Lucas Silva Martins

Finger Vein Recognition - A study on biometrics authentication

Area of interest: *Computer Science*.

Advisor: David Menotti.

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Abstract

The demand for simple and secure methods for personal identification has increased steadily. In this thesis I present the study of an authentication method using finger veins, a non-invasive and internal manner to obtain data personal data. This study presents a few techniques used in the literature, and also shows an implementation of finger-vein recognition using low resolution images obtained with NIR devices, going through image extraction, preprocessing and template matching, getting a result of up to 92.505% correct matches, with an EER of 10.822%. This work does not tackle feature extraction, but considers a few preprocessing methods that could be used to implement it.

Keywords: biometrics, finger vein, vein, personal authentication, pattern matching.

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List of Acronyms

DINF	Departamento de Informática
PPGINF	Programa de Pós-Graduação em Informática
UFPR	Universidade Federal do Paraná

Chapter 1

Introduction

Biometrics are being used as a form of authentication to improve upon the shortcomings of knowledge authentication, such as the user forgetting the password or having it stolen and leaked. It increases the security of systems because each persons biological features are unique and hard to conterfeit.[Liu et al., 2017]

This brought another security problem. The data is considered unique for an individual, and won‘t change in a short period of time (permanence functionality). So, now we use an information that can identify someone for a long time to authenticate that user in one or many systems. In case this data is stolen, one will lose authenticity with that specific biometric trait.

No biometrics has yet been developed that is completely fool proof. Face recognition can be easily fooled without the use of extra sensors, and even then, the data it requires is available publicly, a person‘s face can be acquired easily nowadays. Fingerprint based biometric systems are also vulnerable to forgery, because fingerprints are easily exposed to others. Also, the surface condition, such as sweat, dryness, or even dirt in the sensor can significantly deteriorate the acquisition of clear fingerprint patterns.[Lee et al., 2009]

Many studies have been published in order to solve a few of these theft-prone methods, such as using range sensors in face recognition, requiring better resolution images from the sensors, or simply looking for data that can‘t be acquired easily, such is the case of finger-veins. The finger-vein data can’t be easily acquired ilicitly or without the cooperation of the subject, this can improve the reliability of finger-vein recognition in real applications.

Finger-vein biometrics main advantages include:

- Non-contact - images are not influenced by surface condition
- Non-invasive data capture
- Live-body identification - only identifiable on a live body (or body part)
- Internal features - the data can’t be acquired without specific sensors
- Small device size - when compared to palm recognition

The main objective of this work is to study the feasibility of finger veins as an authentication system, and display the obtained result after implementing preprocessing techniques found in the literature, used to avoid common problems with images obtained by the Near Infra-red sensors. The contribution is the use of methods from various papers in the literature, together with the usage of the Zero Mean Normalized Cross-Correlation template matching algorithm, to evaluate the similarity between two or more images.

This thesis will be presented as following: Introduction - this chapter, used to give a brief view of the theme. The Basics is a chapter to explain the theory and technology used to solve the challenges. In the Literature review I present a few studied papers and important topics and methods proposed by them. The Proposal chapter shows the methods and approach used to obtain the results. And as a conclusion, the Validation chapter displays the results obtained after applyng a studied method.

Chapter 2

Basics

2.1 Theory Basics

2.1.1 Region of Interest

According to [Brinkmann, 1999], a region of interest (ROI) is a user-specified area, that can be used to limit certain calculations to within its boundaries. Using the ROI to limit calculations is done when one desires to concentrate on tuning a particular area of the image. The ROI is usually the area of the image with most of the information used to differentiate one image from another.

2.1.2 KNN

KNN (K-Nearest Neighbors) is a method in which the category of an observed x is decided on a basis of majority vote of the nearest k neighbors.[Cover, 1968] And according to [Zhang et al., 2006]: "The NN classifier deals with the hugely multiclass nature of visual object recognition effortlessly"

2.1.3 Gabor Filter

Gabor filter,Gabor filterbank,Gabortransform and Gabor wavelet are widely applied to image processing, computer vision and pattern recognition. This function can provide accurate time-frequency location governed by the “Uncertainty Principle”. Such Gabor fillters have been widely used in various applications . In addition to accurate time-frequency location, they also provide robustness against varying brightness and contrast of images.[Kong et al., 2003]

2.1.4 CLAHE

In some cases, when grayscale distribution is highly localized, it might not be desirable to transform very low-contrast images by full histogram equalization. In these cases, the mapping curve may include segments with high slopes, meaning that two very close grayscales might be mapped to significantly different grayscales. This issue is resolved by limiting the contrast that is allowed through histogram equahlization. Combination of this contrast limiting approach with the aforementioned adaptive histogram equalization results in what is referred to as Contrast Limited Adaptive Histogram Equalization (CLAHE) [Reza, 2004]

2.1.5 ZhangSue

A fast method for extracting the skeleton of a picture, it consists of removing all the contour points of the picture except those points that belong to the skeleton. [Zhang and Suen, 1984]

2.1.6 True Positive - False Negative

True Positive happens when the system matches an image with the right class.

