Chapter 2
A Novel Perspective on Hand Vein Patterns for Biometric Recognition: Problems, Challenges, and Implementations

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2.1 Introduction

In biometric applications, a relatively new technology is emerging, namely the optical scanning of superficial vein patterns. In order to be viable, a biometric parameter has to be easily identifiable but hidden from view so that it cannot be reproduced or simulated. It can be observed that the veins of the human body do not leave external marks like fingerprints, are not easily falsifiable like the voice, cannot be disguised like face traits, and are extremely hard to covertly extract during and after the lifetime of an individual in order to be reused by an impostor. In the same time, the technology used to acquire the vein pattern has reduced costs and is not invasive, requires minimal cooperation from a person, and is largely a noncontact procedure that allows it to be used where hygienic concerns are an issue [1].

Some of the most important requirements for a biometric system are the uniqueness and permanence of the biometric parameter used for recognition. Even in the case of complete uniqueness, a biometric system should be sensitive enough to be able to accurately discriminate between samples acquired from different individuals.

A review of the scientific literature shows that the visual structure of the veins is a unique property of an individual both in the retina [2, 3] and in the hand [1, 4–7]. Furthermore, it is often assumed that the localization of arteries, veins, and capillaries is specific to each person [7, 8]. Due to the novelty of the technology, the scientific studies related to the uniqueness of the vein model are rather scarce.

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From a medical point of view, the cardiovascular system is formed first in the human body. The exact reason for the actual shape and path of veins, arteries, and capillaries is not completely known but, until now, from the study of the scientific literature, the probability of finding two individuals with the same vein pattern is very low. In vitro studies of the cells' spatial distribution show the automatic forming of blood vessels and the migration of cells in order to create a connected vascular network. The migration process and the dynamic aggregation result in a fractal-like behavior at both a small and a large scale [9]. Taking this premise into account, while it is impossible to predict the future blood network arrangement, a realistic vein model simulation has to take into account different aspects such as:

- The local anatomy,
- The blood irrigation requirements, and
- Other case-specific hemodynamic constraints—veins anastomose frequently, redundant vein paths.

In this manner, while there is a comfortable variation degree for a discrimination detection system, the veins are not randomly formed. Thus, in order to guarantee the uniqueness parameter, designing and implementing a vein pattern recognition system is not a trivial task.

A possible vein network arrangement belonging to a person's hand can be observed in Fig. 2.1.

The second property mentioned in this chapter is the permanence of the vein pattern. A biometric recognition system is only useful if an individual can be identified after subsequent scans on different timeframes. For blood vessels, there are three processes that can modify partially or totally their network:
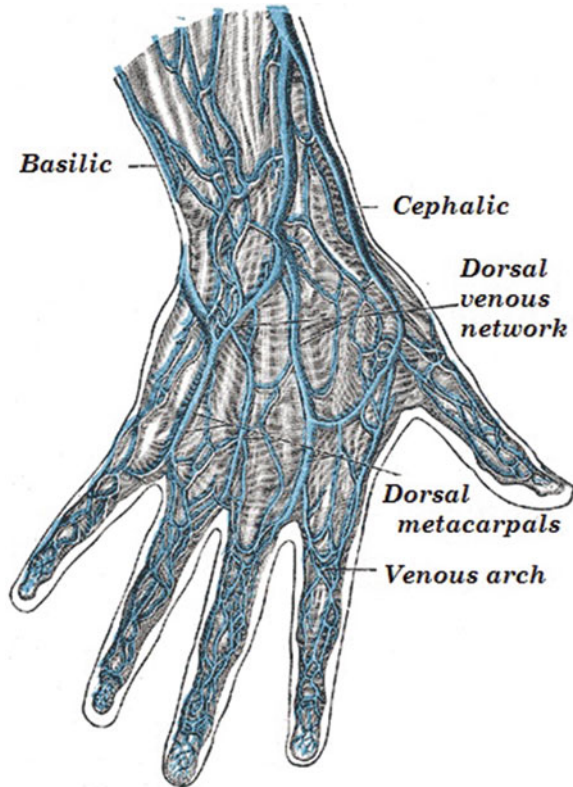
- Natural changes of the vascular system over the course of a healthy individual's life
- Changes in the vascular network due to traumas or diseases
- Changes of the blood vessels due to surgical interventions

From the genesis of the blood vessels during gestation, most differences in the pattern as an individual grows up are related to the overall size and position of the network. Veins will get thicker or thinner or exhibit irregularities but the general path will remain mostly unchanged. Taking into account the fact that this model is unaffected by superficial wounds or lacerations of the skin, it is a viable biometric parameter for scans taken at large intervals of time from each other [3]. In extreme cases, such as surgery that can modify—through sectioning, rerouting, grafts, etc.— the vein model, the biometric device can reenroll the individual or compensate the modifications between two successive scans by using automated algorithms.

Condensing the three presented processes that can modify the vein pattern, several concerning factors are:

- The degree of pigmentation or discoloration of the skin. Color changes triggered by sun exposure, pigmentation due to old age, or even the native color of the skin do not interfere significantly with the vein scanning process as validated in [11]

Fig. 2.1 Possible vein
network in the back of the
hand [10]

Basilic

Cephalic

Dorsal
venous
network

Dorsal
metacarpals

Venous arch

- Blood loss—a relevant factor since a lower quantity of blood could diminish the absorption rate at the vein level
- Medical conditions that are known to cause blood vessel constriction or dilatation
- Reduced number of blood cells, anemia, or other diseases that may modify the normal amount of deoxidized hemoglobin
- Deep skin cuts or surgical procedures that may potentially modify the vein model (although common skin problems should not interfere with the actual detection of the vein pattern)
- Environmental factors such as differences in altitude, prolonged change in hand orientation, physical stress, etc.

From a permanence point of view, using the vein pattern as a biometric feature is correct because it is a parameter with predictable modifications during the lifetime of an individual and the types of surgery or diseases that can completely modify the model in the hand region are rare and can be compensated through reenrollment. Nevertheless, in order to minimize the complexity of the scanning algorithms, vein pattern detection should be performed on individuals close to adulthood for a less drastic modification of the blood vessel network from one scan to the next. In [12], it is also observed that, generally, no major growth happens during the adult life and

the conventional interval of stability is between 20 and 50 years. It is also suggested to accept individuals aged less than 20 but in this case, reenrollment should be performed yearly for optimum scanning results [12]. At a later age, the vascular system reduces its dimensions and changes in trajectories. Experiments have shown that this interval can be safely extended with very few exceptions [1].

A complete feature comparison between veins and other biometric parameters is difficult since there are no comprehensive studies showing correlated experiments with different biometric methods. Even when using pure technical parameters such as False Acceptance Rate (FAR), False Rejection Rate (FRR), or Equal Error Rate (EER), the environment conditions are not the same between scans of different technologies; The Failure to Enroll (FTE) parameter is often undescribed and there is no common dataset of individuals scanned with multimodal biometric devices.

