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Human Biometric Traits: A Systematic Review Focusing on Vascular Patterns

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Abstract

Authentication methods based on human traits, including fingerprint, face, iris, and palm print, have developed significantly, and currently they are mature enough to be reliably considered for human identification purposes. Recently, as a new research area, a few methods based on non-facial skin features such as vein patterns have been developed. This literature review paper explores some key biometric systems such as face recognition, iris recognition, fingerprint, and palm print, and discusses their respective advantages and disadvantages; then by providing comprehensive analysis of these traits, and their applications, vein-pattern recognition is reviewed.

Introduction

Recognition plays a key role in today's society, being necessary to authorise individuals to gain access to resources, services, physical locations or information. It is not feasible to manually authenticate and recognise individuals in large datasets. In this context, biometrics offers great advantages over traditional authentication methods in terms of reliability and validity. Authentication methods based on some human traits have developed significantly and, currently, they are mature enough to be reliably considered for personal identification purposes (Varastehpour, Sharifzadeh, Ardekani, & Sarrafzadeh, 2018; Lebovic, 2015). In brief, biometrics refers to the measurements of some human characteristics which differentiate one person from another (Ellenbogen, 2012). Human beings have unique physical and behavioural features, thus researchers can take advantage of these for recognition purposes (Lebovic, 2015).

Biometric-based identification is also widely used for forensic investigations; however, research is still limited in the field of biometric systems for some particular crimes such as rioting and participating in the creation of child pornography, where criminals usually cover their faces and only non-facial skin is partially observable. Recently, as a new research area, a few methods based on non-facial skin features such as vein patterns have been developed (Sharifzadeh, Zhang, & Kong, 2014). However, these methods suffer from several weaknesses in different cases, ranging from skin diversity and hairy bodies to subjects with a high volume of dermis due to adiposis, in which the vein pattern cannot be uncovered (Sharifzadeh et al., 2014).

This review first provides a brief explanation of human biometric traits such as fingerprint, palm print, dorsal hand and iris; then the components and computational methods for recognition of vein patterns are described. The authors then review different types of biometric traits and their state-of-the-art applications, before explaining the vein pattern as a biometric trait and categorising vein-pattern recognition techniques. The paper goes on to explain the physiological background with insight into the architecture of veins and arteries, then describes the way in which blood vessel images are captured through different techniques, and follows with a review of computational methods.

Background

The Concept of Biometrics

In the history of biometric traits, various identification applications have been attempted and, generally, these applications can be divided into three categories:

1. commercial usage such as credit cards, e-commerce procedures;
2. governmental activities such as national ID cards, passport controls;
3. forensic investigations such as criminal identifications and missing persons (Jain, Bolle, & Pankanti, 2006).

There are basically two types of biometric traits, either inside the human body like DNA and vein pattern, or outside the human body such as fingerprints and palm prints (Lebovic, 2015). Taking advantage of recent computational progress, researchers are currently able to work on biometric features inside the human body (Lebovic, 2015; Vacca, 2007; Podio & Dunn, 2001). Compared with traditional external features, these internal features have higher accuracy while being less vulnerable to forgery (Jain, Hong, & Pankanti, 2000).

Types of Biometric Traits

As shown in Figure 1, biometrics are usually categorised into two classes: a) physiological characteristics, and b) behavioural characteristics (Jain, Nandakumar, & Ross, 2016). For all human beings, the traits in both these classes are unique and individual.