False Negative happens when the system says an image is not from a specific class, but it actually is from that class.

2.1.7 Template Matching

A basic problem that occurs in image proccessing is to determine the position of a given template t in an image I. According to [Kai Briechle, 2001], the position of the given pattern is determined by a pixel-wise comparison of the imaeg with the template that contains the desired pattern. Usually the template is shifted across the image, and the comparison is calculated over the current image area.

2.2 Technology Basics

2.2.1 OpenCv

"OpenCV was designed for computational efficiency and with a strong focus on realtime applications. (...) Because computer vision and machine learning often go hand-inhand, OpenCV also contains a full, general-purpose Machine Learning Library (MLL)." [Bradski, 2008]

2.2.2 JSON

JSON (JavaScript Object Notation) is a lightweight data-interchange format, it is a text format that is completely language independent but uses conventions that are familiar to programmers of the C-family of languages

Chapter 3

Literature Review

In the literature many methods have been used to extract information from infra red finger images, a few of them are described in this chapter.

In [Miura et al., 2004] a line-tracking algorithm is used to find the vein patterns. This algorithm uses the previous know information of the direction of the veins (from the base to the tip of the finger) to find a cross-sectional profile. When searching from one side of the finger to another, it is possible to find a valley of grey level pixels, where the vein is represented. Upon finding such a valley the algorithm searches for the deepest point within it (the darkest pixel), and from it starts moving in a specified direction, looking for another grey pixel. It is executed many times, using multiple random pixels as starting points. This makes for the robust extraction of patterns of finger veins. Each time a pixel becomes the current tracking point is stored in a matrix with same size of the image. Therefore, an element of the locus space that is more frequently tracked has a higher value, and is considered to be part of a vein.

In [Xi et al., 2017] a binary template method is used to create discriminative templates between various images. The authors obtain templates from the images in which the distance between templates from different subjects is maximized, and templates provide maximum information about subjects. Afterwards they use supervised learning with SVMs to obtain the matching results.

In [Yang et al., 2017] a spatial curve models is used to better extract vein-ridge information. To further improve the method, the authors propose a weighted spatial curve filter (SCF), which gives a lower weight to the pixels that are further away from the curve center. With this they could estimate an orientation field on the image, and create a vein vector field. This method has good results on extracting the vein and estimating their widths, and so the vector fields obtained are good representations of the template images.

One of the few papers that tackle a multimodal system is [He et al., 2010]. In this paper the authors treat the combination of data in the multiple systems with extreme care, and don't explain much about methods used to extract features/templates from the data sets used in their experiments. The main topic is the many normalization methods that could be used to fuse data from the different biometrics systems, from min-max, which normalizes the values in the range [0-1], based on the min and the max values found, Z-score, that depends on the mean and standard deviation of the scores, SVM and then the proposed normalization: Reduction of High-Scores effect, that is based on the min-max, but uses the $mean + std - min$ values to normalize the data. With the proposed method the authors reduced the effect of outliers in the normalization, achieving a better result than with the other normalization methods presented by them.

The encryption of template data is discussed in [Liu et al., 2017]. Instead of storing the original template extracted from the finger vein image, they propose a scheme that uses random projection to encrypt the data using a user provided password. The authors also use Deep Believe Networks (DBN), which can learn the mapping relationship between input and output, to generate secure templates during the enrolment process. The DBN will receive the image and a key as parameters, and give a secure template as the output, which can be stored in the system database.

The results obtained in a few of the studied papers are displayed in table 3.1. Of the displayed results, [Lee et al., 2009] uses an LBP feature extraction and [Yang et al., 2012] makes an improvement over the LBP method. After investigating the LBP data, and observing a consistency of bit values, they proposed a method that stores the position of these consistent bits from multiple samples of the same individual, then, when comparing a sample they only compare the consistent bits. This may result in better performance in recognition and in the matching time. This algorithm has two stages, it first needs to be trained to obtain the Best Bit Maps for each individual, and only latter it can be used for recognition.