Furthermore, a highly cited scientific paper containing very valuable data regarding biometrics has one of the most used comparison charts between biometric technologies [8] presented in Fig. 2.2.

Using **H**igh, **M**edium, and **L**ow to describe the fulfillment of each of the seven important biometric traits, it can be seen that hand veins are classified as Medium for most parameters. This table is being consistently reused throughout modern scientific literature even if the authors of the original paper declare that the "comparison of various biometric technology is based on the **perception of the authors**" [8] and the paper was published in 2004 when vein biometrics was in its

Biometric Identifier	Universality	Distinctiveness	Permanence	Collectability	Performance	Acceptability	Circumvention
DNA	H	H	H	L	H	L	L
Ear	M	M	H	M	M	H	M
Face	H	L	M	H	L	H	H
Facial thermogram	H	H	L	H	M	H	L
Fingerprint	M	H	H	M	H	M	M
Gait	M	L	L	H	L	H	M
Hand geometry	M	M	M	H	M	M	M
Hand vein	M	M	M	M	M	M	L
Iris	H	H	H	M	H	L	L
Keystroke	L	L	L	M	L	M	M
Odor	H	H	H	L	L	M	L
Palmprint	M	H	H	M	H	M	M
Retina	H	H	M	L	H	L	L
Signature	L	L	L	H	L	H	H
Voice	M	L	L	M	L	H	H

Fig. 2.2 Biometric technology comparison according to [8]

Fig. 2.3 Biometric parameters of various technologies according to [5]

False Acceptance Rate (FAR) & False Rejection Rate Comparison (FRR)		
Authentication Method	**FAR (%) =**	**If FRR (%) =**
Face recognition	~ 1.3	~ 2.6
Voice pattern	~ 0.01	~ 0.3
Fingerprint	~ 0.001	~ 0.1
Finger vein	~ 0.0001	~ 0.01
Iris/Retina	~ 0.0001	~ 0.01
Fujitsu Palm vein	**< 0.00008**	~ 0.01

infancy. On the other side of the spectrum, new synthetic data from Fujitsu [5] place palm vein recognition over fingerprints, face, voice, or iris with accuracy parameters on the same level or higher than retinal scans as seen in Fig. 2.3.

It can be seen that, due to the lack of scientific studies regarding actual performance experiments between different biometric technologies, any comparison is inherently biased.

Various research concerning vein patterns points to the viability of this parameter as a strong biometric trait when required scanning conditions are met. Fingerprints and iris scanning have the advantage of more complex patterns and can perform adequately even under less than perfect conditions. On the other hand, veins are intricate but the total model has less extractable features and requires perfect scanned images in order to have a high discrimination rate.

The main advantage of vein patterns as a biometric feature lies in the sum of its parts. Most biometric features are consistent in the case of vein models without major drawbacks allowing the technology to potentially substitute other traditional methods.

2.2   Vein Pattern Scanning Using Optical Methods

While most superficial veins are good candidates for biometric recognition, the veins in upper limb extremities are preferred. Finger or hand veins have intricate structures but they reside very close to the surface of the skin and can be easily acquired. In addition, hands and fingers are directly observable with reduced pilosity and sufficient mobility and they create minimal acceptance issues from the individuals being scanned by a biometric system.

This section of the chapter will reveal the optical background for vein scanning and propose a modular structure for an accurate vein scanning hardware device based on previous research.

2.2.1 Vein Pattern Visualization

While almost invisible under normal lighting conditions, vein patterns can be visualized if the blood vessels are exposed to infrared radiation. Due to the different absorption rates of infrared radiation in various types of tissue, a vein scanning device is able to pinpoint the location of veins while ignoring arteries and the surrounding tissue.

To achieve this effect, lighting should be performed under a tight optical window, namely 760–870 nm which is consistent with the near infrared portion of the electromagnetic radiation spectrum. This radiation is strongly absorbed by the deoxidized hemoglobin (Hb) present in the vein vessels and it is slightly less absorbed—near the top of the window—by the oxidized hemoglobin (HbO) in the arteries as seen in Fig. 2.4.

It is also worth noted that, as the diameters of arteries are as small as approximately 1/3 of those of targeted veins in the finger or hand, it is reasonable to assume that most of the visualized blood vessels are veins [12]. In addition, water, very commonly found in tissues, has a very low absorption rate at this specific radiation domain.

Hemoglobin is the main component of the red cells found in the blood stream that carries oxygen from the lungs through arteries and helps in the transport of carbon dioxide from tissues through veins back to the lungs. The high level of absorption is due to the fact that a single red cell contains about 280 million hemoglobin molecules [14].
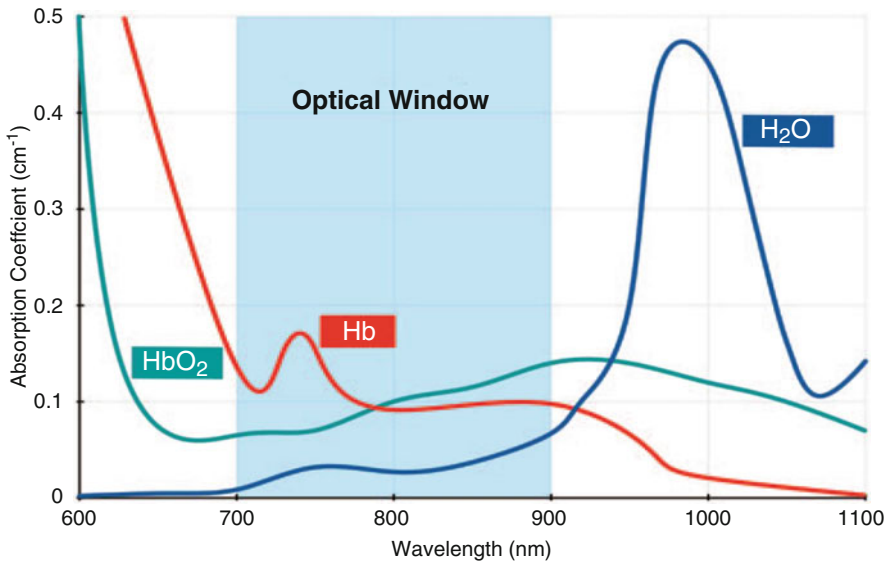

Fig. 2.4 Near infrared optical radiation window for a vein pattern recognition device [13]

The nature of the scanning method also helps secure the validity of the biometric parameter, since the presence of blood in the veins acts as a liveness proof; if blood ceases to flow through the blood vessels, the absorption method yields inconclusive results.

Using this optical window, a vein recognition system can be implemented but several factors have to be taken into account such as:

- Tissue optical diffusion,
- Depth of the scanned veins,
- Strong radiation filtering due to the water in the tissues or the tissues themselves, and
- Diffuse and specular reflections from the outer layers of the skin—specific lighting configurations have to be devised.