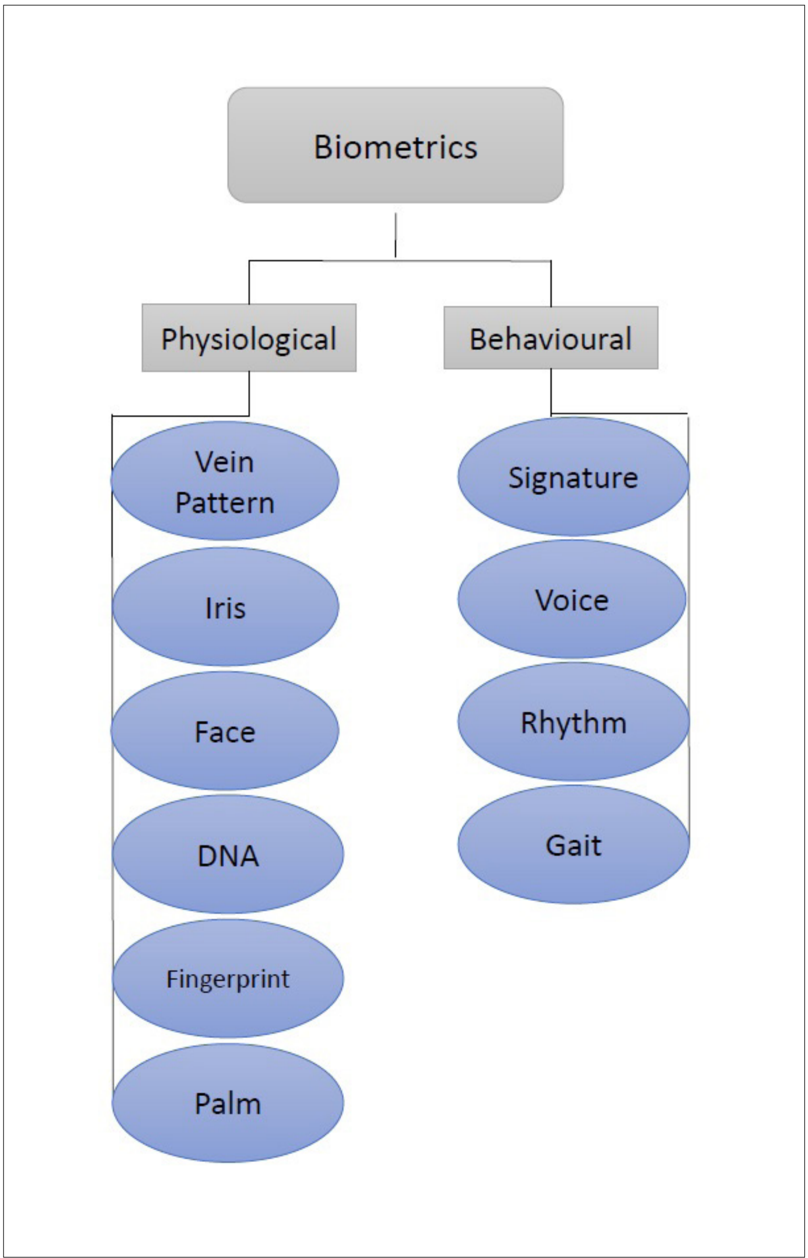

Figure 1. General classification of biometric characteristics.

Behavioural characteristics are related to the patterns of human behaviour such as typing rhythm, voice, gait, signature (Sahidullah, 2014), and physiological characteristics are related to body features such as palm print, fingerprint, face, hand geometry, iris, vein pattern (Sahidullah, 2014).

Lack of advanced facilities and the absence of effective identification technologies in the past necessitated the use of behavioural characteristics such as signature for authentication purposes (Jain, Ross, & Prabhakar, 2004). With advances in technology, behavioural characteristics are more vulnerable to forgery in comparison to physiological characteristics because behavioural features are outside the human body and are prone to counterfeiting (Podio & Dunn, 2001; Jain et al., 2006; Yu & Qing, 2009).

Currently, both behavioural and physiological characteristics are still being used for identification purposes, with different levels of accuracy. To follow, some of the physiological features are reviewed.

FINGERPRINT

The fingerprint is one of the oldest biometric traits, and has been successfully used in several applications. In 1891, Juan Vucetich started to categorise fingerprint collection in Argentina for the first time (Yu & Qing, 2009).

Everyone has individual fingerprints. A fingerprint is made of various ridges and furrows on the pad of the finger, and identities can be recognised by the pattern of these features (Shi & Govindaraju, 2009). As a popular identification method, the fingerprint is currently used in many organisations and security systems, such as police stations, forensic investigation departments, and for password authentication on laptops, smartphones and digital locking doors (Shi & Govindaraju, 2009).

The advantages and disadvantages of fingerprints are as follows (Shi & Govindaraju, 2009):

Advantages:

- High level of accuracy in good-quality images
- Easy to use
- Can be used for all the fingers

Disadvantages:

- Unable to be used for all subjects, particularly for older people or manual labourers
- Ridges and furrows on the fingers may change over time
- Requirement to install specialised devices
- As an exterior feature of the human body, they are vulnerable to forgery (Kono, Ueki, & Umemura, 2000)

PALM PRINT

The use of palm prints started after 1858, in the civil service of India, when Sir William Herschel recorded the palm prints of his illiterate employees on the backs of their contracts (Van Maanen, 2016). This was the first time that a palm print had been used as a biometric trait for identification purposes. During recent decades, a palm print has become a common biometric trait to identify illiterate people (Vacca, 2007).

Palm prints contain unique information including ridge flows, ridge characteristics, various tracks and lines on the palm. All these features show a genuine pattern that differentiates one person from another (Vacca, 2007). However, palm print use has grown more slowly than other biometric traits due to the lack of computing capabilities and technologies (Van Maanen, 2016).

Over the past few years, the palm print has become more popular among forensic investigators and security services. In European countries between 2013 to 2015, at least 30% of criminal evidence was provided by palm prints, obtained from steering wheels, windowpanes, gun grips, etc. (Van Maanen, 2016).

There are many techniques and methods that have been used to align and match palm-print features. Most of the preprocessing algorithms employ the key points between fingers to set up a coordinate system. Preprocessing involves five common steps:

1. binarising the palm images;
2. extracting the contour of hand and/or fingers;
3. detecting the key points;
4. establishing a coordinate system;
5. extracting the central parts (Han, 2004).