Table 3.1: Results obtained in the literature

Reference	*Method*	*Database - finger x samples*	*EER*
[Miura et al., 2004]	line tracking	339 x 2 images	0.145%
[Lee et al., 2009]	LBP	480 x 10 images	0.081%
[Yang et al., 2012]	Best Bit Map	106 x 14 images	0.047%
[Xi et al., 2017]	binary code	106 x 6 images	0.088%
[Yang et al., 2017]	vector field	30 x 10 images	≈0.02%

3.1 Data sets

There are not many publicly available finger-vein data sets, and the ones that are don't have enough samples to allow a analisys about the scalability of this kind of biometrics. In this regard it is possible that finger-veins are not exactly unique amongst every human being, but a matching pattern was not found so far. But even in the case finger-vein is not truly unique, we can still use it in a biometric system. Using it together with a fingerprint identification, for example, could prove to be really useful for a stronger biometric recognition.

In most of the studied papers the authors had to create their own databases, but now there are at least two that are available upon request.

3.1.1 SDUMLA-HMT Database

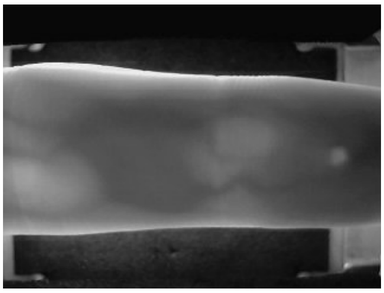


Figure 3.1: Index finger obtained from the SDUMLA-HMT Database

Dataset obtained from [Yin et al., 2011]. In the capturing process, each subject was asked to provide images of his/her index finger, middle finger and ring finger of both hands, and the collection for each of the 6 fingers is repeated for 6 times to obtain 6 finger vein images. This database is composed of 3,816 images. Every image is stored in "bmp" format with 320 x 240 pixels in size.

3.1.2 PKUrate

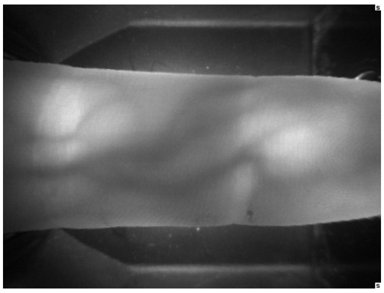


Figure 3.2: Finger image obtained from the pkurate Database

Data set obtained from [pkurate, 5 20]. The image format is bmp, 256 grayscale, 512 x 384 pixel resolution. All the images were captured using devices manufactured by YANNAN Tech. Since all images are captured by the same device, samples from the same finger may have the same size and orientation, but this is not guaranteed. There are 3 data sets, all with 1000 * 5(fingers) images, one of the data sets has images captured in an indoor environment, one in real world usage, and the other one contains data that may show low similarity in one class, and high similarity between different classes.

Chapter 4

Proposal

In this chapter the many methods used to obtain an experimental result in this thesis will be displayed. The chapter was divided in sections and subsections in the order studied that they were studied by the author.

The proposal of this thesis is to study the various steps necessary for using finger veins as a personal authentication method, showing the main issues that were found in the bibliography and by the author, and also show a few of the advantages of using finger veins.

Figure 4.1 shows the flow of the algorithm, first of all I preprocess the obtained image, then use it as a template or extract features from it. After this the obtained data is used in the matching process, so that we can allow the user to continue with what he was trying to get authorization for.

4.1 Obtaining the images

4.1.1 Image Extraction

The finger vein data is extracted using a fairly simple sensor. It needs to extract the patterns of the veins in a finger using a CCD sensor to obtain an image, and a set of near infra-red leds, with the finger being placed in the middle of these. The NIR (Near Infra Red) lights can transmit through a finger. Since hemogoblin absorbs more NIR radiation than other tissues, the veins cast a dark shadow on the image plane. With this we can record the finger-veins successfully. The NIR lights can be refracted, absorbed and scattered by the biological tissue. This causes many errors and needs to be solved in order to get a reliable recognition system. This will be better discussed and explained later on. The images used in the experiments were obtained from the SDUMLA-HMT Database [Yin et al., 2011].