As mentioned earlier in the chapter, the veins of the upper extremity are divided into two sets, superficial and deep. There are many connections between these two sets of veins but due to the optical constraints of the scanning method and the relative depth of each of these two sets, the system is only able to detect superficial veins—since they are placed immediately beneath the integument between the two layers of superficial fascia [15]. The actual measured range of the optical penetration is in the range of 0.1–3 mm [11]. Two optical coefficients determine the total acquisition distance, an absorption coefficient $\propto_a$ and a scattering coefficient $\propto_s$.

The resulting image of a vein pattern under near infrared radiation can be seen in Fig. 2.5.

2.2.2   Structure of a Hand Vein Recognition Device

Most hand vein pattern recognition devices used for research and algorithm testing follow the same recipe and usually contain the same hardware modules as observed in [16–19].

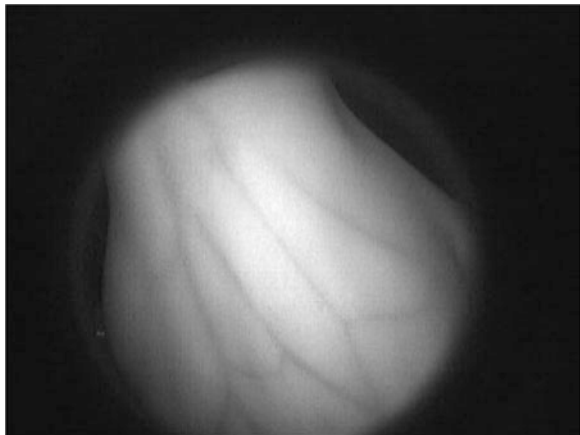**Fig. 2.5** Low resolution vein scan using the NIR optical window

Fig. 2.6 *Left*: Hitachi finger vein scanner. *Right*: Fujitsu palm vein scanner [5, 6]

Commercial applications have a strong emphasis on finger veins and palm veins [5, 6] all research being coordinated by two major companies, Hitachi and Fujitsu. Figure 2.6 depicts working vein pattern scanners from the entities mentioned above.

Outside of the realm of commercial applications, a review of the scientific literature has failed to observe a complete proposal for an accurate vein pattern recognition system.

Since vein capturing is an optical process and through several years of iterations and experiments [11, 20–23], a complete optic-electrical structure for a hand vein pattern detection device has been devised and is being presented in this chapter. The scanning modules are optimized for the palm veins and dorsal hand veins but they can be extended for finger or forearm veins with minimal modifications.

The complete structure of a hand vein scanner involves the use of several components and modules:

- A CCD or CMOS camera with high sensitivity to the sub-spectrum of infrared radiation used. For biometric purposes, the camera has to take a snapshot of the vein pattern or, depending on the application requirements, offer real-time image processing with the help of progressive scan algorithms. The subject of the cameras will be revisited later in this chapter since several important parameters must be modified in order for the system to capture accurate vein patterns.
- An illumination source, either single or multispectral, capable of providing constant radiation without hotspots, variable intensity and achieve a high contrast between blood vessels and the surrounding tissue, without illumination artifacts [11]. The central wavelength of the emitted radiation must be a part of the tissue optical window described in Sect. 2.1 and it has to be arranged in a configuration that diminishes specular and—to some extent—diffuse skin reflections.
- A set of optical filters that increase the quality of the raw pictures taken. Taking into account the fact that the skin is a highly reflective medium that interferes with the acquisition process, previous research has documented the use of polarizing

filters, light guides, and foil diffusers [11, 20, 21]. In addition, an infrared band-pass filter matching the spectral signature of the radiation source has to be employed in order to reduce environmental influences. The filter characteristics also need to take into account possible red-shift or blue-shift from the angle of the lens and radiation emitters' position.

- Depending on the setup, a mechanical constraint system has been employed by several researchers [16–19] in order to force the hand position under the scanner. In this manner, the resulting vein scans are captured from the same position in space thus simplifying the processing algorithms. In the same time, a constrained system diminishes one of the advantages of a vein pattern recognition device—the possibility of a full no-contact and hygienic procedure.
- A sample position detection with rotation and translation extraction. If a constraint system is not used, the scanning device has to gather all relevant data regarding the spatial representation of the user sample. It is a dual module since the hand presence must first be detected using optical, ultrasound, or microwave sensors and then the orientation of the hand has to be inferred using different technologies—mono or stereo cameras, hand motion capture, photogrammetry, or structured lighting [24].
- A liveness detection mechanism. While veins offer significant native spoof protection due to the nature of the acquisition process that requires flowing blood, there are possible fraud techniques that employ materials with similar absorption and transmission characteristics as real blood vessels or living human tissues. In constrained systems, capacitive arrays and additional optical sensors can be employed in a multimodal liveness proof system that reduce the spoofing attempt success. In a free-hand position device, the use of laser grids, stereo cameras, and complex software algorithms [24] can mitigate the identification risks.

While position invariance is a difficult task, all modern scientific approaches presented in this chapter only use the sensing element—infrared sensitive camera—for determining vein pattern trajectories. As mentioned in the last paragraph, using one presented solution by adding a structured light scanner and using several photogrammetry algorithms, the relative position and orientation of the hand to the camera can be inferred.

Software vein processing algorithms can then remap the vein model on a "flat" surface by compensating the tilt angle. This effectively solves the pitch and roll problem for a significant angular range—simulations and experiments have shown $\pm30°$. Yaw solving is purely a software rotation algorithm based on hemodynamic constraints or—after software thinning—a bifurcation/ending point count and is a relatively known method.

A representation of a hand vein capturing hardware device and its modules can be visualized in Fig. 2.7.

One of the roles of a hardware biometric device is to provide sufficient accurate data to lower the computational resources needed by the software algorithms used for processing the vein pattern. The resulting data should be as noiseless as possible and provide a good contrast between the veins and the surrounding tissue [25].
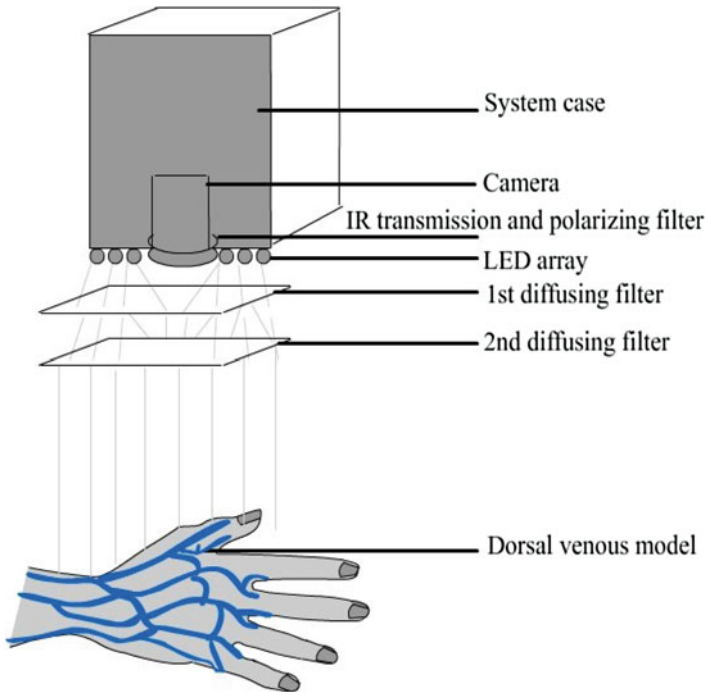
Fig. 2.7 Possible structure and modules for a hand vein scanning device [11]

By using all the filters described earlier, many of these concerns are eliminated since the CCD camera will only record the relevant data and the price of the hardware device remains low. Adequate filtering also permits the use of higher or lower wavelength infrared sources thus increasing the flexibility of the system and increasing the number of applications it can be used for. Depending on the type of application, the result of the scanning process is either a single image or a sequence that must be processed in real time.