Advantages and disadvantages of the palm print are as follows (Van Maanen, 2016):

Advantages:

- Enforceable in low resolution: the patterns can be picked up with simple images
- Easy to use
- Cheap devices for recording palm prints
- Not sensitive to external factors

Disadvantages:

- Unstable: tracks and lines of the palm can change over time
- Needs longer processing time and powerful algorithms for extracting and matching ridge patterns
- Large dataset
- High maintenance costs for equipment
- Susceptible to forgery

FACE RECOGNITION

Face recognition is one of the successful biometric systems used for authentication purposes through facial features (Jain et al., 2006). Facial features include 80 nodal points on a human face, which are unique in each case, except between some identical twins (Jain et al., 2006). Some of these points are as follows (Bonsor & Johnson, 2006):

- Chin
- Cheekbones
- Jawline
- Depth of eye sockets
- Distance between eyes
- Width of nose

The procedures and steps are the same for all face-recognition techniques. These steps are (Jain et al., 2006):

- Capture raw data, which is acquired from the device
- Process distinct features, which are extracted from raw data and converted to digitised or encrypted data
- Enroll the record, which is stored for future comparison during identification
- Verification by matching/mapping a sample with the main database

These steps can be applied to all features of the human face. They can help to distinguish features for measuring and comparing with samples.

Face recognition has several advantages and disadvantages, as follows (Masupha, Zuva, Ngwira, & Esan, 2015):

Advantages:

- Facial features can be captured at a distance
- High speed for matching and mapping features
- Face recognition techniques can be made invariant to size, orientation, and lighting

Disadvantages:

- There are some factors, such as image quality, image size, face angle and insufficient light, that affect the face recognition process
- Facial features can be changed easily by growing hair, moustache, beard or adding glasses, etc., so it is susceptible to forgery
- Facial features can change during a person’s lifetime and images need to be up to date

IRIS RECOGNITION

Iris recognition is one of the significant biometric systems, with high accuracy and flexibility for authentication purposes (LG, 2003). In fact, the iris is the only internal organ that is visible from outside the human body (LG, 2003). The iris is located behind the cornea of the eye and in front of the lens, and is unique for each human.

Iris recognition includes three main steps, as developed by Dr. John Daugman (Jain et al., 2006): the first step is to capture a person's iris photographically as they stand in front of a camera; the second step is to convert the iris image to what is called IrisCode. In this step, the digital image is filtered to map segments of the iris by an algorithm. These segments include furrows, the corona of the iris, rings and freckles, which are mapped into the different phasors and stored in a computer (Jain et al., 2006). The final step is to match the IrisCode from storage with the IrisCode from the new sample and evaluate their similarities to each other (Jain et al., 2006).

Advantages and disadvantages of iris recognition (LG., 2003):

Advantages:

- IrisCodes are unique for each human being
- Iris recognition can be integrated with security systems or can operate alone
- The iris is formed during the first 10 months of a human life and remains unchanged for the rest of life
- Iris pattern is not vulnerable to theft, change or fraud

Disadvantages:

- Iris recognition is a new technology; thus, the relevant equipment is expensive
- The subject must be in front of the camera at a specific distance, otherwise the camera is not able to take an accurate picture
- The accuracy of iris recognition can be decreased by using a cosmetic or optical lens.

Iris recognition is more reliable and less vulnerable to forgery than biometric traits such as fingerprint and face recognition. Currently, it is mostly used in airports and police stations (Jain et al., 2006).

BIOMETRIC TRAIT APPLICATIONS

Biometric traits have been used in security systems to protect data and assets in recent decades. Biometric technologies have the complexity, capabilities and performance to verify a person's identity. Government departments, including police, and nongovernment sectors such as industry can use biometric traits such as fingerprint, finger vein, face, hand geometry, palm print, dorsal hand, DNA, vein pattern, iris and retina, voice and signature for identification purposes (Podio & Dunn, 2001). In the following, examples of applications that have used biometric traits are introduced.

Voice recognition is one of the common biometric systems that is used in shopping networks such as QVC and financial brokerage houses like Charles Schwab (Vacca, 2007), for the purposes of authenticating customers and carrying out transactions. With help from this system, customers can place orders or check their accounts without waiting for operators (Vacca, 2007).

Currently, some states in the USA are using a fingerprint as an additional feature for drivers' licences to prevent tampering and fraudulent activities. In some countries, prison visitor systems use face recognition, fingerprint and hand geometry to identify visitors and avoid identity swapping (Vacca, 2004).

Facial recognition systems have been implemented in many airports for finding criminals and terrorists among the crowds. Furthermore, the UK and The Netherlands have used facial recognition in streets, junctions and subway stations to detect terrorists and fugitives (Vacca, 2007).

