# A study on the shape of the phalangeal joint in finger vein images

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## Abstract

Not only can the position of the phalangeal joint improve finger vein recognition. By drawing the segments of the joint by hand, it was found that the shape of the joint holds identity information. A couple of methods to segment the joint were explored, namely watershed, level sets and optimal paths. Watershed and level sets were both sensitive to the veins in the image, watershed more so than level sets. Both of these were also very sensitive to lighting irregularities at the edge of the finger. The implementation of optimal paths was very simple, but already more robust than both watershed and level sets. For future studies a new method that improves upon the optimal path implementation is proposed.

## 1 Introduction

Finger vein recognition is a technique that is used in the field of biometrics. It is a promising way to identify a person, as the veins in one's finger can only be captured when they are alive, it is hard to copy the vein patterns, since it is not exposed to the outside of the body and the pattern can be captured contactless. Previous research has mostly focused on finding the vein pattern in fingers. However, a small body of work exists on finding the joint in the images. The position of the first phalangeal joint is then used to improve the matching process of the finger vein patterns. The position of the joints does not have to be the only information that can be used to improve the finger vein pattern recognition. In the images containing the veins, the joints can be identified to have a certain shape. This paper concerns the questions whether the phalangeal joints hold any information of identity and what methods can be used to extract that information from the finger images. The main contributions of this paper are as follows:

1. To introduce a new insight that the shape of the phalangeal joint holds information of identity.

2. To propose several methods of extracting the shape of the joint and show how effective they are.

## 2 Related work

Light in the visible spectrum does not travel through the skin. Therefore, the images used for finger vein recognition are captured using near-infrared (NIR) light to capture the structures inside the finger. The hemoglobin in the blood absorbs the NIR light, while other tissues in the finger refract the light. This causes the finger veins to show up darker in the images. However, it is not only the veins that can be distinguished in these images. The physiology

of the phalangeal joints, located between two of the three phalanges in a finger, let trough more NIR light than the rest of the fingers. [8] A small body of work exists on using the phalangeal joint to improve finger vein recognition. The most basic methods find the column in the image of the finger that has the largest brightness. When matching the veins, the patterns are laid over each other so the veins match up. [8, 7] Not all capturing devices have regular lighting, so this method is not always reliable. To combat this problem, a moving elliptical window is used to find the centre of the joint. [6] reference does not find the centre of the joint, as the brightness of the image will influence the above mentioned methods. Instead, the right edge of the joint is found using two moving windows. Using this method the vein patterns can be matched in a more precise region. [4]

# 3  Analysis

Based on the previous work it can be concluded that based on the brightness of the image, the joints of the finger can be found. However, that does not conclude that the joint has a particular shape that can be extracted from the image. Using the dataset collected by Ton B. [5], more images of fingers can be studied to find whether the joints have a particular shape or not.
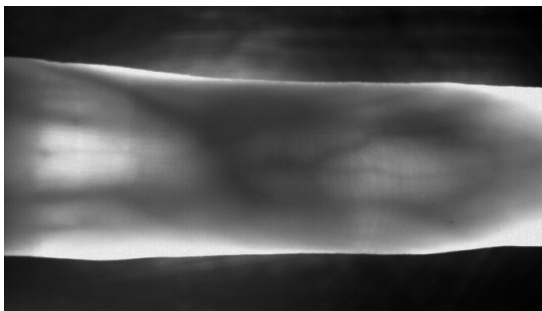


Figure 1: A near infrared image of a finger in which the joints can be seen

In figure 1, the joint on the left is brighter than the rest of the finger. Furthermore, hor-

izontal lines can be seen marking the beginning and start of the joint. Most images in the dataset have clear lines of contrast marking the left joint. In this paper, only the left joint will be considered, as it is the biggest of the two and easier to find.

## 3.1  Segmentation by hand

To know whether the shapes of the joint hold any information of identity, they will have to be segmented by hand and matched. The guidelines for this segmentation are as follows:

1. The segment should consider the lower phalangeal joint. In the case of this dataset, the left joint.

2. The segmentation of the joint should range the complete width of the finger.

3. The edges of the segment should be mostly horizontal.

4. The edges of the segment should run along the line of contrast.

5. If there is no contrast line, then the edge should be horizontal, or run from the contrast line above to the contrast line below.
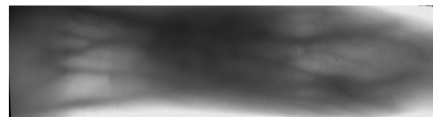


(a)
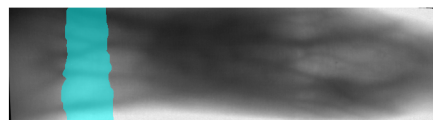


(b)

Figure 2: The original image of the finger (a) and the segment of the joint laid over it (b)

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This was done for 24 images of the dataset, which contained 4 images of 6 different fingers.