Results of the efficiency of these hardware modules have been partially demonstrated and quantified in [11, 23, 24] and current research is focused on finalizing a large database of accurate raw scans of the vein pattern on the dorsal part of the hand.

2.3 Problems and Challenges in Vein Pattern Applications

In comparison with other traditional biometric parameter—fingerprints, voice, signature, or the iris pattern—the vein model as a biometric trait is not completely studied. There are several scientific questions still unanswered regarding hardware and software approaches to the correct feature extraction of vein patterns. There are

no known studies on the possible multispectral character of the radiation sources or the influence of chromophores, melanin, or adipose tissues on vein scanning accuracy [26]. The influence of the environmental factors is not quantified [27] and in some commercial systems and scientific literature there are few systems with robust algorithms that support 1:n applications—recognition and not solely verification [24, 27].

On another vein, the low-cost entry point for a makeshift vein hardware scanner has created many opportunities for scientific researchers to implement algorithms and feature extractors. However, the quality of the raw images acquired from these systems is often very low [24, 28, 29] and the effect has been opposite: there are inconsistencies between different hardware devices to the point that raw images differ substantially for cross-reference algorithm verification. Furthermore, the samples used by different researchers are often confined to their own research and are unavailable to the general public.

This determines **a first set of important problems**: *the acquisition technology is not standardized, the algorithms are often optimized for a small number of samples, and the methods and techniques proposed in various scientific papers cannot be replicated due to the lack of access to the original image set*. These problems and limitations are easy to spot in reference papers such as [30] that determines vein parameters using image acquisition under multispectral illumination techniques [31], variable sliding kernels [32], using Gabor filters or other examples such as [33–35] where the acquired images are suffering from the uneven illumination or the algorithms cannot be reproduced by other authors in their detection systems. These problems are difficult to solve because the domain has not reached a level of maturity specific to other biometric methods.

The proposed hardware structure in this chapter aims to help in solving these inconsistencies by providing a modular acquisition system and using it as a potential standard proposal, thus accelerating the development of algorithms and methods that can benefit from correctly acquired samples using a robust system.

A second set of problems is determined by the *lack of a consistent vein pattern image database that allows for the study and implementation of applications for biometric feature extraction.* These two sets of problems are interconnected since a proper hardware device helps create accurate databases of vein patterns. In the same time, an increased number of correct databases reduce the need for a perfect hardware device for *all* researchers.

As mentioned, generating images of the vein model implies the development of an experimental system—with relatively modest costs—but with a noticeable complexity regarding the construction and the detection modules. In this case, the lack of image sets that can be used as a study base substantially reduces the quantity and quality of analysis methods and algorithms that can be implemented in the scientific world. In other biometric domains, these databases exist and allowed for the rapid advancement of the respective biometric processing technologies. Regarding the vein pattern, there are a select few recent attempts for the finger veins [36–40], palm veins (MSP and CASIA) [41–44], or wrist veins (PUT) [45, 46]. One of the most important areas for vein pattern image acquisition, the veins in the back

of the hand—the main focus of the research by the author of this chapter—is not represented properly. Databases of this kind are both low in numbers and in the number of downloadable samples, at the time of writing this chapter the Bosphorus Database has 1575 collected images from 100 subjects—mostly from the left hand [47], while GPDS Database offers just 1020 images collected using geometric constrains [48, 49]. One of the larger vein pattern databases with 2040 samples—NCUT (North China University of Technology; hand-dorsa vein dataset)—has been unavailable to researchers outside of China.

It can also be observed that, in order to supplement these real samples, **most biometric methods benefit from synthetic databases**. The most obvious example is the SFINGE fingerprint database [50] but other parameters can also be generated such as the iris pattern [51], palm print [52], or finger veins [53]. In the palm or dorsal veins, these synthetic databases are not existent and a section of this chapter will present the advances and refinements from the research initiated in [54] in order to complete the real images database with a system that can generate synthetic veins in the back of the hand. Even if the morphogenesis of the vein patterns is still a relatively unknown process [14], there is still sufficient data in order to create realistic models of the vein structure. Simulated "raw" images have been obtained by recreating the pattern starting from influence and crossing points while taking into account the anatomic, hemodynamic constraints and the way in which superficial veins often anastomose.

Together with the obvious biometric applications, the localization, acquisition, and visualization of the vein pattern has **important implications in medicine**. Needle insertion for intravenous access is a common procedure with an incidence of 80 % of the patients found in hospitals [55, 56]. Although a peripheral vein can be accessed on the first try, for a significant number of patients, the medical staff can need from 2 up to 10 tries for successful needle insertion [56, 57]. The causes of multiple tries are determined by: lack of venipuncture skills, lack of appropriate medical care [58, 59], or one of the medical situations commonly defined as difficult peripheral venous access [60]. In all these cases, visualizing the vein pattern by using a contrasting technique to separate them from the surrounding tissue can improve the success rate of the venipuncture [61, 62]. In the medical field, there are a number of commercial implementations created to solve this problem, for example: VeinViewer [63], AccuVein [64], Veinsite [65], or VascuLuminator [66] but *commercial systems are often restrictive, with high acquisition costs and a proprietary interface that does not allow for adjusting acquisition values* [56, 61].

Using modern methods for visualization, there is a basis for experiments regarding the education of the medical personnel and the development of researches into assisted venipuncture by augmenting the vein pattern visibility in the intravenous site.

2.4   Modern Perspectives on Vein Structure Recognition

Since the first articles regarding the use of veins for biometric recognition, the technology used has employed low-cost, low-quality hardware devices for the vein scanning process. In addition, there are very few studies regarding vein patterns characteristics and virtually no information in terms of ergonomics, reliability, and performance of vein pattern identification devices. As mentioned in the beginning of the chapter, the use of synthetic databases can reduce the need for high-performance hardware devices and software detection algorithms can be tested against multiple cases. These include resilience to different hand poses, device placements, and orientation of the biometric parameter under the scanning device in both constrained and free-hand scenarios.

2.4.1   Ergonomics and Hand Pose Assessment in Vein pattern Identification

A review of the literature has shown that there is no known data regarding ergonomics and hand poses in a vein pattern biometric system. Individuals will have medical or personal preferences and different hand orientations in an unconstrained biometric device. Furthermore, even in the case of a geometric constraint for the system, the angle of attack for the gripping mechanism and the relative height of the forearm in relation with the dorsal or palm part of the hand are different from scan to scan. Automated algorithms can compensate to a certain degree but if the variation is over a predetermined threshold, the acquisition will suffer.