The voting system is another field where biometric technology is used to avoid cheating in many parts of the world. In addition, in some cities, ATM machines use face recognition, finger vein, fingerprint, palmprint or palm vein to recognise customers' identities in order for them to access their accounts and for transactions (Vacca, 2007). Many big companies like Compaq, Sony, Fujitsu and Samsung use finger-vein, fingerprint or iris recognition in their products such as tablets, notebooks and cell phones to avoid data theft and to limit access. Many credit card companies such as American Express, Visa and Mastercard use a fingerprint instead of a smart chipset for authentication purposes (Vacca, 2004).

In Disneyland and other private companies, hand geometry has helped in permitting customers to enter. Hand geometry can provide information that will help to avoid fraud and also gather data about visitor statistics. Furthermore, Canada and Germany use facial and iris recognition for safe-deposit boxes in some places like airports and train stations (Vacca, 2004). Biometric traits have major benefits for industries, government and private companies. For governments, biometrics can give precious data in order to authenticate human characteristics. In industries, it can provide access limitation for time, persons and location. Generally, biometrics can help to authenticate customers and employees with more speed and accuracy than other systems (Podio & Dunn, 2001).

Mechanism of Biometric Technologies

Biometric identification systems are complex and capable, and they use several tools for recording and capturing photos (such as camera and scanner), or measurements of exclusive characteristics, and they use computer hardware and software in order to extract these characteristics (Vacca, 2004).

Depending on the applications, biometric technologies can be used in two modes of verification (authentication) and identification. As Figure 2 shows, for each of them, biometric systems have the same process, which can be divided into separate steps:

1. enrolment
2. verification
3. identification (Vacca, 2004).

These steps are described in the following section.

ENROLMENT

In the enrolment process, the biometric system is trained to identify a specific person who provides an identifier such as an identity card. Then, the biometric is linked to the identity specified on the identification document, and a person shows the biometric such as fingerprint, iris or face to a usage device (Vacca, 2007). The distinguished features are located and one or more samples are extracted, encoded and stored as a reference template for measuring and comparing. Depending on the technology, a person's identity can be provided from devices such as a microphone for recording voice, a scanner for scanning fingerprints or a camera for taking pictures, then these features are processed with the organisation's algorithms for extracting, encoding and storing information, in order to make a reference template (Vacca, 2007).

Many factors can influence the generation of a template, such as minute changing in positioning, distance, pressure, environment and other factors (Vacca, 2007). Based on the biometric information captured by the device, each template is unique. Consequently, a person may need to show biometric information several times to enrol and gain access. Depending on the biometric system, the reference template may represent a combination of the captured data, or various enrolment templates (Vacca, 2007). The overall success of the biometric application is related to the quality of the template(s), because biometric features change with the passing of time and the biometric system needs to recapture and re-enrol in order to update the reference template. For more information, some of the reference templates can be updated by new technologies during matching operations (Vacca, 2007).

In addition, the quality of the identifier is another factor in the enrolment process. As mentioned, the identifier specified on the document template is related and linked to the reference template, and if the system cannot distinguish a true identity, the system links these features to a false reference template (Vacca, 2007).

VERIFICATION

The verification system is the next step in enrolment, and verifies the person is who he/she claims to be. In verification, a person's identities (features) are taken from tools (such as fingerprint scanner) and processed through the algorithms in order to make a trial template and compare it with the reference template stored in the system during enrolment, to distinguish the individual's trial and stored template maps (Vacca, 2004).