## 3.2 Matching the segments

To match the segments, normalized cross correlation is used. Cross correlation slides two segments over each other and calculates how much the segments overlap. Normalized cross correlation does the same, but it subtracts the mean of the image from each pixel first, causing the result to always be between -1 and 1.
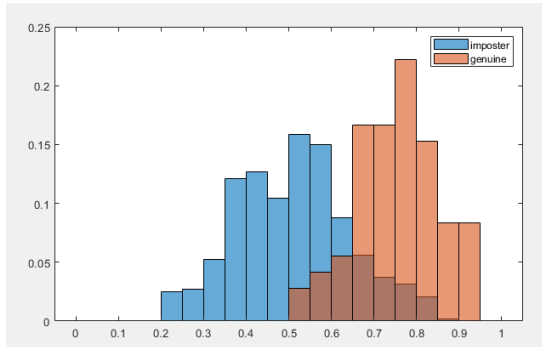


Figure 3: The normalized cross correlation for the segments drawn by hand

The equal error rate lies around a normalized cross correlation of 0.66. The error is around 13% for both the genuine matches and the imposter matches.

# 4 Methods

Numerous methods exist for image segmentation. Based on the structure of the joints, a method is needed that can find the edge of the joint, without being influenced by the veins. The images will first be prepared for segmentation. Using the outline of the finger, the image can be turned to correct for any skew. Everything outside of the finger cropped from the image. Next, using an elliptical window, the location of the centre of the left joint is found. A region of interest is created around the centre of the joint, making the image roughly a square.
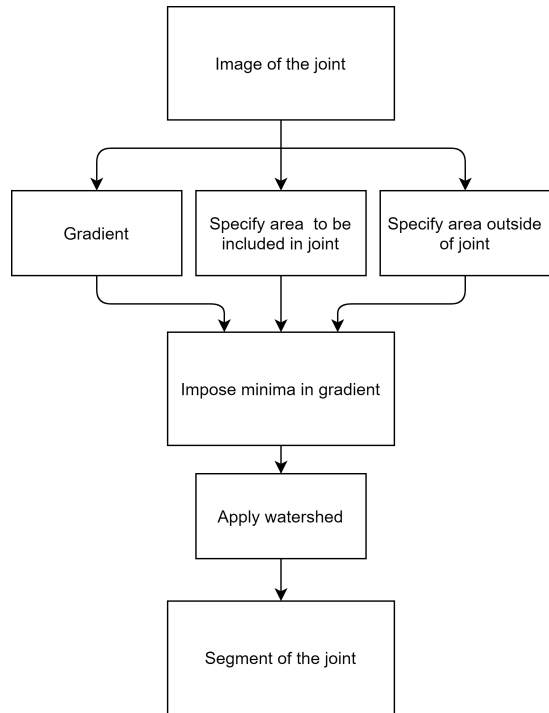
## 4.1 Watershed



Figure 4: Block diagram for the watershed method

Figure 4 shows the full method used. A watershed algorithm start by finding every minimum value in an image. Every iteration, the pixels next to the minimum are compared to the level. If the value of a pixel is equal to the level, it is added to the area of that minimum. If a pixel can be added to two areas in the same iteration, it becomes the edge between these two areas. [3] The resulting segment should have edges where the contrast is highest. However, the watershed algorithm does not find edges in contrast. In stead of applying watershed to the original image, it will be applied to the gradient of the image. Since the contrast is highest where the edge should be, the gradient will be higher there, than the surrounding pixels. When applied to an image, the watershed algorithm will produce as many segments as there are local minima. To make sure only two segments are created, local minima are imposed

only in the area that is certainly at the centre of the joint and at the edges of the image, where the joint is no longer.

## 4.2 Level Sets

Level sets are an iterative algorithm that is used to find edges in images. An initial region is provided, which grows based on the gradient of the image. [2] After every iteration the region is corrected with the initial region, to make sure the full initial region is included in the final segment.

## 4.3 Optimal Path

The last method that was tried is a rough implementation of a shortest path algorithm. The edges of the joint are on a contrast line. This means that the left edge should be the optimal path for which the summation of the pixel values on the right subtracted by the summation of the pixel values on the left is the highest. This is implemented in an algorithm that first finds the centre point of the joint's edge by sliding a vertical line over the image and calculating the difference between the adjacent pixels on the left and the right of that line. Where the difference between the right and left is highest, a point will be drawn at the centre of that line. Using the centre point, both the top and the bottom point can be calculated in similar fashion. However, this time the end of the line is always connected to the centre point, while the other end is connected to a point, that slides either over the top of the image, or the bottom. Again the difference in brightness between both sides of the line is calculated. For every possible point, the angle between the initial vertical line and the new line is also calculated. The difference in brightness $C$ and the angle $\alpha$ are used to find the energy using equation 1.

$$E = k_1 C + k_2 \alpha^2 \tag{1}$$

The points with the maximum energy are the top and bottom of the edge.

Using these three points, more can be added with a similar approach. However, for every new point, two lines are used to calculate the contrast. One line is connected to the point above and the sliding point, while the other is connected to the sliding point and the point below it. The same equation for energy still applies, however $k_1$ and $k_2$ might be slightly different.

