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VeinDeep: Vein Pattern Based Biometric Authentication

by

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Abstract

With growing dependence of people on their computers through the advancement of technology in recent times, there is an increased emphasis on the need for security in such systems. People are entrusting their devices with more critical information such as bank details, passwords and personal information. There is a growing need for devices to be able to correctly authenticate people, ensuring they are in fact the owners of the device, rather than simply someone who knows the password to it.

While using biometric features to authenticate users is not a new concept, the techniques used traditionally in this regard are lacking. Thumbprints, facial and iris recognition systems are all at a risk of being bypassed simply via opportunistic access to the same biometric features they utilise to prevent opportunistic access. This in turn defeats the purpose of the authentication systems themselves.

VeinDeep offers a solution to this predicament by utilising a biometric feature much more robust in itself to opportunistic access. Vein patterns on the hand dorsum can be difficult to capture without the knowledge of their proprietors, while also requiring complex technology to do so. Furthermore, vein patterns are unique for each hand, and bear no genetic homogeneity in their branching within the body. This means that vein patterns can be used to uniquely identify a person, resolving the above mentioned issues with authentication based on shared secrets.

This report demonstrates a low cost system for authenticating users using vein patterns in the users hand dorsum. Through its experimentation techniques and results, it further demonstrates the difficulty involved in acquiring a user's vein patterns through opportunistic access to bypass such a system. Furthermore, the implementation of this system utilises technology that is soon to be integrated into mainstream devices, making it a relevant, pertinent and cost-effective solution to preventing opportunistic access.

Acknowledgements

Firstly, we would like to thank our advisor Dr Salil Kanhere for guiding us through this year and always staying very supportive and level headed as we hit each of our many roadblocks.

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Finally, the largest recognition goes to our families who supported us mentally and financially throughout our entire schooling lives. We could not have done this without you.

Abbreviations

AVA Arterio-Venous Anastomoses

IR Infrared

OpenCV Open Computer Vision

PIN Personal Identification Number

ROI Region of Interest

SDK Software Development Kit

SHA-1 Secure Hashing Algorithm 1

SR Short Range

SSL Secure Socket Layer

TP True Positive

TN True Negative

FP False Positive

FN False Negative

EER Equal Error Rate

FRR False Rejection Rate

FAR False Acceptance Rate

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Chapter 1

Introduction

In our ever-developing, technologically advanced world, security - particularly authentication - is becoming increasingly important. People are putting more and more faith in their devices, leaving passwords and bank account details on digital keychains. The only thing standing in between them and malicious users is a fingerprint scan or short, easily guessed or discovered password.

The problem with many current authentication systems is that they fail to uniquely identify a person, rather only confirming that they know some sort of information (i.e. Password, PIN, secret question). Another downfall is that Hashing Algorithms, used to represent passwords and other sensitive information, age and degrade, becoming vulnerable for attack and unfit for use. A recent example of this is SHA-1, with many browsers now not accepting SHA-1 SSL certificates [Goo17a]. These systems require the use of complex infrastructure, generally also proving them to be expensive and difficult to implement.

This vein of thought is what highlights the necessity of biometric authentication, the security verification relying on the examination of unique biological characteristics of users. This authentication method does however possess its own inherent flaws. Biometric authentication may also be compromised by resourceful attackers. Fingerprints can be stolen, voice recordings can be replicated, iris patterns can be snatched from social media; the existing biometric authentication techniques are lacking. In fact, current biometric authentication systems are further limited in that damage to bodily features such as fingerprints or irises may hinder use of such systems, potentially excluding legitimate users.

We will be continuing the work of a former UNSW thesis student, Henry Zhong, on the Veindeep project [Zho], porting it to a new, more versatile, portable and scalable platform and conducting further research into the area. We have developed a system for identifying users using the vein patterns found on their hand dorsum. The system's intention is to quickly and accurately identify users based on their vein patterns. This technology has the advantage of biometric redundancy if we do not limit ourselves to hands; if some region of the veins becomes damaged, another can be used in its place. The importance of this Thesis lies in the physical characteristic that is used to identify the user: the veins found in their hand. Unlike other biometric data, vein patterns are incredibly difficult to steal and hence use to fraud access control, lowering security risk.

This authentication technique makes use of widely available technology, meaning that it has the potential to be integrated into a wide range of devices readily available today. The device used is reasonably cheap, making it accessible for all kinds of users, either in a personal or commercial capacity.

We also performed further research into the possible environmental and physiological factors which may impact the accuracy of our system. This data allowed us to improve our design and potentially identify flaws in this form of biometric authentication.

1.1 Outline

This thesis is divided into the following chapters. Chapter 2 describes related work and research pertaining to past development in the field of vein pattern based biometric authentication and the factors that affect it. Chapter 3 discusses our design in depth - both hardware and software. Chapter 4 describes the experimentation carried out in order to judge the accuracy of our produced system. Chapter 5 delivers the results from this experimentation, with an analysis of the data following. Chapter 6 concludes the report, posing potential future designs to further this authentication system.

Chapter 2

Background

2.1 Biometric Authentication

Biometric Authentication is a technique that employs the conversion of biometric data into a format that can be interpreted by a piece of software or computer with the aim of then comparing it to an authorized template. While similar, it is differentiated from biometric identification, which aims to identify a user based on quantified biometric data [Gem17]. Biometric technology can be broadly categorized into two classes based on measurements taken:

Physiological Measurements are the quantitative representations and virtualizations of biological features. This is a frequently utilized category of measurement. Examples of biometric authentication technology that utilize this type of measurements include fingerprint scanners and iris, retina and vein pattern recognition.

Behavioural Measurements are the quantitative representations of measurable patterns in the user's activity. Examples of this measurement type include voice and gesture recognition.

Biometric authentication techniques that employ physiological measurements are generally more reliable, with measured biological features (fingerprints, eyes) rarely changing throughout user's life. Behavioural measurements tend to be more fickle, with a multitude of factors potentially changing the user's behaviour and hence impacting their measurements. Biometric authentication systems analysing behavioural measurements are also generally at a higher risk of being compromised, with behavioural patterns more easily captured or reproduced than biological features.