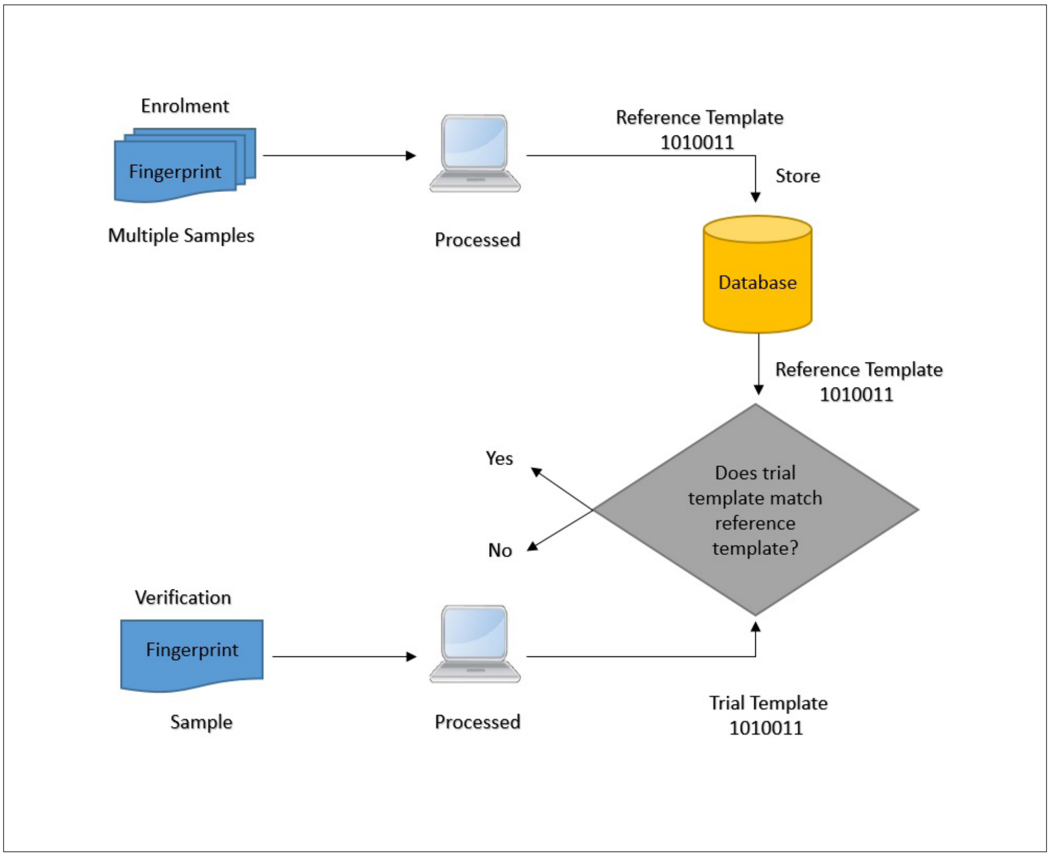

Figure 2. The biometric identification process (Vacca, 2007, p. 25).

Verification systems often include a monster dataset from dozens of millions of enrolment templates that are predicated on matching the individual's presented biometrics against the reference template. Most verification systems can predict match/non-match features in approximately one second and let the user who claims identity access resources (Vacca, 2007). As shown in Figure 2, the verification system is referred to as 1:1 (one-to-one) matching, which means that an individual's biometric is compared to one biometric template in the database (Vacca, 2007).

IDENTIFICATION

The identification system is the next step after enrolment (Vacca, 2007). The trial template is compared with the stored reference template of all individuals enrolled in the system, unlike the verification system, which compares and locates the reference template of each person with the present identifier (Vacca, 2007). The identification system is named as 1:N (one to one or many), because an individual's biometric is compared to multiple biometric templates in the database (Vacca, 2004).

Basic Components of Biometric Systems

There are various discrete components in biometric systems and each of them can be unique. However, as Figure 3 illustrates, most of the biometric systems can be divided into five components or subsystems (Wilson, 2010):

1. Sensor/data capture
2. Feature extraction
3. Data storage/template storage
4. Matching/mapping algorithm
5. Decision process

1. SENSOR/DATA CAPTURE

Sensor/data capture is a significant process of the biometric system, and can be acquired as images or signals, which are then converted to digital format for recognition purposes. The quality of the sensor is very important and it can directly affect the system's result. The biometric data should be of high quality because a low-resolution image or bad signal can give false results or affect accuracy (Wilson, 2010).

2. FEATURE EXTRACTION

After collecting raw data by sensor/data capture, the system needs to extract features from raw data; this is where feature-extraction algorithms come into play. The extraction process extracts the distinctive features from the raw data and converts them to digital format. Depending on the extraction algorithms, these features are completely unique and can be different from the features extracted by another algorithm, even for the same case (Wilson, 2010).

The feature extraction, performed during the enrolment and verification process, is used to create a reference template with personal data in the enrolment process. The next step is the enrolment template matching with each frame of the scanned image in the verification process (Wilson, 2010).

3. DATA STORAGE/TEMPLATE STORAGE

After selecting distinctive features by use of extraction algorithms, these features are collected and stored in data storage/template storage. The template can be stored in a biometric capture device such as a smart card, or a distributing device such as a personal computer (Wilson, 2010).

4. MATCHING/MAPPING ALGORITHM

Once the features are in the template storage, the matching algorithm compares a reference template with a new sample and finds similarities (Wilson, 2010). The percentage of similarities shows how similar the reference template is to a new sample.

5. DECISION PROCESS

The decision process is based on a similarity result. This result is gained from matching algorithms and making the system-level decision for the identification and verification transaction (Wilson, 2010). Based on the percentage of similarity, errors can be increased or decreased; indeed, the number of similarities affects the system's accuracy.