# 5 Experiments and Results

To verify how effective every method is at extracting the correct segment for the joint, they will be compared to the segments made by hand. If a method produces segments for each image, the segments will be matched with each other, to see if the genuine pairs have a better matching score than the imposter pairs.

## 5.1 Watershed

The watershed method did not work properly for every image. For some fingers, no segments were created at all. If a segment was created, most of it's edges did not line up with the hand drawn segment. The segments did not reach the full width of the finger.

## 5.2 Level Sets

The segments made using level sets are similar for the same finger. However, they do not always line up with the edge of the joint. Furthermore, the segments do not span the entire width of the finger and the method shows inconsistent behaviour for different fingers.
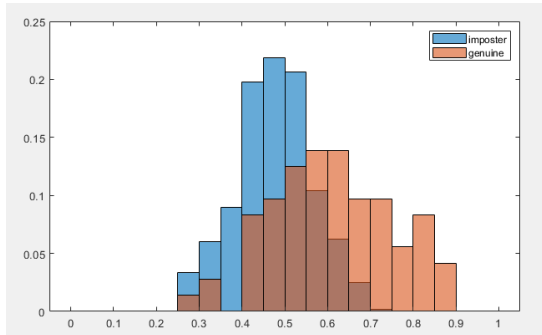
4

Figure 5: The normalized cross correlation of the segments created using level sets

Despite the aforementioned, the histogram shown in figure 5 shows that the segments hold some identity information. At the equal error rate of 0.5, the imposter and genuine match error both lie around 30%.
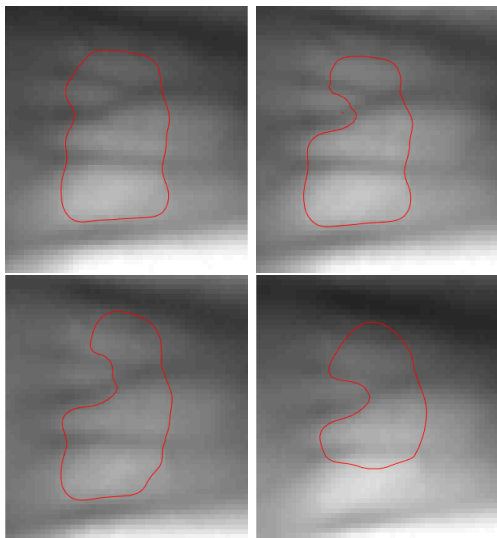


Figure 6: The segments created using level sets for different images of the same finger

## 5.3  Optimal Path

Even thought the implementation is very rough, it finds the edge of the left joint. The constants that define the energy $k_1 = 7$ for the top and bottom points, $k_1 = 30$ for the new points and $k_2 = 1$ for all points.
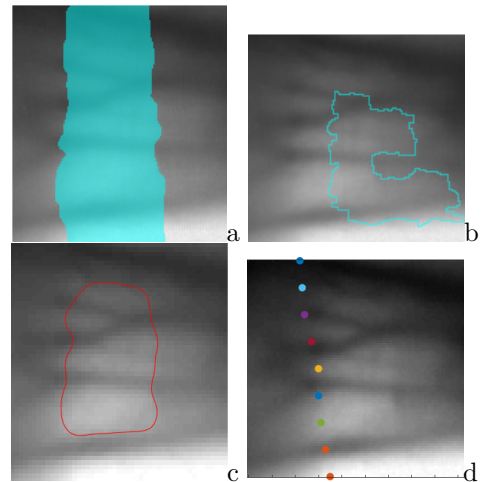
## 5.4  Comparison



Figure 7: The identified edges of the joint by different methods: segmentation by hand (a), watershed (b), level sets (c), optimal path (d)

Figure 7 shows the different methods side by side. The edges of the segment from the watershed method do not match with the segment made by hand. There is a lot of leakage to the right past the edge. The segment does not reach far enough to the left to find that edge of the joint. The edge of level sets does line up with the edge of the joint for this particular image. However, it does not reach the top and bottom of the image. For a lot of images, the edges of the veins were too strong for the segment to grow to the desired shape.

## 6  Discussion

The watershed method is not preferred, as the edges of the veins are so much larger than the edges of the joint, that the joint is not found correctly. This is presumably due to the fact that by imposing local minima, the gradient is changed so much that other lines of contrast, like that of a vein, become more prevalent than the edge of the joint. The level set method worked really good for some images, but for others the veins had too much influence

or lighting irregularities caused it to stay in a certain shape. The implementation for finding the optimal path is very basic, but also very promising. It could be improved by making the algorithm iterative. After multiple points are placed, the algorithm could use these to correct any mistakes. An other option is to make this algorithm more like Dijkstra's algorithm [1]. The energy for multiple paths starting at the centre point, and the path with the highest energy will be the edge of the segment.

# 7 Conclusion

Even with a small dataset it can be shown that the shape of the phalangeal joint in images used for finger vein recognition hold identity information. Out of the methods tried to extract this shape from the images, optimal path tracking was the most promising. Watershed proved to be too sensitive to the veins trough the joint, while level sets were too sensitive to lighting issues. An improved method is proposed for future research.

# References

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