Using an inertial motion capture glove—part of the Perception Neuron full body suit [67]—172 individuals were scanned with 12 positions for each hand. The first six hand poses were unforced and each individual was asked to place their closed fist with the dorsal part of the hand pointing upwards towards the sensing system. A visual guiding system comprised of a pair of triangulation based proximity sensors and two visible lasers was used as an indication for a relative placement of the sampled hand. The last six poses were constrained using a fixed cylinder grip underneath the sensing system. Using the Perception Neuron available sensor fusion and inverse kinematics algorithms, the position and orientation of the forearm, hand, and fingers was calculated for each scan. Figure 2.8 presents the inertial glove used and the test system. In this setup, no actual veins were scanned, all the experiments were directed at determining average user hand positions or natural state poses for the hands under the scanner.

In an unconstrained scenario, after analyzing the position and angles of each subsequent scan for a person it can be observed that the average deviation from the first to last sample is 12–27° in the horizontal X axis and 4–16° in the horizontal Y axis. In addition, the last three samples exhibit a lower angle deviation due to the adaptation of the user to the scanning system. For each individual, four subsequent

Fig. 2.8 Ergonomics test system and inertial glove hand poses

scans taken at 1 h intervals were acquired. Sets three and four exhibited the lowest angle deviation in the same set but there was no visible correlation to the angle of the first two sets. Further research is required to estimate the importance of muscle memory or acquired learning but the results show that untrained users will converge towards a static position and orientation given enough tries. Coupled with the fact that horizontal angle differences are easily compensated through software algorithms, an unconstrained system is a viable option for the veins in the back of the hand.

The difficulty arises in the accurate determination of all vertical, Z axis poses' deviation and for 18 individuals, the difference from the vertical axis was between 7 and 19°. Vein scanning becomes impossible after a vertical orientation threshold, experimentally determined to be 10–15° in the vertical plane so that veins are not visually lost due to hand occlusion. In order to solve this problem, a "suggestion" mechanism was used. Each user has been allowed to freely position the hand under the scanner but a visual cue system comprised of the two visible lasers was devised. Each laser blinks with different speeds until the user achieves a correct range of the vertical axis orientation underneath the sensor and the lasers.

The experimental results have helped in tweaking the angles and position of the system for user ergonomics and correct scanning. However, for the proposed hardware setup described in Sect. 2.2, it is cumbersome and difficult to use a contact based position sensing device. Using the research results obtained in [24], a module

Fig. 2.9 Leap Motion camera attached to an Oculus Rift virtual reality headset

containing a stereo infrared camera [68] is introduced in the system case. After calibrating the orientation and matching the results with the data obtained from the inertial system, the vein pattern recognition device is able to determine position and orientation of the user's hand in both fist closed and open fingers position.

Several edge cases have been tested where the users' hand poses have been constrained by their body position and by surrounding objects. In order to accurately simulate real-life scenarios, a virtual reality system has been employed. Using an Oculus Rift DK2 model coupled with the stereo Leap Motion camera used for the hand pose study, users are being presented with various environments and scenarios. The hardware components and the test data from the Leap Motion camera are shown in Fig. 2.9.

In order to test the correct placement (both height and orientation) of a fixed vein pattern recognition system, each user was presented with a virtual vein scanner at different height, distance, and orientation towards the user. For each case, the user needs to insert the hand under the scanner unaided. Relative position and angles of the hand to the simulated vein scanner have been recorded using Leap Motion raw data correlated to the coordinate system of the Oculus Rift external camera.

Minimum hand angle deviations on all axes have been recorded for a relative position of the simulated scanner between the shoulder level and ½ distance between shoulder and complete downward pointing hand. By analyzing the distribution of the user heights across the test study—1.51–1.93 m—the correct placement for a vein scanner—in normal conditions—is 1.21–1.44 m from the ground level—satisfying 92 % of the user dataset.

Using virtual reality environments, biometric and medical visualization data can be exposed in a rich, collaborative manner while creating user scenarios difficult to achieve using real constraints.

2.4.2 Synthetic Vein Pattern Generation

As mentioned in Sect. 2.3, vein patterns do not benefit from synthetic databases or generation platforms. The apparent chaos in the forming of blood vessels presents several challenges as opposed to synthetic fingerprint or iris generation where the rules have clearer outlines. Since veins have less key points and extractable features than other traditional parameters, it is important to accurately replicate the behavior of the vessels down to the level of local angles or model direction inside the hand. In addition, since—to some extent—local anatomy and hemodynamic needs together with several signaling molecules dictate the overall shape of the pattern, it is impossible to completely predict the exact structure of the total vein network.

The goal of a synthetic database is to provide plausible samples with a high degree of customization and using thousands of previously acquired samples as reference, it is a possible endeavor.

In the creation of the proposed vein simulator application, the software workflow involves using Embarcadero Delphi as the simulation programming software, Autodesk 3D Studio Max for creating hand masters or blanks, and Epic Unreal Engine for accurate rendering of final hands and hand poses. Blanks are created for both hands and the correct angle of the model is taken into account when the simulated blood vessels are introduced into the hand.

One of the important rules in vein creation is related to the preservation of connectivity—veins cannot be unconnected—and the development of the model branches has to follow a statistical distribution that should be efficient in irrigating the entire hand tissue.

In addition, simulated hands should not be perfect, veins do not possess the same thickness, their depth greatly varies underneath the skin and the hand may be covered with hair, have a distinct curvature or there could be significant environmental influences.

External factors should also be taken into account. Variations in illumination can completely modify the accuracy of the scanned pattern as can be seen in Fig. 2.10. Camera performance and noise, its sensitivity to the desired spectrum, position of the hand in relationship with the scanner, or the lack of uniformity of the lighting system are all important error-generating situations.
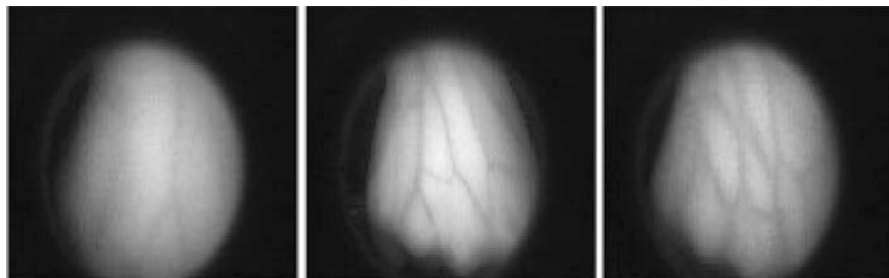

Fig. 2.10 Scanned hand vein pattern images under different illumination and acquisition scenarios [54]

The proposed hardware system in Sect. 2.2 of the chapter solves several of these issues by providing a high-quality raw scan of a hand vein pattern. Nevertheless, any synthetic image should be able to contain as many error-generating situations as possible. As mentioned before, vein pattern algorithms are often optimized for small datasets or perfect scanning conditions and a setup that allows for the creation of "fake" vein models should establish the real accuracy of an algorithm.