It is not by any means a new field of science and technology, with the first recorded systematic capture of hand images for use in authentication dating back to India in 1858. Sir William Herschel developed a system to prevent people not employed by the Civil Service from collecting paychecks [Gem17]. Biometrics have come a long way since then, now incorporating complex technology to identify and authenticate users. With such intricate and expensive hardware and software, many biometric authentication systems (such as iris recognition) are somewhat inaccessible for personal use by the public, utilized mainly in a commercial setting by well-funded organizations.

2.2 Past Work

A former UNSW thesis student, Henry Zhong, developed VeinDeep, a biometric authentication system analyzing vein patterns in the user's hand dorsum [Zho]. He used the Kinect V2 sensor (see Figure 2.1) and the Kinect for Windows SDK to develop the application [Mic17].

The Kinect V2 was able to take correct exposure level ROI snapshots, unlike the original Kinect sensor. This model, designed for Xbox-developed movement based games, had an IR blaster which was too powerful to take clear ROI snapshots without the use of a dampening filter. Henry was able to apply this filter and take reasonable snapshots of the hand dorsum. These snapshots were furthered by extracting and converting the image into vein pattern data. He consequently implemented and tested comparison algorithms on real subjects. This allowed for a proof of concept to be developed as far as the use of vein pattern based authentication was concerned.

Henry's implementation, unfortunately, was limited in the choice of the platform that he used. The Xbox Kinect V2 failed to reach market success and was never integrated into a complete computing system. It remains only a tool for developers making desktop applications for Windows or games for the Xbox One. The camera itself, while also being quite large by design, does not have feasible prospects for being integrated into a portable device such as a tablet.

Further work within vein pattern based authentication can be found in Lingyu Wanga, Graham Leedhamb and David Siu-Yeung Choas 2007 paper *Minutiae feature analysis for infrared hand vein pattern biometrics* [WLC08]. Herein the researchers implemented a unique method to analyse the minutiae features found on the veins at the back of the hand dorsum, such as the bifurcation points and the ending points of the veins. This is very similar to our proposed solution to vein pattern analysis, which is discussed below.

Similar inquiries were undertaken and published by Sang-Kyun Im, Hyung-Man Park, Young-Woo Kim, Sang-Chan Han, Soo-Won Kim and Chul-Hee Kang in their paper *An Biometric Identification System by Extracting Hand Vein Patterns* in the year 2000 [IPYWK+01]. The researchers implemented an FPGA processor to perform the vein pattern extraction using a shift-and-add architecture. Some benefits of this approach include the low cost of manufacturing FPGAs, as well as their added benefit of increased throughput and reduced execution time.

Research into vein pattern comparisons was furthered by Jian-Da Wu and Chiung-Tsiung Lius work, where they utilized Neural Networks to compare the vein patterns [WL11]. In their paper, titled *Finger-vein pattern identification using principal component analysis and the neural network technique*, they describe how they utilized a near infra-red emitter to scan the vein patterns *inside* the finger. While the algorithms are different, their vein pattern identification process is quite similar to ours. It consists of three computational steps: Extraction, Classification and Pattern matching.

Figure 2.1: The Xbox Kinect V2

2.3 Physiological Research

When investigating vein pattern based authentication, physiological changes and responses of such patterns must be considered as these changes may affect the success or accuracy of the system. We must understand how environmental factors may affect physiological measurements taken by our application and attempt to accommodate for them in order to achieve a higher accuracy in authentication.

A study performed at the National University Hospital in Singapore has revealed that increases in environmental temperature result in a significant increase in the diameter of superficial (surface) veins [HGMP16]. This study revealed that subjects experienced up to 22 percent increase in size of their superficial vein diameter after an increase in temperature from 26C to 43C.

Likewise, there is research stating that exposure to the cold will result in vasodilation, the local increase of vein diameter. Cold-induced vasodilation is a natural process that occurs within the human body to prevent peripheral tissue damage [JP17]. This biological process occurs when there is a sudden drop in neurotransmitters released from the muscular outer coating of AVAs due to exposure to the cold. AVAs are the connection points between two blood vessels, being vital in the regulation of blood flow. Increases in blood flow and hence the sizes of the veins allow heat to propagate into the surrounding tissue, minimizing the damage. In instances of extremely low temperatures, cold-induced vasodilation is minimal, with preservation of key organs and hence also the organism, taking priority. This phenomenon has been observed in cases of hypothermia. While being a natural physiological response, it is possible to enhance the cold-induced vasodilation response of the body through repeated frequent exposure to the cold.

Chapter 3

Design

3.1 Hardware

After much research and discussion, a list of hardware requirements of the technology was developed. The hardware must be an active IR system, possessing not only an infrared camera but also an infrared blaster. The blaster is necessary due to the fact that infrared radiation emitted naturally from the body (hands, in particular) is not intense enough for an infrared camera capture. This makes it difficult to clearly differentiate veins from other tissue. The blaster emits infrared light which is consequently absorbed at different levels by different tissue. These different absorption levels consequently mean that larger, more distinguishable infrared levels are reflected into the camera, allowing better contrast between veins and surrounding tissue to be detected (see Figure 3.2).

Originally, we searched for a phone or another portable device, such as a tablet, that met the necessary hardware requirements. Unfortunately, these hardware requirements were not met by any portable device on the market. Research was put into potentially using a device that utilized Google's Project Tango [Goo17b] platform however no such device was found that was equipped with an IR blaster alongside the standard camera. This platform also proved unsuitable as infrared camera streams are not directly available.

Thorough research revealed that one of the few suitable technologies that fit our requirements was the Intel RealSense Platform [Int17]. RealSense is a cheap, widely distributed technology employed by developers to make virtual mapping, 3D imaging and interior mapping applications. It has been integrated into several devices already, including laptops and desktop computers produced by ASUS, Dell, HP and Lenovo. All RealSense products employ a single high definition RGB and two IR cameras along with an IR blaster.

We elected to purchase and use the short-range RealSense camera, the SR300 (see Figure 3.1) due to its operational range of 20-120cm. This range is more practical in the context of our project than other RealSense models such as the R200. Such models operate at a larger range, using a more intense infrared blaster, which would overexpose captured IR images.