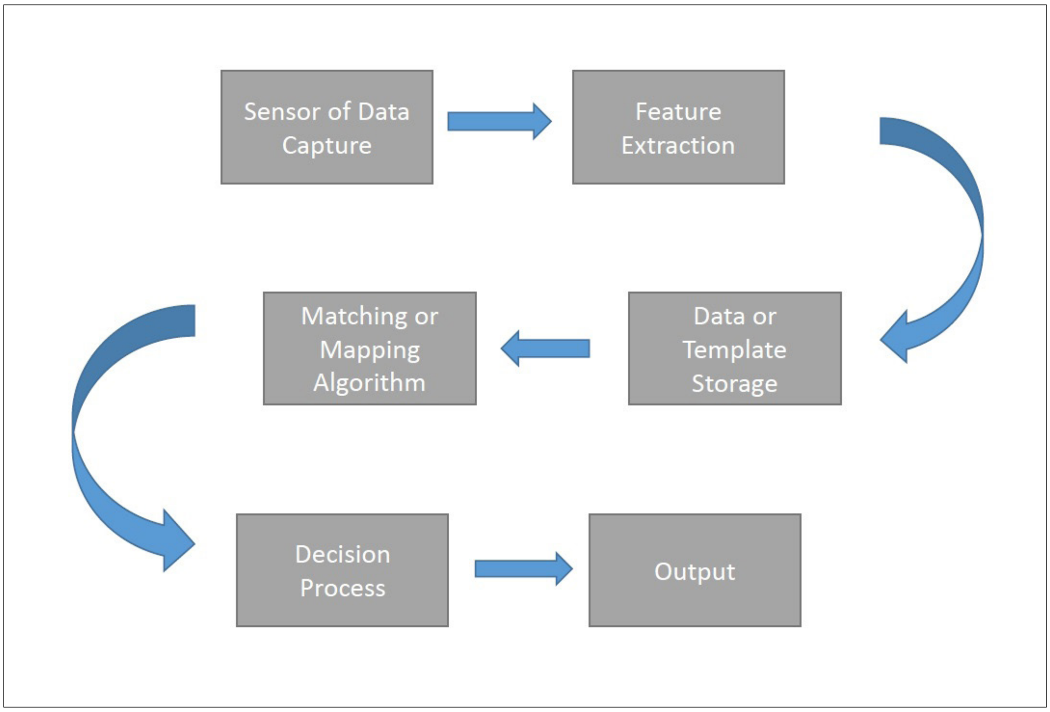

Figure 3. Components of the biometric system (Wilson, 2010, p. 59).

Importance of Biometrics

Biometric traits have been used for authentication for many years and, recently, as science and modern technological tools have developed, they have assumed a more prominent role for recognition purposes. Using biometrics for identification purposes has the advantages of reliability, accuracy, ease of function, speed of running systems and avoidance of fraud (Vacca, 2004).

In fact, most companies and governments prefer to have a secure system with the least difficulty for their users, such as a biometric system that only needs a microphone for recording voice, a fingerprint scanner, or a camera for taking a photo. In addition, when a system is working with biometrics, it can have greater accuracy and avoid any human mistakes. For example, for over a century, most governments have used fingerprints as an identifying method, and right now there is a great deal of scientific data supporting the idea that no two fingerprints are alike (Vacca, 2004).

Crime prevention and identification of perpetrators such as masked gunmen, rioters, sexual abusers of children, etc., are very significant issues for governments and police forces (Zhang, Tang, Li, & Kong, 2014). Due to improvements in technology and computer science in recent decades, researchers have been equipped with many different tools that can help recognise criminals.

As described previously, there are many types of biometric systems, and each of them has pros and cons and does not fit all needs. Among these biometric security systems, vein-pattern recognition is one of the newest and most secure, has a high level of accuracy and is less vulnerable to forgery than other systems. In the following section, the literature explains vein patterns as a new biometric trait and then the components and computational methods for recognition of vein patterns are described.

Analysis and Interpretation of Vein Pattern

VEIN PATTERN

Vein-pattern recognition (VPR) usually refers to vascular-pattern identification. Researchers have argued that the vein patterns of each human body are exclusive to that specific individual and do not usually change over life; moreover, they are inside the human body, therefore less vulnerable to forgery (Vacca, 2007). A human's identity can be recognised by vein patterns that are located near the surface of the skin in fingers, palms or dorsal hands, or legs and arms (LG, 2003). Radiating near-infrared light (NIR) and laser imaging technology are two common methods of vein-pattern visualisation that reflect the blood vessels of the human body (Vacca, 2007).

VPR was introduced for the first time in 1984 by Joseph Rice, whose identity had been stolen, leading to the fraudulent use of his bank account. He tried to make a vein-pattern recognition prototype by use of photodiodes and a computer (Davis et al., 2008). Years later, Fujitsu Group made a scanner that was able to read the vein patterns of the palm of the hand and recognise identity (Amin & Mohammed, 2015). In 2000, this authentication system was presented as the first commercially available vein-pattern recognition system, able to identify vein patterns on the back of the hand (Vacca, 2006).

VPR devices can identify the vein pattern through the haemoglobin that flows in the veins (LG, 2003). Haemoglobin is an iron-containing protein pigment in the red blood cells, which transfers oxygen from lungs to blood tissues by arteries and returns the carbon dioxide from blood tissues to heart and lungs by venous blood (LG., 2003). Venous blood is dark red and in some parts of the body such as the veins of the hand, it is closer to the skin than arteries (LG., 2003).