The procedure used to extract features from real vein images is based on the algorithm created by the authors in [11, 20]. Parameter extraction in a normal vein recognition algorithm starts with a local adaptive threshold and a thinning operation performed on the vein model including optimizations of the branches such as pruning and elimination of unconnected segments [11, 22]. Synthetic models start from a known network of nodes, terminations, and intersections—using an updated version of the crossing number [69]—and create the connecting segments based on several rules—segments have a slight curvature, more than one segment can connect to an intersection but not to a node, longer segments are created first, etc. Starting from these influence points, hand dimension constraints are applied so that vein points do not fall outside the hand model and veins occupy at least 80 % of the entire hand surface. In this way, for each influence point, the software will extrapolate the branches in between, while obeying the general flow and direction of the model.

The model is optimized to resemble a near infrared scan but—based on known behavior of radiation inside the human tissue—other wavelengths can be tested and simulated.

The simulation algorithm creates a structure having a series of intersecting curves with a width of 1 pixel. Creating the desired thickness is performed using a dilation algorithm with automatic or manual constraints—total dimensions of the model determine overall thickness, longer and major veins can have a larger surface, etc.

A snapshot of the actual dilation process involving automated vein thickness is shown in Fig. 2.11.

The vein pattern is embedded in the generated blank hand and the whole model is scaled based on a lookup table containing statistical data regarding the average
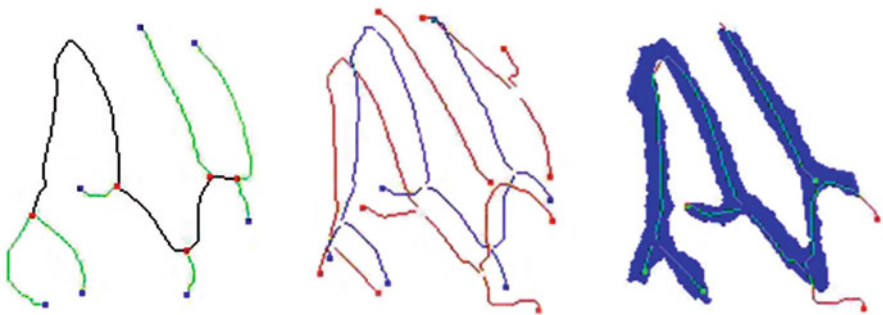

Fig. 2.11 Reconstruction of the vein pattern at full width. *Left*: simulated vein centerline with key points, *middle*: trajectories for possible vein thickness, and *right*: complete vein model after dilation algorithm [54]

correlation between age, sex, and hand dimensions. Subsequently, a gradient texture is applied on both the vein model surroundings and the outer surface of the skin. The texture values are calculated using a contrast variation coefficient C_v based on the following formula [54]:

$$C_v = \frac{\sum\limits_{y=1}^{m}\sum\limits_{x=1}^{n}\left(P_{x,y} - P_{x+1,y}\right)}{xy} + \left[\max\left(P_{x,y} - P_{x+1,y}\right) - \min\left(P_{x,y} - P_{x+1,y}\right)\right]/10 \tag{2.1}$$

where:

$P_{x,y}$ represents the intensity value of a pixel at coordinates x, y in the image

$P_{x+1,y}$ represents the intensity value of a pixel at coordinates $x + 1$, y in the image

m, n are the width and the height of the area of interest in pixels

max, min are the maximum and minimum values of the differences between adjacent pixels

A representation of the outcome of the texturing algorithm can be observed in Fig. 2.12. The simulated vein pattern is also pruned and optimized according to the hand and vein geometry constraints presented earlier.

A robust vein simulation platform allows researchers to create edge-case scenarios for recognition algorithms. In the same time, by correlating the results of the ergonomics and position case study presented in Sect. 2.4.1, simulated vein patterns can be mapped in the desired position and orientation to better mimic real-life cases.

2.4.3   Vein Biometrics in a Connected World

Traditionally, for biometric systems, the main concern is the identification of the individual and the storage of the template in a simplified form in order to serve as a comparison based system. Due to tight computational requirements and preservation of data constraints, many of the parameters relevant to a medical application are discarded since the system has to compensate for vessel constriction or dilation, age difference between scans, modifications of the normal blood flow, etc.

Fig. 2.12 Texturing algorithm applied to simulated veins. *Left*: simulated vein centerline, *right*: texture gradient applied to vein model—for insertion into simulated hand
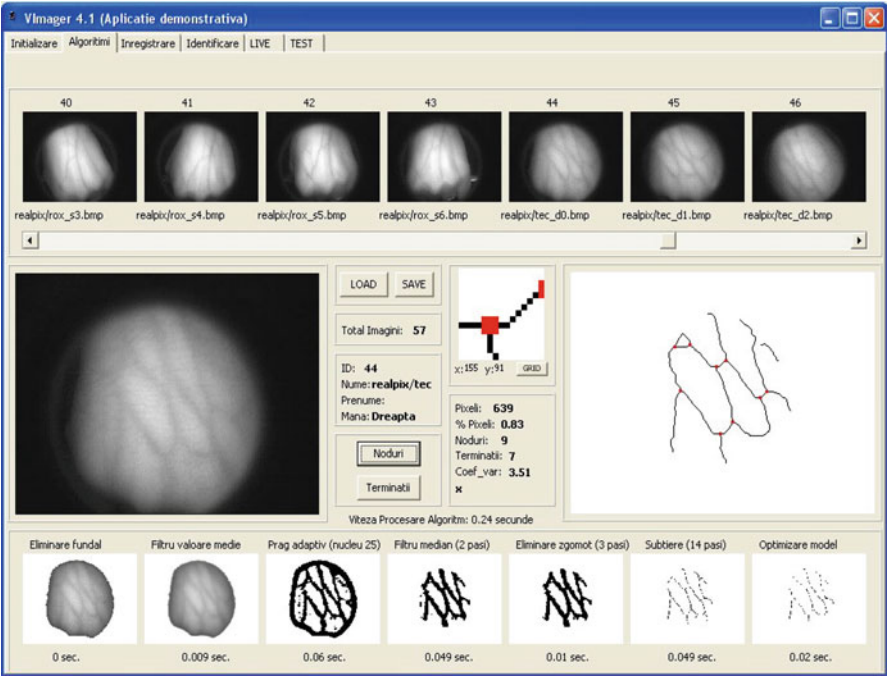
Fig. 2.13 Vein image processing and feature extraction algorithms in the VEINSIM application [11]

The algorithms are built in such a way that they isolate, enhance, and then reduce the vein model to a series of lines, usually one pixel wide as shown in Fig. 2.13. In this particular case, the dataset storage is performed by emphasizing and extracting the unique features for any individual and converting them to an array of values representing, for example, the number of segments, endings, and bifurcations in the pattern, the total segment length, relative angles between lines, intervein distances, etc.