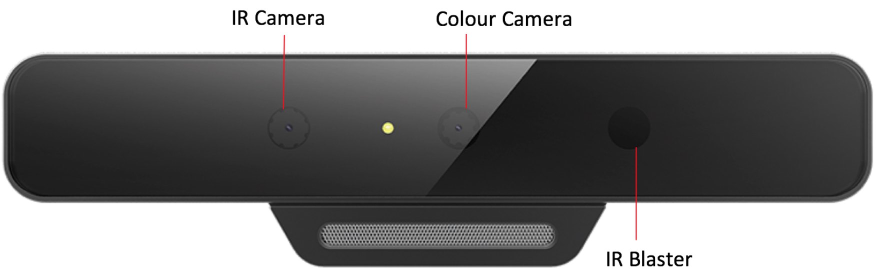


Figure 3.1: The Intel RealSense SR300

3.2 Software

3.2.1 Overview

The intricate workings of the VeinDeep authentication system can be broadly generalized into three high level algorithmic components: extraction, conversion and compari-

Figure 3.2: IR Image of Forearm Veins from SR300

son. Extraction utilizes a multitude of algorithms to transform the image data obtained from the IR and Depth streams into cleaner, more useful information. This information is then processed in the conversion step to obtain a binary sequence that represents the same vein pattern. The conversion to binary patterns is essential because it plays a vital role in the third part of the process ,comparison, wherein we employ various algorithms to compare this vein pattern to the existing standard for similarity. Below, we discuss each of the three above mentioned components in greater detail.

3.2.2 Extraction

The extraction process uses the snapshots obtained from the IR and the Depth stream from the SR300 camera. Images gathered using the IR Stream utilize the IR blaster and predominantly record reflected IR light. As discussed above, veins absorb slightly more IR light as compared to its surrounding tissue, and hence the veins captured by the SR300 appear darker than the surrounding skin (see Figure 3.2). Furthermore, the depth image, obtained using a combination of the IR and colour streams at almost the same time as the IR image, provides a visual representation of the distance of each object in the image from the camera. Brighter colours represent objects that are further. This feature of the depth image helps us separate the hand pattern from the background. These images hence represent different information, and each of them serve their purpose within the extraction process. The extraction process is carried out in four steps, namely ROI extraction, masking, cleaning and thinning.

The region of interest is extracted from the image using hardcoded pixel coordinates. The RealSense camera produces IR and Depth images with resolutions of 640x480 pixels. The ROI is a tiny subset of this resolution, and the hardcoded pixel values are used to cut out the ROI from the depth and IR images.

We then obtain a silhouette of the hand dorsum using the depth image. As mentioned above, the depth image uses color to represent distance from the camera, with darker objects being closer to the camera (apart from the background). As can be clearly seen in the depth image (see Figure 3.3), the hand dorsum is darker, whereas the rest of the image is made of lighter shades of grey and the background black. We hence use a threshold filter to remove the black background and the lighter coloured sections of the image that do not represent the hand dorsum. The hand dorsum is set to be within a certain range of the camera, and this distance can be defined using colour intensities. These intensities allow us to differentiate between the hand dorsum and other objects in the depth image.

We extract the untreated vein pattern by applying an adaptive threshold filter to snapshots obtained from the IR stream. Since the silhouette is calculated on an ROI-sized image, we do not have to identify and remove whatever forearm data is present in the original image (since it is dealt with during extraction).

This depth-image-silhouette is now used as a mask to extract the hand dorsum out from the ROI-sized IR image. Originally the veins appear darker than their surroundings, however the image is inverted in the masking process. This allows the veins to appear as bright white patterns on a black background.

In the cleaning process we firstly apply a 4-connected components algorithm. We chose the 4-connected components algorithm over its 8-connected counterpart as the cleaned result better represented the original vein patterns found on the hand. Using a minimum vein size of 20 (derived experimentally) we reduce the image to only contain vein patterns larger than the minimum vein size. We then used a kernel of size 19 to trim white spaces and perform further clean up operations.

The cleaned veins are trimmed to remove any further white space, and the resultant trimmed image is then ready for thinning. In order to minimise the execution time of the subsequent comparing of sequences, we reduce the number of pixels required to be compared using a Line Thinning Algorithm. Originally we used the standard line thinning algorithm for thinning the vein patterns in the image. This involved the iterative use of erosion, dilation, subtraction and bitwise-or functions. The algorithm seemed to provide inconsistent results, and we were never able to achieve thinned veins which were one pixel wide. We furthermore also tried to use Morphological thinning (see Figure 3.4). While this provided attractively structured one pixel wide vein patterns,the inconsistencies in the branching that ensued made testing and comparing highly unreliable.

Our final line thinning algorithm scours each row of the vein pattern binary image taken from the extraction process. For each section within a row of veins (white pixels), we find the column number of both the start and the finish of the constant pixel colour. Using these two coordinates we are able to calculate the middle pixel coordinate of the contiguous white segment and replace the potentially wide segment with a singular white pixel.

Figure 3.3: SR300 Depth Image

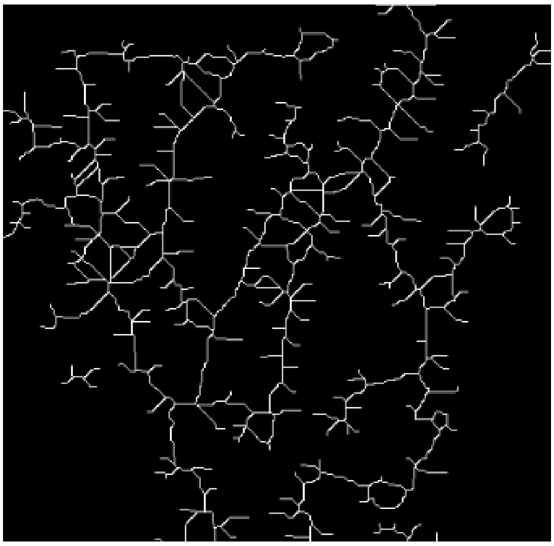


Figure 3.4: Morphologically Thinned Vein Pattern

3.2.3 Converting to Sequences

The conclusion of the extraction marks the inception of the conversion step, wherein we convert the binary image of the vein pattern data into a binary sequence. This step, as mentioned above, is essential as it provides a platform for the comparison step to be applied efficiently and accurately.

In order to represent the pixel data as a sequence of points, we traverse the thinned vein pattern image, finding the (x, y) coordinates of each white pixel. We store these coordinates within a vector ready for the next step of the process.