There are a few computational methods of vein-pattern recognition. By using a range of skin parameters such as the concentration of haemoglobin, the concentration of melanin and depth of dermis, these methods are able to recognise vein patterns (Sharifzadeh et al., 2014).

VPR can be more accurate than other biometric techniques, and has many advantages, some of which are listed as follows (LG, 2003):

- Veins provide biometric features that are relatively stable, robust, large and can be easily extracted.
- Vein patterns are resistant to fraud. They cannot be easily accessed, they are not vulnerable or changeable, and they cannot be observed by the naked eye. Furthermore, vein-pattern recognition systems work in the form of binary and encrypt the data in the template.
- Vein-pattern recognition systems have high output accuracy and low false levels.
- The outputs of some biometric traits, such as fingerprint, face recognition or iris scanning, can be affected by many external factors, whereas vein pattern is less susceptible to many external factors.

FINGER VEIN

Due to developments in technology and by using vein-pattern features, scientists have been successful in finding and developing a new identification method, which is called finger-vein pattern recognition (Matsuda, Miura, Nagasaka, Kiyomizu, & Miyatake, 2016; Wang & Leedham, 2005; Zhou, Lin, Jia, & Song, 2007; Fu, Cui, & Xiong, 2010; Zhang, Han, & Ma, 2006).

Finger-vein identification systems are more accurate and reliable than fingerprint identification systems. This technology was started in the mid-1990s by Hitachi central research laboratory and it has been revealed that this biometric trait is robust and competitive in comparison with other biometric features (Davis et al., 2008).

Finger-vein recognition has several advantages and disadvantages, which are listed as follows (Wen & Liang, 2010):

Advantages:

- A finger vein provides good distinction between individuals and is more accurate than other biometric features.
- Except for the size of a person’s finger, a finger vein does not change over time.
- Finger veins are inside the human body.
- Finger veins have a large, robust, internal pattern.
- Finger veins cannot be easily observed, damaged, obscured or changed.

Disadvantages:

- Fingers have different bone and muscle thicknesses, and there are some areas that might be dark or bright; in this area, the contrast between the finger-vein pattern and background is low, especially in dark or bright skin, so it is difficult to tell which is vein or background (Wen & Liang, 2010).

HAND VEIN

In recent years, hand-vein methods have been developed for recognition purposes. In comparison with other parts of the body, veins are more available and visible in the hand area (Sharifzadeh et al., 2014). In fact, the human body has a lot of veins that cannot be recognised, such as those very deep in the body and with many layers of fat above them. Therefore, scientists prefer to use hand veins for authentication of human beings, as these veins are thick and also closer to the surface of the skin (Sharifzadeh et al., 2014). Currently, researchers are interested in the palm (Lin & Fan, 2004; Malki & Spaanenburg, 2007; Ladoux, Rosenberger, & Dorizzi, 2009) and dorsal hand veins (Kumar & Prathyusha, 2009; Zhao, Wang, & Wang, 2008; Wang, Li, Cui, Shark, & Varley, 2010).

The palm and dorsal hand veins are unique and have been used with high accuracy in human identification. In comparing palm and dorsal veins, some researchers believe that palm veins are better and more robust than dorsal veins (Xueyan & Shuxu, 2008). They claim that diversity of skin and hairy bodies are two significant problems for uncovering vein patterns while, for all human beings, the palm of the hand is white and there are no hairs, so devices can reveal veins accurately (Lin & Fan, 2004).

On the other hand, some researchers claim that it is better to use finger veins than hand veins as, for the same accuracy, systems or applications need to do more processing regarding more features in hand veins (Zhang & Hu, 2010).

Physiological Background

CARDIOVASCULAR SYSTEM

The cardiovascular and lymphatic systems are two main parts in the circulatory system, which are found in humans and most animals (Gray & Standring, 2008; Widmaier, Raff, Strang, & Vander, 2008). The main function of the cardiovascular system is to maintain homeostasis and provide what each cell needs in the body for consumption or storage, including oxygen, nutrients, minerals, enzymes, hormones and other substances. Furthermore, it has several important roles such as regulating and delivering heat to all parts of the body, recycling or excreting metabolism residuals, and helping the immune system (Gray & Standring, 2008; Widmaier et al., 2008).

There are two main circulations in the cardiovascular system, the pulmonary and the systemic, which are both connected to and supplied by the heart. Homeostasis is maintained by the systemic circulation loops from the heart to all other parts of the body. The pulmonary circulation loops from the heart to the lungs release carbon dioxide and re-oxygenise the blood vessels of the lungs (Gray & Standring, 2008; Widmaier et al., 2008).

