint. The groups recommended for classification are Arch, Right Loop, Left Loop and Whorl, and to rejects fingerprints that do not fall into any of these 4 categories.

7. Conclusions

While investigating the process of fingerprint-based user authentication it was found that it should be broken into three main groups of image pre-processing, classification, and feature extraction and authentication. Within these three topics there are many subsections which must be addressed.

A software package was created that implement's pre-processing techniques as suggested in the Greenberg et al. article [8] to make a one-pixel thick skeleton of the fingerprint to prepare it for classification and feature extraction.

A few other functions were looked into and have been created but were not implemented into this pre-processing method, but may be implemented in further research.

The recommended method of classification is calculating the Poincare index to find the singular points in combination with ridge line tracing. The recommended groupings include Arch, Right Loop, Left Loop, and Whorl.

8. Recommendations

The quality of the results from the pre-processing stage of the fingerprint authentication will greatly affect a systems ability to successfully classify and reliably match biometric features. Within the pre-processing stage the most important process is by far the filtering of less then perfect images. In this project we used a method of image pre-processing based on the Greenberg et al article [8]. This article used a Wiener filter. In the equation used to create the Wiener filter convolution mask an estimate of the noise variance is required. We used a method suggested by Jain to perform this calculation. This decision should be reviewed or compared to another method used to estimate the noise variance. After Wiener filtering and thinning the Greenberg et al article suggests the thinned image should be morphologically filtered to remove spurs, false bridges and to fill false ridge gaps. Near the end to this project we implemented some basic methods to remove spurs and false bridges. These methods should be reviewed, most likely by implementing an alternate method from another article. A method to fill false ridge gaps needs to implement as there is no function to perform this in the software package. Two other methods of filtering commonly suggested in fingerprint articles use Gabor or Isotropic filtering techniques [8]. Although these methods may be mathematically complex and computationally intensive they should be implemented to asses their merit.

During the scope of the project other functions mentioned in the method such as the function to find the orientation of the ridge structure, normalize an image and perform background segmentation were written but not fully tested. These functions should provide assistance in future research but require testing. The normalize function requires an assigned value for the mean and variance that the image is normalized to. A reasonable method to assign these values needs to be determined [9]. The background segmentation function has two variables that affect its function and need to be considered in any future use. These variables are the block size of each segment and the threshold value that determines if a block is segmented or not. The function that calculates the orientation of the ridge structure within the fingerprint image was written but, needs to be tested and potentially needs to have a consistency check function added to ensure noise does not cause invalid results. The software package should be streamlined by implementing a function that performs convolution. Right now each function that now each function that performs a convolution operation has this operation embedded within it.

The next step in this project is to classify the fingerprints that have been filtered through the image processing functions. The gradient function which was created when beginning some of the advanced filtering techniques can be used to map the fingerprint's local orientation. Most classification schemes use this orientation value in tandem with other approaches to classify the fingerprint. A classification method has been suggested which uses the Poincare index along with pseudoridge tracing to classify the fingerprint into either the Arch, Left loop, Right loop, or Whorl class. After that, minutia points are located and mapped, then compared to a database of fingerprints.

In the long term this project should look at taking the whole authentication process and converting it to a form that can be run on an FPGA. By designing the system to process redundant calculations in parallel, such as matrix convolution, the entire system will be much faster and allow it to be ported to an embedded system.

9. References

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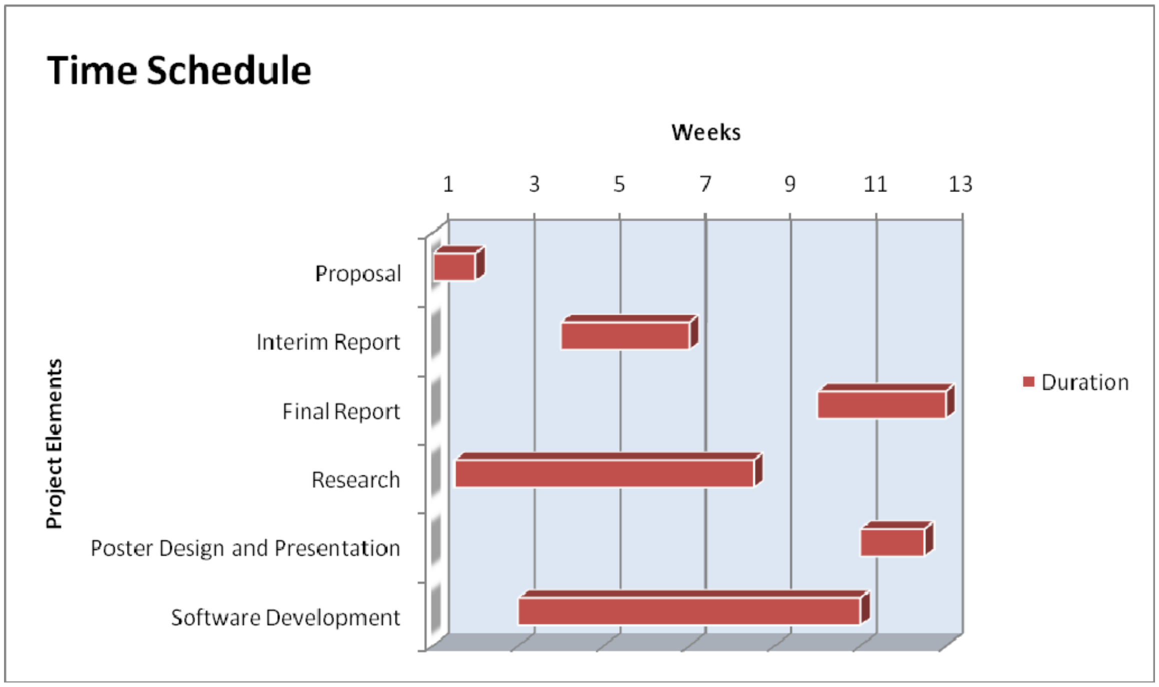
Appendix


Time Schedule
Weeks
1
3
5
7
9
11
13
Project Elements
Proposal
Interim Report
Final Report
Research
Poster Design and Presentation
Software Development
Duration