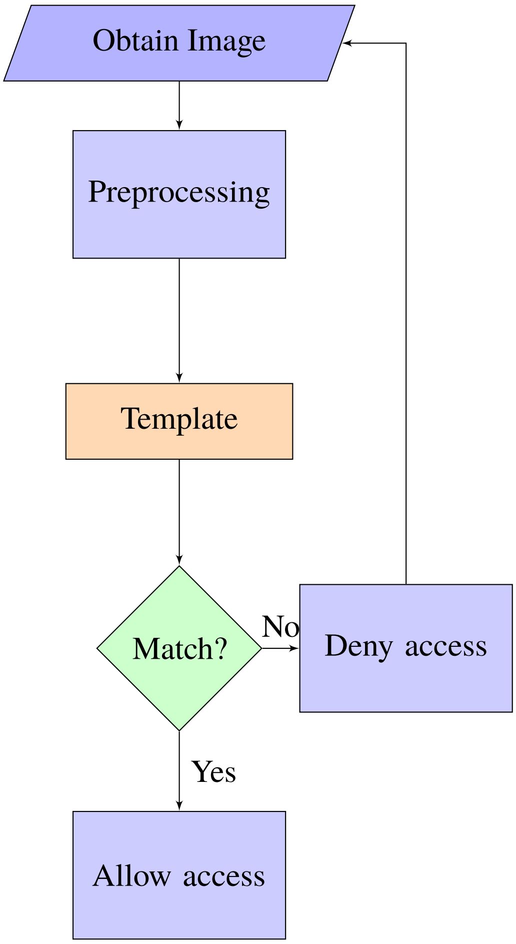
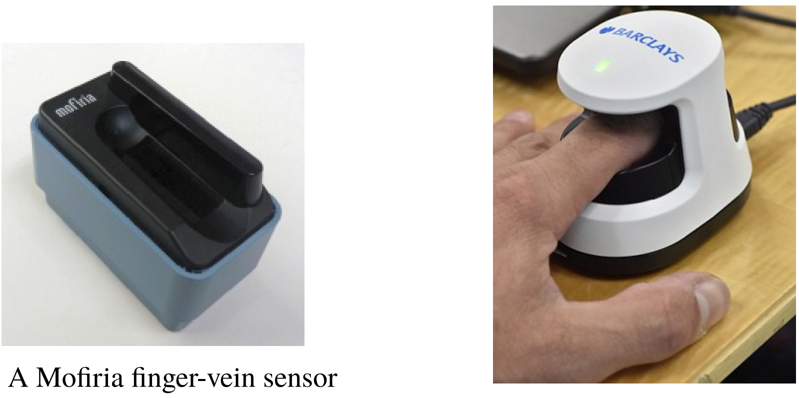


Figure 4.1: Proposed authentication process



(a) A Mofiria finger-vein sensor

(b) A barclay finger-vein sensor

Figure 4.2: Examples of sensors

4.1.2 Region of Interest

In [Yang and Shi, 2012] the image ROI is acquired in a fairly simple and efficient way. The NIR lights penetrate the region between the finger bones much easier than it penetrates bones. For this reason the area with synuvial fluid between the bones is usually the brightest in a finger-vein image. Using this information we can search for a region with a pixel width and use it

Figure 4.3: Index finger x ray

to find the ROI of the image, as seen in figure 4.4. I found this process to be easiest, and the most effective one, after reading and comparing several methods, and so this was implemented and the results can be seen in figure 4.5

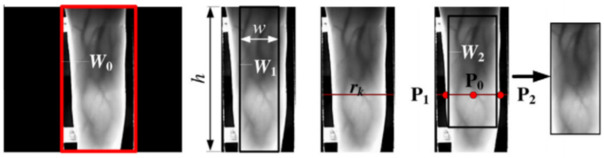


Figure 4.4: Finding the region of interest [Yang and Shi, 2012]

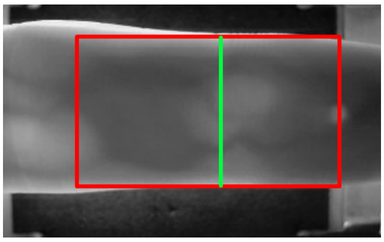


Figure 4.5: Extracted ROI

4.2 Preprocessing

The biggest issue with finger-vein images is the differences that occur when retrieving the images, light scattering and even finger rotation and translation that occur during the authentication process. These can cause errors in many algorithms, so this is an important part of the finger-vein recognition process.

4.2.1 Image retrieval

The finger-vein can have several modifications caused when retrieving the images with minor modifications. In cold weathers the veins are much thinner than normal, causing errors when retrieving the pattern of such veins. Another common error is caused by the rotation or movement of the finger while obtaining the images, a finger that is rotated during the image acquisition can cause finger-veins to overlap, or change a few important minutiae, making the authentication harder.

4.2.2 Light scattering

Another effect that happens with finger-vein images is the effect of light scattering. This happens because the light scatters when it gets deflected from a straight path, for example by irregularities in the propagation medium, particles, or in the interface between two media. This fenomena can be lessened by using visibility restoration strategies such as the one used in [Tarel and Hautière, 2009].

4.3 Preprocessing Implementation

The preprocessing is described in figure 4.6. From the original image in the dataset, I acquired the region of interest, applied an histogram equalization(CLAHE), a gabor filter to improve the visibility of the veins and then binarized the image and applied a thinning algorithm to it. With this I obtained the images shown in figure 7.4.