To exemplify the process depicted in Fig. 2.13 and briefly mentioned in Sect. 2.4.2, a particular set of algorithms used in previous research for vein feature extraction involves several stages of image processing. After the background is successfully removed, a median filter is applied to the dorsal hand image. Using a locally adaptive threshold with a 9–25-pixel nucleus, the image is binarized with a strong emphasis on the vein pattern. The artifacts created by the thresholding process have a low degree of importance for vein scanning because even if the veins become artificially thicker, the last step of the process is a thinning algorithm. Using a custom thinning operation that has strong rules preserving connectivity between diagonal and vertical lines—following the natural flow of the blood model—the process ensures that all the veins are reduced to a 1-pixel width set of lines.

Even without a destructive operation such as the thresholding algorithm, veins usually suffer from thickness modifications due to medical conditions, altitude, physical effort, exposure to heat, etc.

After further optimization—removing unconnected segments, pruning extraneous branches, and restoring lost segments—the feature recognition module is activated. Using the feature extraction and storage model presented in [11], a sliding kernel is applied to all parts of the vein model. The operation checks for connections between the center pixel—if it belongs to a vein—and the border pixels of the kernel classifying the center as being an intersection, a termination, or a simple segment point. After calculating the total number of nodes and terminations, additional data can be determined in the form of number of segments, all relative angles between segments, and the total length of the model.

In Fig. 2.13, the vein pattern has nine nodes and seven terminations, and 639 pixels is the total length of the model. Without any compression techniques, a full stored dataset of the vein model of an individual occupies bellow 400 bytes including all relevant data. Extended research performed in [1] has shown that this rather simple approach can yield encouraging biometric evaluation parameters. In this particular case, for a database of 612 individuals, the FAR is 0.012 % and the FRR is 1.03 % with a comparison threshold of 67 % for the lowest percentage of EER equaling 0.092 %.

Working with single images per individual is also an advantage because processing speed is an important factor that has to scale up in relationship with the size of the sample database.

All these factors define the workflow of a vein detection device as a standalone machine with limited processing and storage capabilities that only serves the identification/verification function. While this is the main task of a vein recognition system, the ability to have devices permanently connected creates unique opportunities. As it has been mentioned in Sect. 2.3 of this chapter, there are very few studies performed on vein patterns, their permanence and uniqueness are viable but not fully tested. There are no researched correlations between the age of the individual and the state of their vein model, the skin color/pigmentation influence, or the difficulty of enrollment at different timeframes.

As biometric technologies mature and the number of civilian security application increases, the amount of collected data will require a shift in the processing and storing model. Using the Big Data paradigm, it can be observed that vein pattern recognition follows closely the three main features of a large dataset such as [70]:

- Volume: vein patterns and the collateral acquired data already exhibit large volumes in current applications; the size will continue to increase at a disproportionate rate.
- Variety: there are many different types of data associated with biometric parameters, as text, extracted features, sensor data, raw scans, individual data, and more.
- Velocity: data is arriving continuously as streams of data, and the goal is to obtain useful information from it in real time.

In addition to the classic 3V model, current Big Data representations include two more Vs:

- Variability: there are potential changes in the structure of the data and how the data can be interpreted.
- Value: the intrinsic value of the information, in the case of biometric parameters the value resides in their own ability to provide security and in the total asset cost insured by a biometric security scan.

The first working models for large datasets were based mainly on the homogenous and structure behavior of global data. Due to the unprecedented rise in collected data "often dispersed across independent systems that are difficult to access, fuse and mine due to disparate nature and granularity" [71], most modern Big Data approaches treat large volumes of information as they are created—unstructured and heterogeneous.

There are clear advantages of non-homogenous data collection in an emerging biometric parameter such as the hand veins. Big Data frameworks provide versatility and adaptability to increasing datasets and offer unprecedented insights in statistical correlation of multimodal features of the individual together with the vein biometry.

Using a modern Big Data framework and workflow, Fig. 2.14 presents a working model for a series of permanently connected vein recognition devices of different types.

Such an infrastructure is capable of acquiring raw images and delivering them online to be stored, processed, and analyzed without the constraints of a real-time verification system. While individual privacy is a very important parameter when it comes to sensitive biometric data, vein images can be anonymously collected without any tracing to the owner of the vein model. The communication channel can also be encrypted using a dual-key pair and the relevant data is stored only for future comparison and analysis.

A dual—Hadoop Map-Reduce and Apache Spark—system for data processing has been chosen for their different capabilities. Both are processing technologies which are able to handle large volumes of data by parallelizing the operations. The biggest difference between them is that Map-Reduce stores all the intermediary results generated during processing on the hard drive; Spark on the other hand uses only the random access memory and occasionally the hard drive—when it is necessary. Depending on the allocation of resources, both systems can function in parallel. Currently Spark is faster and there are hints that it will replace Map-Reduce in the foreseeable future.

There are a number of storing systems for the input data (raw data) that would allow storing large amounts of unstructured data. The ones that are worth mentioning in the context of biometric datasets are the following:

- Plain files (csv, binary files, etc.)

  - In this case, there will be only a limited number of file formats and all these formats need to be supported by the component that will be responsible for the parsing of the input data
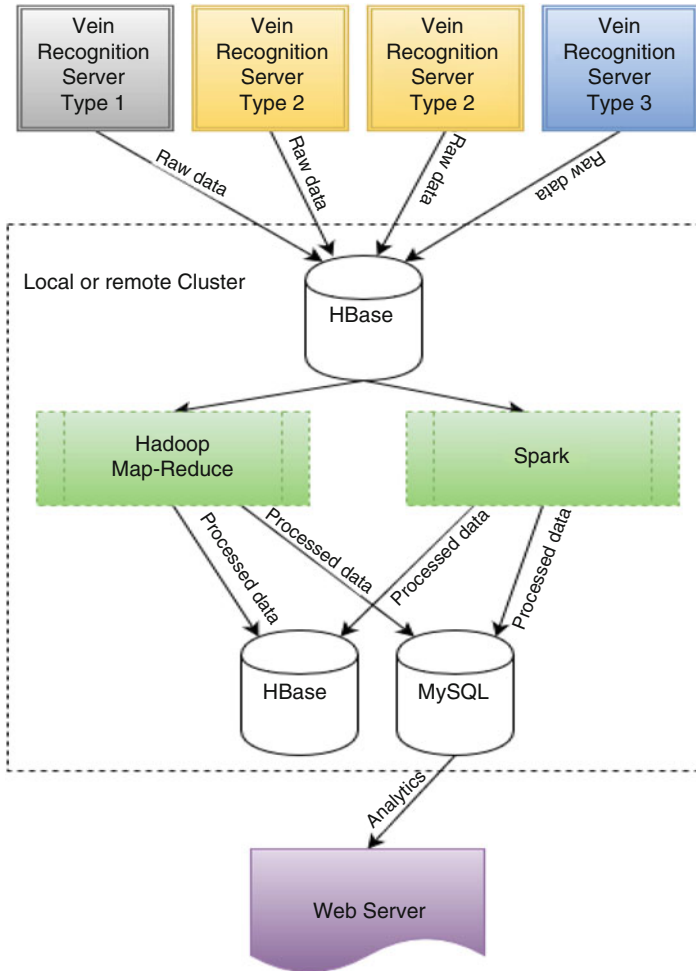
Fig. 2.14 Proposed infrastructure and workflow for a network of vein recognition devices

- – This approach is a good match with the distributed system proposed in Fig. 2.10 allowing for parallel processing but the main drawback is that it is extremely difficult to extract certain types of data (for example, cross-correlated field information, e.g., young male subjects from a certain day, or the data for which the processing returned an FTE error, etc.)