3.2.4 Comparing Sequences

In order to calculate the similarity between two extracted sequences of points, we use the Gaussian function. Firstly, we calculate the sum of the Euclidean distances between each of the pixels in the thinned test image. We then do so for the reference image that we are currently calculating the similarity with. Finally, we calculate the Euclidean distance between each of the pixels in the test and reference images. These values are used to determine our similarity score (Eqn 3.1).

In order to express the algorithm mathematically, we must define values.

- R is the sequence of points extracted from the reference vein pattern currently being compared against. Likewise, T is the sequence of points extracted from the test image.
- r is an individual coordinate of R. t is an individual coordinate of T. $r \in R$, $t \in T$
- $\|r - t\|$ is the Euclidean distance between coordinates r and t
- $KF(r, t, \sigma) = \exp(-(\|r - t\|^2)/\sigma^2)$. σ is the kernel width which penalises the mis-alignment of the pixels of the thinned test and reference images. An optimal value for σ was determined experimentally.

The similarity score between each set of test and reference thinned vein patterns are calculated using the following formula:

$$\sum_{r \in R} \sum_{r' \in R} KF(r, r', \sigma) + \sum_{t \in T} \sum_{t' \in T} KF(t, t', \sigma) - 2 * \sum_{r \in R} \sum_{t' \in T} KF(r, t, \sigma) \tag{3.1}$$

The threshold of similarity scores that result in a match was determined experimentally through extensive preliminary testing across a number of test subjects. If the similarity score calculated is below this threshold, the application alerts us a match has been made (see Appendix 1).

3.2.5 Optimizations

Multiple Reference Images

In order to improve the accuracy of the system, five reference images are stored to be compared to each test image taken. Comparing test images against five reference images gives a larger threshold for variation when attempting to authenticate. It is unlikely that users will be able to perfectly replicate a singular hand position consistently, and we account for this with numerous similarity scores under a certain, lower precision, similarity score resulting in a match. This feature was added to the system after preliminary testing delivered disappointing matching accuracy scores.

While this feature does improve the chance of a genuine user scoring a legitimate match, it does also increase the probability of a false positive result. Having more reference images stored increases the chance that one variation on the reference user's vein pattern is similar to the test image provided. We have attempted to minimise this risk by requiring a number of the similarity scores generated to fall within the less precise threshold in order to result in a match.

Aiming Silhouette

Throughout preliminary testing, it became obvious that subjects were not able to consistently reproduce the same hand position that they used when recording their reference images. Subjects were attempting to recreate precise hand positions and angles solely from memory. These initial tests revealed that they were unable to consistently reproduce the hand positions taken in their reference images, resulting in no positive match being made. In order to combat this issue we sought to produce an outline of their hand and overlay it onto their test image window, allowing them to more closely replicate the distance from, and angle to the camera that they placed their hand. This outline provides a reference for users, allowing them to more easily replicate the hand position they used in their reference images, allowing them to reproduce the hand angle and fist grip they used.

Using the Canny (Edge Detection) function provided in the OpenCV library, we generate an outline of the user's fist (see Figure 3.5), based on the depth image taken from their first reference image stored. This outline silhouette is then overlaid onto all subsequent frames taken by the system until a new first reference image is stored, replacing the Canny image.

The overlaid Canny image means that users are able to produce five reference photos that are much closer in similarity score to each other than with no assistance aiming. With more similar reference and test images, the accuracy of the system dramatically improves, minimising differences in patterns due to variables such as hand angle and distance from camera.

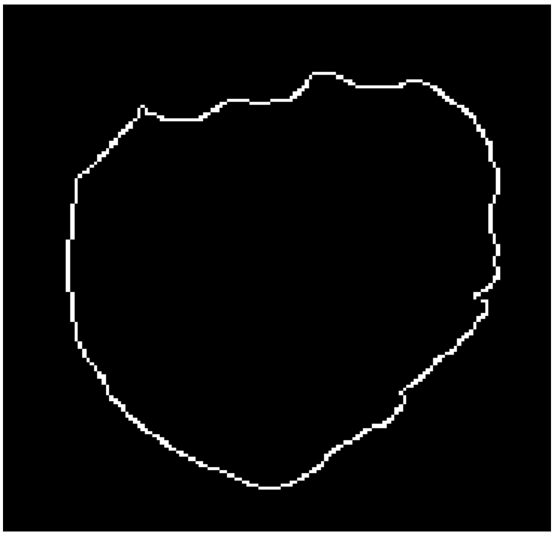


Figure 3.5: Canny Edge Silhouette of Left Fist

3.2.6 Simulating Physiological Changes

The physiological consequences of various environmental factors (such as exercise, atmospheric temperature, hydration, and so on) can be summarised by the effects that they have on the widths of the veins at the back of the hand dorsum: the width of the veins either increases or decreases. Hence, instead of modelling such changes in real life by performing tests on subjects post exercise or post water-fasting, we decided to model such changes algorithmically on the computer by increasing and/or decreasing the width of already-captured vein patterns and then testing them against the standard references (see Figure 4.2). Simply implementing functions that modify user's extracted vein patterns, either increasing or decreasing them in diameter allowed much more control over the percentage of change observed. Realistically, it would have been incredibly difficult to quantise the shift in vein diameter observed in test subjects when actually either increasing or decreasing their body temperature. This method would prove much more difficult for assessing the impact these changes would have on our system.

In order to reduce the width of vein patterns extracted, each row of pixels in the image is considered. For each continuous series of white pixels in the row, the first and the last pixel's column coordinate are observed, allowing us to calculate the width of the section. Using our selected percentage decrease, the desired width of the section is determined and the pixel data is then modified, using the centre of the white pixel sequence as a constant. A similar method is followed when increasing the width of vein patterns, with extra considerations put into place for edge cases.

Chapter 4

Experimentation

4.1 User Authentication

4.1.1 System Setup

The experimentation for the system was carried out on two machines; a Windows 10 virtual machine on a 2014 Macbook Pro and a HP Spectre running Windows 10 natively (see Table 4.1).

The system was written in C++ in Visual Studio using the Visual C++ 2017 compiler, utilising the OpenCV 3.3 library and the Intel Realsense SDK.

The Intel RealSense SR300 was mounted on top of each laptop (see Figure 4.1) with subjects seated in front, allowing them to comfortably position their hand dorsum within the camera's operational range of 20-30 centimetres.