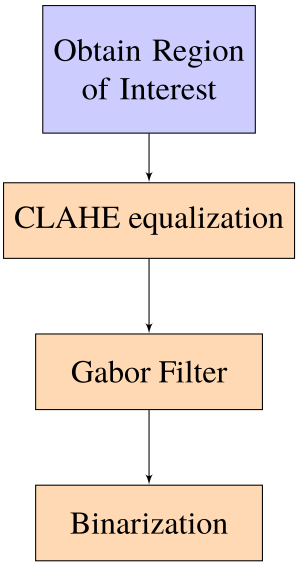
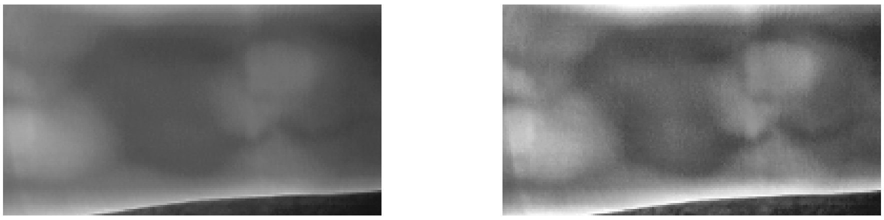


Figure 4.6: Preprocessing flow chart

4.3.1 CLAHE

The finger-vein images can't be equalized with an global histogram because, as mentioned before, the light does not pass through the many tissues of the finger with the same intensity, so the Contrast Limited Adaptive Histogram Equalization method was chosen to equalize the images. The results are shown in the figure 4.7

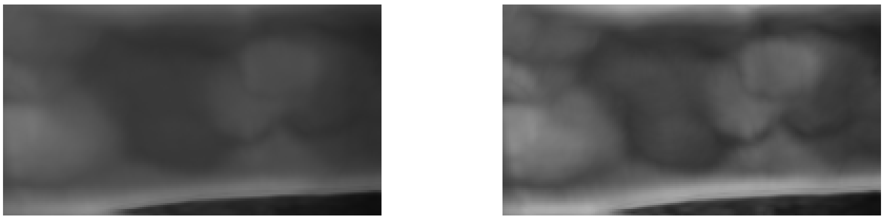


(a) Original ROI (b) ROI after CLAHE equalization

Figure 4.7: ROI images with CLAHE equalization

4.3.2 Gabor Filters

Gabor Filters are used to analyse whether there are any specific frequency content in the image in specific directions in a localized region around the point or region of analysis [Yang and Shi, 2012]. That means a certain filter is used to find patterns that follow a direction specified in the kernel that is being used. By using filters in multiple directions it is possible to extract finger-vein patterns with a good integrity. The parameters used in the gabor filters were tested empirically, to ensure the best values are being used, an example of an image obtained after aplying a gabor filter with bad parameters is shown in fig 4.9



(a) Gabor filter applied on 4.7(a) (b) Gabor filter applied on 4.7(b)

Figure 4.8: ROI images with Gabor Filter

Figure 4.9: Example of wrong parameters used in gabor filter

4.3.3 Binarization

The images were then binarized, using a simple threshold function. If the pixel value is above the threshold it is modified to 0, otherwise it is set to 1 (in a normalized image, with values in the range [0..1]). Afterwards the image was eroded to remove small pixel blobs that could be found.

(a) Example of binarized image

(b) Example of eroded and binarized image

Figure 4.10: ROI images with Gabor Filter

4.4 Template vs Minutiae

There are two main ways of matching a pattern with a person. One is storing the information as a pattern, or a image, and the other is extracting features from this pattern, and storing them in various formats. The advantage of the pattern format is that is stores more informations, making the algorithms that use this method a bit more less prone to false-positive/true-negative results. On the other hand, extracting minutiae from the finger-vein images makes the information much easier to be stored, cryptografied, minimized and transmitted in safer ways. This also allows the implementation of mechanisms to guard the user's privacy. Keeping the original authentication and the user-specific factors is the primary task of the secured template. Even when his/her data are matched with other users, the privacy of the data should remain intact. [Liu et al., 2017].