- • MongoDB
  - – Complete NoSQL database that allows for the storage of large amounts of data—preferred in many Big Data implementations.

- In the context of large processing batches for biometric raw data and associated information, MongoDB is not optimized for computational-heavy parallel operations being fast to write and slow to read when accessed from Hadoop or Spark.

- HBase

  - Apache HBase is colloquially called the Hadoop database because it is a NoSQL database running over Hadoop. As mentioned in [72], "it combines the scalability of Hadoop by running on the Hadoop Distributed File System (HDFS), with real-time data access as a key/value store and deep analytic capabilities of Map Reduce." Balancing the distributed nature of the HDFS with the need to access relevant information, HBase is both capable of querying individual records and offering complex correlations for reports on very large datasets.
  - It is implemented to work with Map-Reduce as well as Spark—being built on HDFS.
  - As it is designed to support queries on massive datasets, HBase is optimized for read performance. When writing data, HBase maintains consistency at the expense of slower write operations [73].
  - Major advantages: random access, single-row lookups and updates, and processing of adjacent key ranges.

Hadoop and its underlying structure are built for managing large sets of data, so a columnar store is a natural complement. Databases normally store information in rows and are therefore optimized for accessing one record at a time. Columnar storage systems serialize and store data by column, optimizing searches and reads across massive datasets [74]. In the context of fast access to information, new technologies such as Apache Parquet—containing per-column data compression—can become the norm in developing specialized storage and data analysis networks in a connected world.

The use of an additional SQL database provides a fast framework for statistics and analytics, processed data is used to populate different SQL tables, and data can be displayed according to a random number of query parameters on a web server or locally.

Such a system is also scalable, for a Proof of Concept processing, local clusters can be inexpensively built. There are use cases where there is just the need to test the software code that processes some specific data and assesses how the results are in relation with the expected result. For this case, there is no need to have access to a large cluster, with a lot of powerful machines. A smaller cluster could be built on a local machine by using three different Docker containers which are configured to communicate between each other.

For the production environment, a cluster of commodity servers could be used that will have to cover the following aspects:

- Data availability—a replication factor ≥ 2 is required and has to be set on the cluster that will assure no data is lost

- Low latency—gigabyte connection between machines in the cluster
- Scale up as the volume of data increases

The model presented in Fig. 2.14 takes into account the future proliferation of vein scanning devices of different types—ranging from mobile devices to fully fledged vein detection systems. Local behavior remains the same; the system will extract relevant biometric parameters for comparison or enrollment. The difference is that, using this proposed framework, local devices can send raw images anonymously to the local or cloud cluster for long-time storing. Using the powerful computational resources of such a cluster, several important scenarios are created:

- Global performance of local vein pattern recognition systems can be assessed based on their type, and matching scores and error rates can be determined from the raw images and the result reported by the local system.
- Algorithm testing can be performed on the collected raw images, for each enrolled individual an untraceable image is stored in the cluster and is available for further analysis.
- Biometric features are just one parameter of an individual scanned hand. Various amounts of data can be collected for correlation purposes. Features such as age, sex, hand shape, vein visibility, degree of pigmentation, hair density, specular or diffuse reflection coefficients, etc., can be stored along with the raw images.
- Collecting large amounts of data offers—as mentioned—unique opportunities for large-scale studies. How is the real permanence of the vein pattern as the individual grows older? What modifications occur in the model during the lifespan of an individual? How much of an influence does light or dark skin have on the robustness of the vein scanner? What is the discrimination rate between individuals? As more raw data is collected, algorithms will have to increase in their complexity since identical features between different people will probably be revealed.
- Statistics for all collected data allows for complex case studies over long timeframes and enables long-term monitoring of individual or global biometric parameters.

While the concept of Big Data is extremely new and biometric applications supporting the paradigm are virtually nonexistent, it is worth mentioning that all technologies and protocols described in this workflow and the subsequent discussion are open-source and are driven entirely by a large user community. While proprietary technologies will probably gather large groups of followers in the foreseeable future, using adaptive open-source software in the first steps of a domain can yield faster and more relevant results in creating a workable standardized pipeline.

It is clear that there are growth opportunities for biometric parameters and especially for emerging technologies such as the vein pattern recognition in the age of the Internet of Things and Big Data paradigms.

2.5   Conclusions

This chapter has presented the current state of vein patterns used as biometric parameters as well as the important challenges and problems that are inherent to the technology. The current degree of acceptance and applicability of the technology raises three sets of important problems described in this work. Several solutions and proposals have been devised in order to mitigate the issues. Using modern methods and approaches to the scanning technology, a complete hardware setup for the extraction of accurate vein patterns has been presented together with user case studies regarding ergonomics, hand placement, and orientation in both constrained and unconstrained setups.

Through the use of extremely new virtual, augmented, and mixed reality devices, ease of use and level of acceptance for hand vein biometric recognition can be quantified. In addition, these technologies will help in the creation of more accurate hand simulations and user scenarios impossible to replicate in real life. Experimental results are shown from the usage of inertial hand motion capture suits for gathering statistics on hand position, user ergonomics, and the correlation and storage of images taken with their position and rotation angle. It also foreshadows the advantages of the immersive data visualization for this technology including extraction of the superficial vein patterns for virtual teaching and medical demonstration.

Equally important, the simulation of vein patterns for synthetic database generation—as a response to the lack of real/simulated hand vein images—is described in the chapter. Research data has been presented with encouraging results in the creation of realistic hands and hand vein models with a high degree of customization for detection algorithm testing, adding to previous research.

The chapter also analyzes the possible inclusion of modern paradigms such as Internet of Things and Big Data into the normal workflow of a connected biometric network. As the quantity of biometric data increases and can be stored for subsequent analysis, several crucial experiments can be performed on datasets impossible to obtain until now. In addition, cross-correlations using additional user data can be inferred and all gathered data can also improve the creation and implementation of vein pattern recognition algorithms.

It is the author's opinion that future research has to involve all challenges presented in this chapter. It is equally important to standardize vein pattern acquisition as it is to create real and synthetic databases for algorithm testing and implementation. It is also vital to perform more studies on each of the main seven biometric features as they relate to the use of vein patterns. As the industry embraces the use of Big Data, biometrics can also greatly benefit from the storage and analysis of unstructured and heterogeneous data and answer important questions regarding the viability of all biometric technologies.

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