4.1.2 Data Collection

Samples were taken from twenty different subjects, ranging in age from 20 to 57 years old. The participants were made up of 13 males and 7 females. Images from both

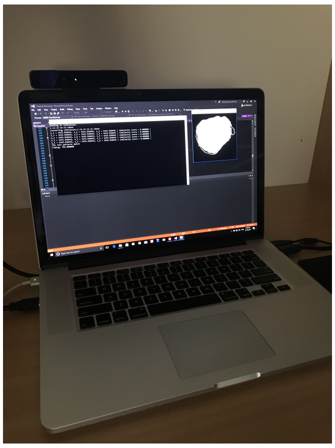


Figure 4.1: SR300 Mounted on Macbook Pro

	Macbook Pro 2014 15" Virtual Machine	HP Spectre
Processor	2.2 Ghz Intel Core i7	2.5GHz Intel Core i7
Cores	2	2
Memory	8gb DDR3 RAM allocated	8gb DDR3 RAM
Storage	256GB SSD	256GB SSD

Table 4.1: Comparison of Experimental Platforms

hands of each subject were collected meaning that data was gathered from a total of 40 different hands. For each hand, 5 reference images and a test image were taken for a total of 240 collected vein pattern images.

For all basic authentication experimentation, data was collected in a computer laboratory environment. Subjects were first shown a demonstration of the system in action to exhibit correct hand placement and usage. The first reference image taken was guided by demonstrators in order to achieve an appropriate fist position to generate a suitable canny silhouette to guide the remaining reference and subsequent test images. Subjects continued saving each of the required five reference images and test image, lowering their arm and then repositioning their fist as closely to their canny silhouette as possible. The subjects were instructed to reset their hand position between each of the reference images and the test image to introduce slight variations in the reference images to improve the likelihood of a possible match.

4.2 Physiological Changes

After the collection of samples from all subjects, four copies of each test vein pattern were created. Running these copies through our increasing and decreasing vein size functions, we were able to make two samples for each simulated physiological change (decreasing from decreasing in temperature, increasing from increase in temperature). For each test vein pattern, an increase and decrease of 11% and 22% were produced. A 22% increase was the average found in physiological tests performed by academics ath the Dow University of Health Sciences, Pakistan and National University Hospital, Singapore [HGMP16]. In these experiments the temperature started at 26°C and was increased to 43°C. An increase of 11% was also tested to simulate a smaller incremental shift in vein size, representative of a more realistic shift (potentially 26°to C 35°C) in temperature and hence vein diameter.

No quantitative data regarding the observed percentage change of vein diameter due to decreases in temperature could be found. In order to produce simulated decreased vein patterns the percentage decrease in vein width was estimated to be the same as that of the increase - 22%. Likewise, an intermediate percentage of 11% was also tested.

4.3 Further Testing

In order to further test the capabilities of our implemented system, other environmental factors were taken into consideration. To test whether changes in external infrared light from the sun impacted the operation of the system, samples were taken both in dark rooms and outside on bright days. The system was tested in both ways; with reference images taken outside in sunny conditions with test image taken in a dark room and vice versa. This process was repeated three times per method.

(a)

(b)

(c)

Figure 4.2: Comparison of Normal Veins Patterns, Increased Vein Patterns (22%) and Decreased Vein Patterns (22%) respectively

Chapter 5

Evaluation

5.1 Results

5.1.1 Basic Authentication

System Accuracy

The confusion matrix for basic authentication can be seen in Table 5.1. Our system was found to have an accuracy of 99.7% with a recall of 0.99 and a precision of 0.79. Figure 5.1 was generated by adjusting the threshold of similarity scores that resulted in a match, recalculating a number of confusion matrices and precision/recall values.

EER is the rate at which FAR and FRR are equal. It is a measurement used to determine the accuracy of a biometric system - the lower the EER, the more accurate the system. The FAR and FRR determined by our system are 0.3% and 0.01% respectively. In order to calculate the EER we experimentally adjusted the threshold of our similarity score such that the FAR was equal to the FRR - in other words, to the point where the FP value was equal to the FN value. This experimentation revealed our EER to be 0.09%.

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{5.1}$$

$$Recall = \frac{TP}{TP + FN} \tag{5.2}$$

$$Precision = \frac{TP}{TP + FP} \tag{5.3}$$

$$FAR = \frac{NumberofFalseAcceptance}{NumberofIdentificationAttempts} = \frac{FP}{TP + TN + FP + FN} \tag{5.4}$$

$$FRR = \frac{NumberofFalseRejections}{NumberofIdentificationAttempts} = \frac{FN}{TP + TN + FP + FN} \tag{5.5}$$

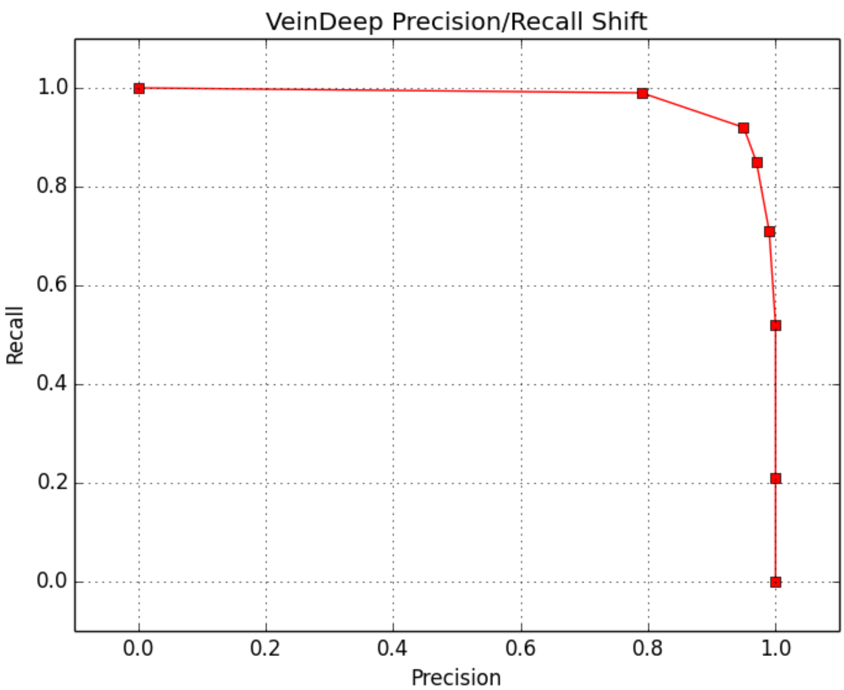


Figure 5.1: Precision/Recall for VeinDeep system at different similarity score thresholds

	Predicted: False	Predicted: True
Actual: False	TN = 19438	FP = 62
Actual: True	FN = 2	TP = 238

Table 5.1: Confusion Matrix for Basic Authentication

System Speed

Due to the fact that the basis of the system relies on the manipulation and processing of pixel data, the execution time of the system when making comparisons of vein patterns varies widely. Users that elect to place their hands closer to the camera within the 20-30 centimetre operational range have a larger ROI and hence, a greater number of pixels in their extracted and reduced vein patterns. In these cases, there is more pixel data, increasing the number of calculations required to compare sequences. The execution time in these cases are comparatively much larger than cases in which the user positions their hand further from the camera, reducing the ROI.