4.5 Template Matching

The flow of the matching is described in the figure 4.11, basically we compute the similarity value of a template vs the templates in a data set, then, from the values that are greater then a predefined threshold, we get the class with the greatest weight within the K greatest values

4.5.1 Zero Mean Normalized Cross-Correlation

$$ZNCC = \frac{\sum_{i=1}^{MN} xiyi}{\sqrt{\sum_{i=1}^{MN} (xi - \overline{x})^2 \sum_{i=1}^{MN} (yi - \overline{y})^2}} \tag{4.1}$$

Where $\overline{x}$ and $\overline{y}$ are the mean intensity values. This measure is widely used in tracking applications, as a measure of similarity between two templates. In this study only the positive correlation is of interest, thus max(0, ZNCC) is used. [Nakhmani and Tannenbaum, 2013]

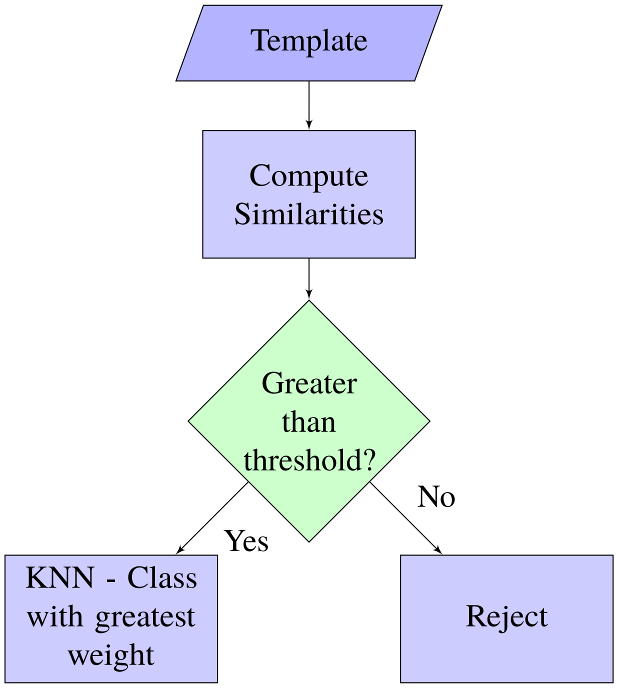
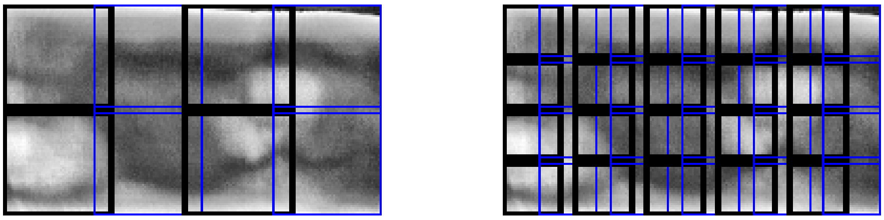


Figure 4.11: Template matching flow chart

To implement this method, the image as a whole was used at first, but this had many issues. Because the images are really similar to eachother, the similarity value between them was greater than 0.97 in most cases, leaving a small margin to differentiate the images of each class.

The method used to avoid this problem was to cut the image in many windows, in order to compare templates with the vein forks and ends(the information which makes each image unique) in many positions of the image, creating a fine grained comparison. With this method alone, the difference in similarity dropped from 0.972 to 0.7 in one specific case, and in the most different images, to 0.3 - 0.4.



(a) Window size 51x51

(b) Window size 27x27

Figure 4.12: ROI images

The algorithm then uses each window to calculate the ZNCC with the window extracted from the same position of the other image being compared. After using this method a better result was observed, this was probably due to the algorithm making comparisons in areas which could display vein features in images of one class, but not of another, being more susceptible to detecting the vein forks and ends. After getting the similarity between all the windows, the mean of all the calculated ZNCCs is used as the value of similarity between the two images.

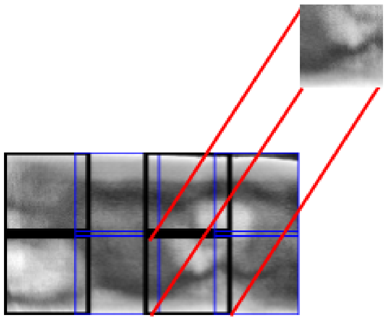


Figure 4.13: Cut of the obtained window

4.5.2 K-Nearest Neighbors

After getting the similarity values, the KNN method was used to choose the matched class of the image being classified. During the tests it was noted that many times the highest similarity was found between images of different classes, but in the set of K highest simmilar images the correct class had more occurences in comparison to others.

To increase the true positive matching, the chosen class was given by the result of a weight function, using the following formula: $(x + 1)^2 - (x + 0.3)$, with x being the position of the class in an array m, wiht size k and sorted in descending order.

For example: with $k = 5$, and $m = [2, 0, 0, 0, 1]$, the resulting weights would be "2" = 0.7; "1" = 21.7; "0" = 22.1, and so, the resulting class would be 0. This formula will only let the class of the image with highest similarity lose if other one was found at least in the 2nd, 3rd and 4th places.

4.6 Conclusion

In this chapter the methods and algorithms used during preprocessing, comparison and matching finger-vein images that were used in the thesis were presented, the next chapter will show the obtained results during experimental tests.