Of the total 20 participants tested, 18 were tested using the application running on a Windows 10 Virtual Machine on a 2014 Macbook Pro. Throughout the course of testing on these 18 subjects (36 total hands captured) the average execution time was found to be 492.7ms. The maximum execution time observed was 832ms and the minimum 295ms.

5.1.2 Further Testing

Simulated Physiological Changes

Experiments that involved simulating the contracting of vein patterns did not induce any change to either the frequency of successful matches or the accuracy of our system. At decreases of both 22% and 11%, all 238 true positive matches were made. The same 2 images that failed to result in positive matches without any change to vein diameter did also, however, fail when the changes were made. Likewise, situations involving dilated vein patterns, again, did not induce any discrepancies with the basic authentication results.

Environmental Changes

When reference images were taken outside in a bright environment and similarity calculated against a test image recorded in a dark room, there were drastic changes for the operation of our system. In each of the three tests conducted, it was not possible to find a match between the test and reference images. This was because the system was unable to extract vein patterns from all the images that were captured outside. We strongly suspect this is a consequence of the large amount of IR radiation prevalent in the atmosphere during day time.

5.2 Discussion

5.2.1 Basic Authentication

Overview

Based on the results, we can clearly see that the system works well to accurately authenticate users using their vein patterns. Users were able to match their five stored references with ease when testing. Furthermore, similarity scores for users attempting to match their vein patterns against other people's references returned scores which were much larger than the threshold for a matching score.

That the system works is a result of utilising a consistent process for collecting and matching the patterns. The standardisation inherent in the distance of the hand from the camera, the intensity of IR light emitted and captured, the consistency of the ROI, and the extraction, masking and other subsequent processes which provide exactly the same output given the same input, allowed the system to be robust, which is essential when matching vein patterns. A stellar example of this was the test involving two identical vein patterns, which when processed returned a match score of zero - a perfect match.

A robust, consistent system is furthermore required due to the inconsistent nature of the human hand. It is nearly impossible to position the hand dorsum in exactly the same position relative to the camera, even with the use of an aid or guidance from demonstrators. Thus, the use of five reference images to compare the test pattern, as opposed to the traditional comparison with one test pattern, allowed for a greater percentage of matches, since it gives the user greater freedom for hand positioning and rotation. It is to also be noted that while more reference images can invite a greater chance of false positives, we found such outcomes were only very rarely manifest. This can be seen through the minute percentage of false positives compared to true negatives.

A large factor to achieving such consistency was through the use of a consistent line thinning algorithm. As mentioned previously, the use of other line thinning algorithms, particularly the morphological skeleton, did not provide such consistency. This was especially due to the offshoots that arise as a result of thinning the image into a pixel wide representation. Such offshoots often proceed to connect with each other, creating a highly inaccurate and inconsistent representation of the original vein pattern. It is inadvisable to create connections between veins if they do not exist in the original vein pattern captured. If there exists a method that can achieve morphological thinning without the presence of these offshoots, then such thinning would be more accurate than our algorithm. However as it stands, our thinning algorithm provides the most consistent and also the most accurate thinned representation of the captured vein patterns.

Anomalous Results

The false positives displayed above occurred only during automated testing. Each reference from the five stored references was tested against every other reference for every other participant. It is to be noted that while a very small percentage of such testing did yield positives that should not have matched, in reality this is very hard to replicate. While such tests help provide metrics on the robustness of the system, they do not reflect very strongly on a real scenarios wherein such inaccuracies may be exploited. For instance, an attacker attempting to bypass another user's stored references using their own hand does not have the advantage of: seeing the user's stored vein patterns, seeing their own generated vein patterns, and hence, attempting to manipulate their generated vein patterns to match the stored ones. The attacker only sees the stored canny outline of the user's first reference. By attempting to match the user's stored outline exactly, the attacker is bound to fail because vein patterns are highly unique, and given a perfect positioning of the hand that matches the outline of the user, the vein patterns will likely never match. A worse tactic however would be for the attacker to ignore the stored outline and attempt to haphazardly match the stored hand pattern - a hopeless brute force.

Issues and Sources of Inconsistencies

We often noticed that the amount of wrist present in the silhouette largely affected the resultant vein pattern that was produced. A large part of the above mentioned standardisation involved ensuring that a minimal amount of wrist was present during testing to minimise the distortion. We employed the use of an outline of the first reference image (see Figure 3.5) to provide a measure of the amount of forearm present, so that the hand and wrist positions could be adjusted to be consistent with the first reference for future images. The flexion (bending of a joint that results in a decrease of the angle between the bones of the joint) of the wrist required to hide the forearm from the camera can sometimes lead to complications, such as soreness of the wrist, which will be discussed below. A better solution may have involved the use of an object detection algorithm, however that would require further research within computer vision, which was outside the scope of our investigation.

While storing references, we ensured that after each reference was saved, the position of the hand was reset. We did this to allow storage of more heterogeneous vein pattern samples, which would later be easier to match. However we found that even with such measures taken into account, it was much easier to get matches occurring when tested in the same sitting as when the references were taken. In other words, if the test subject stored some references and then left the testing area temporarily, i.e. midway through testing their vein patterns against their references, we found that it was strikingly simpler to obtain matches before the test subject left the area as opposed to after.

We believe these inconsistencies arise due to irregular positioning of the hand with reference to the camera. When the test subject returns, the angle of their wrist with respect to the plane of the camera can vary significantly depending on various factors, namely: the height of the table/chair, how they choose to sit on the chair, how much flexion they can induce in their wrists to reduce exposure of the forearm to the camera, how far away the camera was from the edge of the table.