Chapter 5

Experimental Results

The results here displayed were obtained from 3816 images in the SDUMLA-HMT Database [Yin et al., 2011]. From it's 106 persons, 2 hands, 3 different finger with 6 images each, the classes were divided using only images of the same finger. With this approach each class has 6 images, and each person was 'transformed' in 6 classes, giving each image 636 simulated classes to be matched to.

At first, the experiments were done without using a threshold to reject images, in these tests the mean of the results was 3530 right predictions and 286 wrong predictions, getting 92.505% of the images correctly matched to their respective classes.

Table 5.1 show the obtained equal error rates for each of the different types of images, with this we can see the real difference between using the ROI images versus the original one, giving a difference in 4 percentage points from the original to the gabor filtered images (with the original one having the lowest EER).

Afterward I started using a threshold from 0.0 to 1.0, and comparing it to the ZNCC similarity value, table 5.1 shows a few of the results obtained when varying the threshol. With this variation I obtained the following ROC curves (figure 5.1). In the end the experiments with the original images gave a better result, this probably happened in the case of this database, with images obtained in laboratory and taking care during the extraction process. In a database obtained during commercial use the images would not be taken with much care, highlighting the problems that the preprocessing techniques were developed to solve and so using the originally obtained images should give a worse result.

Table 5.1: Results obtained with the Binarized images, with different threshold values

	correct	*wrong*	*rejected*
`.92`	74.109%	3.302%	22.589%
`.80`	83.988%	3.616%	16.012%
`.75`	92.122%	3.852%	4.026%

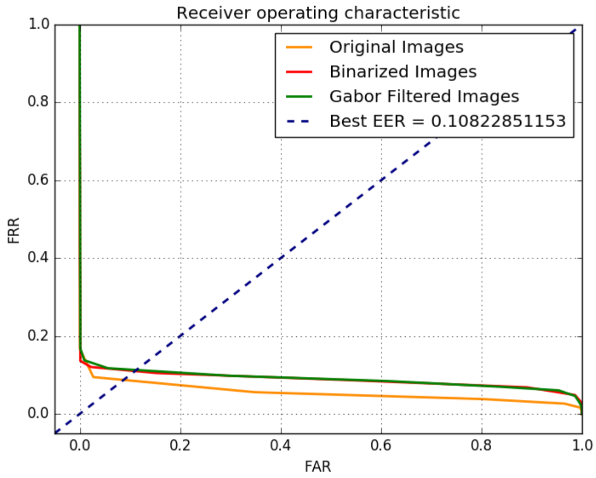


Figure 5.1: ROC curve

Table 5.2: Best EER values obtained

Original images	10.822%
Gabor Filtered	14.557%
Binarized	18.107%

5.1 Discussion

The results displayed in this chapter showed that the template matching with the original images, without any preprocessing got a better result than with the preprocessed ones, this probably happened because during the ROI extraction we lost a lot of information. In this case this information was enough to give a better EER.

As the preprocessing was done to avoid possible problems, such as finger rotation, and also to allow for an easier extraction of minutiae, I don't consider it as being a useless process in this case, but necessary for future works and was also good for comparison reasons.

Chapter 6

Conclusion

This thesis showed an study on finger-vein as a personal identification method, talking about the image extraction through preproccessing - feature extraction and finally the matching process. The obtained results are not enough for use in a commercial biometrics system, but the study of this method, not yet used in our country, and with the many security breaches happening with other biometrics systems nowadays, has brought a better understanding of personal authentication and the security risks of using biometrics for personal identification. The code used to implement the main techniques presented in this thesis are available at `https://github.com/lsm12/finger_vein`

6.1 Future Works

Several tests, adaptations and experiments have been left out due to lack of time (i.e other template methods to define the similarity of two images). Future work concerns testing the proposed method in different data-sets, to have a better understanding of the reason why the preprocessing steps didn't make the end results better.

Some of the ideas I would like to test in the matter are:

- Multimodal Biometric System - Testing the finger-vein together with fingerprints seems like the best method to utilize finger-vein recognition. This would allow one to use all the study done on fingerprints, together with the main advantages of finger-veins (the difficulty of gathering the information without one's knowledge).
- Feature extraction - The automatization of the feature extractions was stalled after the bad results obtained after testing various distance measuring methods. I would like to study more on the matter, because the tests done in this thesis were made with low resolution images, maybe the results would be better with better ones.

- Preprocessing - A lot of methods seen in the studied bibliography were left behind, due to personal preferences. A better study of the impact of other preprocessing methods would impact on the end result of personal authentication.
- Bigger Datasets - With a bigger dataset the problems encountered arise, this would also bring a better understanding of the best methods to use in finger-vein biometrics
- Feature criptography - Using extracted features would give a easier way of storing finger-vein information. This allows us to use many criptography methods to store a person's data, increasing the overall security.