We furthermore noticed that some subjects experienced discomfort while trying to store references or attempt matches, due simply to the steep flexion of the wrist that they were utilising. While some people were comfortable resting their forearms on the edge of the table or on their thighs, others were comfortable suspending them unsupported in the air. We noticed that arms that were resting or supported produced results faster, as opposed to those who did not. Such results indicate that steadiness of the hand is a contributing factor to the ease of obtaining matches. Within the Future Work section below, improvements that can help minimise such errors and shortcomings are discussed.

5.2.2 Physiological Changes

The results demonstrated in our experimentation involving the artificial increasing and decreasing of vein patterns shows the resilience of our system. No change to the success rate of true positive matches were seen, meaning that it is likely that physiological changes observed due to shifts in temperature would not affect our system in a real life scenario.

The inability of changes in vein diameter to causes inconsistencies in our matching accuracy is a result of of the line thinning algorithm performed in the extraction process. What was originally intended as a tool in order to avoid having to compare hundreds more pixel coordinates, lowering execution time, ended up being the solution to the changing vein diameter dilemma.

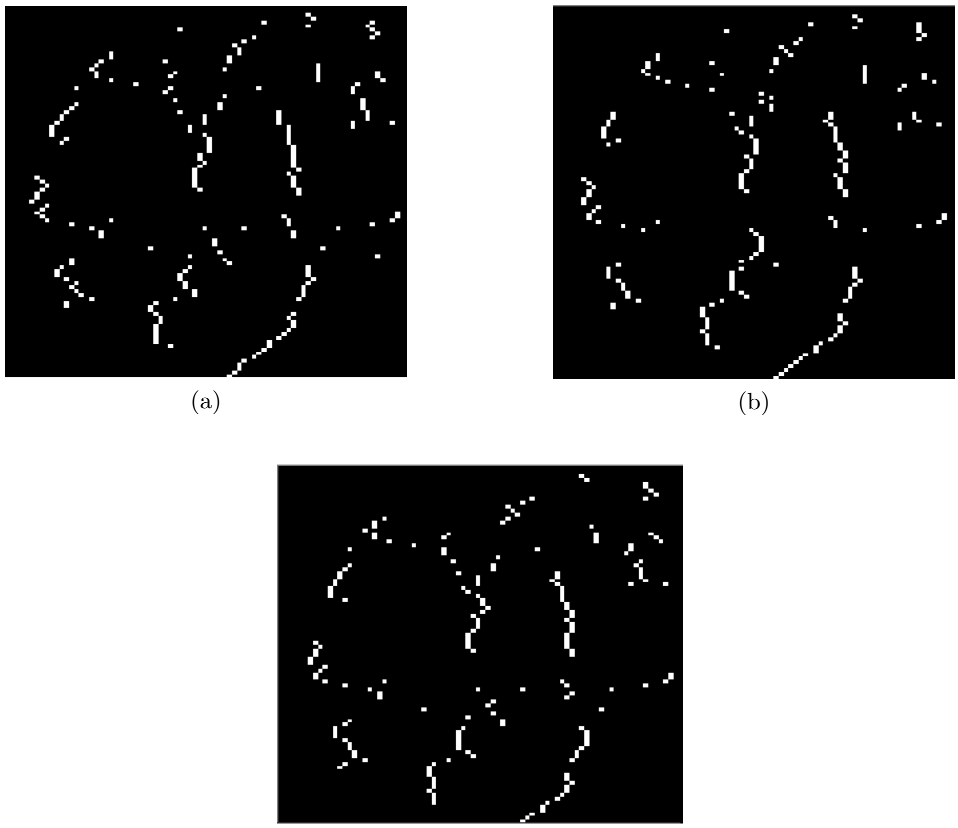
Through observation of produced thinned patterns (see Figure 5.2), it can be seen that the line thinning algorithm, for the most part, counteracts the shift in vein diameter. What appears as a large difference in vein pattern images post increasing/decreasing seems negligible after the line thinning algorithm is applied. As the increasing and decreasing functions shift the size of vein patterns from the centre of each detected vein, the process is more or less negated by the line thinning algorithm which reduces the patterns to only their centre pixel (for each continuous white row section).

During preliminary testing of the increase and decrease of vein patterns it became clear that the percentage change would have to be much higher to have a heavy impact on the difference between thinned vein patterns. While testing the functions it was demonstrated that similarity scores would increase and begin not causing matches of vein patterns after 40% increase/decrease in diameter, at which point intersecting lines in the vein pattern began shifting large sections of white pixels in thinned vein patterns. It is at this level of percentage shift that tests incorrectly return false negative results.

5.2.3 Further Testing

Further experimentation regarding the environment in which both reference and test images are taken revealed that the system failed to work in the presence of external IR interference from the Sun. When the system was tested, photos were not taken with the camera pointed directly into the Sun. Despite this fact, the IR stream was way too exposed to correctly extract a vein pattern. The IR stream was so over exposed that it was unable to generate a depth image and participants were unable to even see their hand waving past the camera in the depth stream window.

The fact that the results were so heavily affected means that the IR reflected by user's



(a) (b) (c)

Figure 5.2: Comparison of Normal Thinned Veins, Thinned Increased Vein Patterns (22%) and Thinned Decreased Vein Patterns (22%) respectively

hands from the SR300's IR blaster is drastically smaller than the IR levels from the sun. This renders this system completely useless for outdoor use. It is, however, suitable for usage in bright rooms as glass seems to filter out a large amount of IR interference and were consistently able to correctly achieve positive matches while sitting closely to windows.

Chapter 6

Conclusion

Overall, while a successful and accurate system, this implementation of the VeinDeep biometric authentication system has a number of shortcomings that would limit it's success out of testing environments. The system is wholly reliant on users being able to correctly reproduce the hand position they used while recording their reference images. This can be incredibly difficult to do, particularly when attempting authentication days after saving reference images, even with the aid of the canny silhouette outline.

In order to be successfully deployed in the real world on devices that make use of Intel's RealSense technology, a number of improvements would have to be made in order to make the system more user friendly.