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Chapter 7

Appendix A - Minutiae extraction

What is displayed here was studied during my experiments, but were not used to obtain the final results of this work, as I was not able to get good results with these techniques. This chapter was added to help in future works, since the image thinning process shown here is an important step to extract finger vein minutiae from images.

In Finger-vein images there are not many minutiae to be extracted, most of the studied papers used only vein bifurcations, and vein ends as minuntiae (fig. 7.1). Before extracting this data from the database with an algorithm, the minutiae were obtained using a manual extraction. A simple software was created, to allow anyone to mark points in an image and inform that point as a vein fork or end. This software then saved the marked point as a JSON object, a format that can be interpreted easily in any programming language.

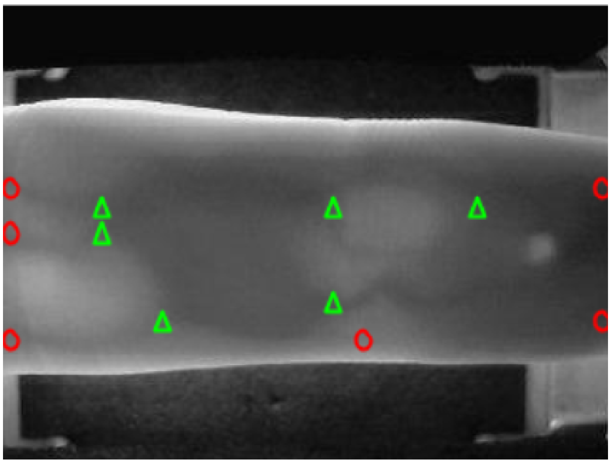
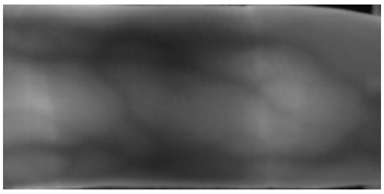
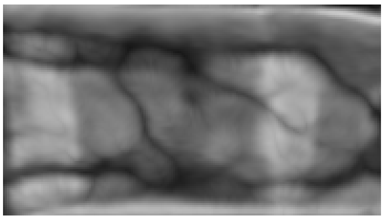


Figure 7.1: Vein ends are marked with a red circle, and bifurcations with red triangles

As we can see from the images displayed so far, the resolution is not great, so it was quite difficult to obtain all the necessary information from each image, losing a lot of minutiae in each one of them, even during manual extraction. To improve this proccess, the minutiae was obtained from prepocessed images, as the one in 7.2(b).



(a) ROI extracted from original image



(b) ROI after preprocessing

Figure 7.2: ROI images

7.0.1 Thinning

After binarizing and eroding the image, the ZhangSuen algorithm [Zhang and Suen, 1984] is applied to the image, to keep only the skeleton of the vein visible. This algorithm was also chosen because it keeps the connectivity of the veins, avoiding vein end features from being added to the images.

After this step the preprocessing is finished and the features can be easily extracted. In this thesis the extraction of features was not completed, and the images were used only for template matching.

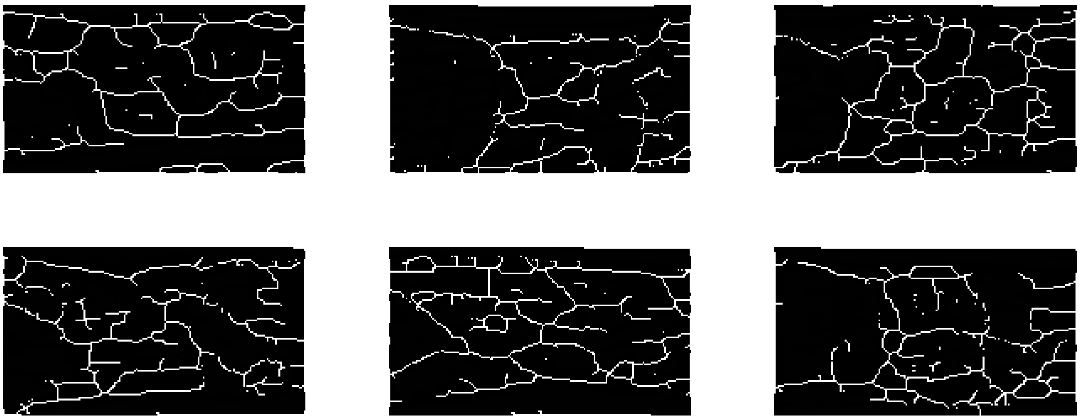


Figure 7.4: Example of images after applying the zhangSuen alg.