6.1 Future Work

6.1.1 Automatic Detection of the Hand Dorsum

It can be seen that a large contributing factor to the inconsistencies within this system is the unsatisfactory implementation of hand dorsum detection. Although the Intel RealSense SDK offers solutions to hand gesture detection and facial gesture detection, there is no implementation that detects a hand-dorsum that is ready to be scanned. We deemed the implementation of a computer vision system such as this out of the scope of our current investigation, but it can be seen that the system is now very strongly in need of such computer-vision utilities.

Automatic detection of the hand dorsum will not only eradicate the issues presented by inconsistent capturing of images - it will make the system much more user friendly in addition to making it universally usable. No longer will a rigid, laboratory like set up be required to obtain consistent matches. Automatic hand dorsum detection will eliminate the problems posed by unsteady hands, soreness through wrist flexion, and all the issues presented above that induce inconsistencies as a consequence of irregular hand positioning.

6.1.2 Rotational Detection and Correction

Automatic hand-dorsum detection can be easily retrofitted to rotational detection and correction to provide an immensely powerful tool. Often the angle of the plane of the hand-dorsum with respect to that of the camera can distort the resultant vein patterns, leading to inconsistent stored references and frustration. However, automatic detection can allow for: the measurement of rotational skew in all three dimensions, and an attempt to either correct the rotational skew or present feedback to the user detailing the excessive rotation of the hand dorsum.

Such calculations are possible with the Intel RealSense SDK and Creative's SR300 camera. Dimensions for the z-axis can be obtained, with the results being stored in the format of [x-pixels, y-pixels, distance to this point in cm]. This information can be used to apply some basic vector algebra to obtain values for the rotational skew of the hand dorsum. Furthermore, if these values fall within a certain threshold, the image can be rotated in all three dimensions to reduce the skew. This improvement could also be used to reject vein snapshots that fall outside of a threshold for acceptable hand planes in relation to the camera, eliminating the acceptance of snapshots with too much skew.

Such improvements can help increase the usability and versatility of the program substantially. When coupled with automatic detection of the hand dorsum, this improvement will make VeinDeep a powerful tool.

6.1.3 Hand Placement Apparatus

As discussed above, the position of the hand constituted a large part of the inconsistencies, particularly when references were stored at a different time of the day to when they were tested against. The use of a placement apparatus, in which the hand can be aimed and held still, could be used to provide a consistent surface area to the IR camera. This would minimise errors induced by the height of the table and the distance of the camera from the hand differing between reference and test images. While this solution reduces the mobility of the system, it can be a viable option for older users, who may not need to utilise a mobile VeinDeep system.

6.1.4 Homographic Transformation

Homographic transformation is a technique that maps identifiable points in one image to corresponding points in another image. It is based on complex mathematics called projective geometry. Homographic transformation is used in order to identify objects in images with the intent to stitch them together to make panoramic or 360°photos.

Homographic transformation could be utilised within the application of VeinDeep. Using a form of object detection or feature extraction, features within depth images such as wrist, dorsum and knuckles could be identified. From here, using the detected points, the detected vein pattern could be projected onto the plane parallel to the infrared camera. This would eliminate the impact on variations in hand angle to the camera. This would improve the accuracy of the system, vastly increasing the usability of the system, potentially making it viable for real world deployment.

6.1.5 Technology Integration

Further down the development and improvement timeline, the VeinDeep biometric authentication system has the potential to be incorporated within the operating systems for devices with integrated RealSense technology. Devices such as mobiles, tablets and computers could utilise the IR camera in their devices to unlock their devices and potentially encrypt sensitive files with their own biometric data.

Bibliography

[Gem17] Gemalto. Biometrics for identification and authentication. http://www.gemalto.com/govt/inspired/biometrics, accessed 8/4/2017, 2017.

[Goo17a] Dan Goodin. At deaths door for years, widely used sha1 function is now dead. https://arstechnica.com/security/2017/02/at-deaths-door-for-years-widely-used-sha1-function-is-now-dead/, accessed 10/4/2017, 2017.

[Goo17b] Google. Google tango. https://get.google.com/tango/, accessed 1/5/2017, 2017.

[HGMP16] Irfan H., Ooi GS., Kyin MM, and Ho P. Revealing maximal diameter of upper limb superficial vein with an elevated environmental temperature. *International Journal of Chronic Diseases*, 2016:1–4, 2016.

[Int17] Intel. Intel realsense technology. http://www.intel.com/content/www/us/en/architectu and-technology/realsense-overview.html, accessed 23/3/2017, 2017.

[IPYWK+01] Sang-Kyun Im, Hyung-Man Park, Sang-Chan Han Young-Woo Kim, Soo-Won Kim, and Chul-Hee Kang. An biometric identification system by extracting hand vein patterns. *Journal of the Korean Physical Society*, 38(3):268–272, 3 2001. An optional note.

[JP17] Sheperd JT. and Rusch NJ. Vanhoutte PM. Effect of cold on the blood vessel wall. https://www.ncbi.nlm.nih.gov/pubmed/6131011, accessed 3/4/2017, 2017.

[Mic17] Microsoft. Developing with kinect for windows. https://developer.microsoft.com/en-us/windows/kinect/develop, accessed 1/4/2017, 2017.

[WL11] Jian-Da Wu and Chiung-Tsiung Liu. Finger-vein pattern identification using principal component analysis and the neural network technique. *Expert Systems with Applications*, 38(5):5423–5427, 5 2011. An optional note.

[WLC08] Lingyu Wang, Graham Leedham, and David Siu-Yeung Cho. Minutiae feature analysis for infrared hand vein pattern biometrics. *Pattern Recognition*, 41(3):920–929, 3 2008. An optional note.

[Zho] Henry Zhong. Veindeep: Smartphone unlock using vein patterns. Unpublished Undergraduate Thesis.

Appendix 1

A.1 Sample Output from Successful Match

Reading in references:1->2->3->4->5->done
Converting references:1->2->3->4->5->done
s_1 = 1099.041790, s_2 = 1181.144558, s_3 = 974.206424 | similarity score = 331.773499
s_1 = 1443.388280, s_2 = 1181.144558, s_3 = 951.289207 | similarity score = 721.954423
s_1 = 965.640241, s_2 = 1181.144558, s_3 = 830.165935 | similarity score = 486.452929
s_1 = 806.774779, s_2 = 1181.144558, s_3 = 597.769529 | similarity score = 792.380279
s_1 = 1067.199293, s_2 = 1181.144558, s_3 = 767.998929 | similarity score = 712.345992
The vein patterns match!