The systemic and pulmonary systems work together to carry oxygen-saturated blood from the heart through a network of blood vessels to all body parts and back to the heart within the systemic loops, and refurbish the blood vessels by re-oxygenising within the pulmonary loops. Within the systemic loop, the heart pumps oxygen-saturated blood at high pressure and fast flow into the arteries and semipermeable capillaries, in order to exchange substances and liquids between slow-flowing blood and tissue. Finally, low-oxygen blood is transferred to the heart again to be re-oxygenised (Gray & Standring, 2008; Widmaier et al., 2008).

There are two group of veins: superficial and deep. The superficial veins are mostly located under the skin and deep veins are commonly covered with connective tissue. The blood is transferred through superficial to deep veins (Gray & Standring, 2008; Widmaier et al., 2008).

VEINS AND ARTERIES

There are major differences between veins and arteries. The blood-vessel walls are comprised of the endothelium, muscle coat and adventitia, which make the arteries thicker, allowing the transfer of a high-pressure blood stream from the heart, or thinner, to adapt to the stored blood volume. The blood volume is distributed into the systemic veins (61%), capillaries (7%), arteries (11%), heart (9%), and pulmonary circle (12%) (Widmaier et al., 2008). The length of the capillary network is around 40,000 km and each has an inner diameter of around 8 µm (Widmaier et al., 2008).

There are advantages to having veins closer to the skin than arteries, such as for thermal regulation or limiting blood loss if superficial injuries damage vessels (because veins carry low-pressure blood) (Widmaier et al., 2008).

DEVELOPMENT OF BLOOD VESSELS

Understanding the development of cardiovascular patterns is crucial for VPR, as they form the basis of vessel structures. In the development of a human, the heart and early circulatory system start to develop in week 3-4 after conception. The pulmonary and systemic circles begin separation during birth and the early circulatory systems completely change during this time (Eichmann et al., 2003). When a baby is newly born, its lungs need to saturate the blood with oxygen by themselves once the umbilical vein and placenta are no longer available for supporting oxygen and nutrients. Therefore, the shortcut between the aorta and pulmonary artery has to be stopped within the first postnatal days. After that, the rest of the arteriovenous structures remain unchanged (Eichmann et al., 2003).

Regarding the formation and genesis of blood vessels, it is still not a clear area and is complicated, but Bondke Persson and Buschmann (2011) identify three types of development:

– Vasculogenesis
– Angiogenesis
– Arteriogenesis

The primary vessel structures and the formation of new blood vessels are described by the term vasculogenesis; however, these structures are mostly formed based on genetics. Angiogenesis describes the structure of capillarisation. These structures are made based on the metabolic processes in order to support oxygen for new tissue growth. The outgrowing of existing blood vessels is referred to as arteriogenesis, which is influenced by hemodynamics. Many parameters should be considered in order to evaluate vessel structures, such as shape and elasticity of the vessel, width of vessel and blood pressure (Bondke Persson & Buschmann, 2011).

BLOOD

The composition of blood is well understood, and consists of fluid plasma and cells. The red blood cells are the largest proportion of cells in the blood, at 99%. The proportion of cellular parts of the blood to plasma is defined as hematocrit, and changes from birth on, levelling at about 40% and 45% for females and males respectively.

Erythrocytes consist of the protein hemoglobin surrounded by a plasma membrane. Foetal erythrocytes differ from those of adults, and contain a nucleus and different types of hemoglobin (HbF). Adult blood contains less than 1% of haemoglobin type A, and the rest is comprised of other types of haemoglobin (Bondke Persson & Buschmann, 2011). Hemoglobin binds oxygen with its iron atoms (Fe^{++}) and, in this way, most of the oxygen needed for the metabolism is transported in the blood to the tissues. Oxyhemoglobin (HbO2) causes the bright-red colour of oxygen-saturated blood in the systemic arteries; due to deoxyhemoglobin (Hb), oxygen-depleted blood in the systemic veins is a darker colour. Less than 1% of the cellular parts contain leukocytes (white blood cells) to support the immune system and thrombocytes for haemostasis (Bondke Persson & Buschmann, 2011).

Arteriovenous anastomosis on the one hand, and the evolutionary principle on the other, make the blood-vessel system more complex than other parts of body. In the vessel system it is not possible to have an equal (or maximal) blood supply in the whole body at the same time. Therefore, there are some shortcuts (arteriovenous anastomosis) for blood regulation that can be closed or opened in different situations (Bondke Persson & Buschmann, 2011).

SKIN AND BLOOD VESSELS

In different parts of the body, the skin can be thinner or thicker; for example, the skin of the hand (from the wrist) is much harder (the epidermis is thicker), and extremely sensitive and vascular compared to the skin of the forearm, while the skin of the fingers is mostly thinner (Gray, 1981). The skin of dorsal hands and palms is different, with the dorsal skin thinner and more flexible, and the palm skin hairless and thicker (Gray, 1981). The skin includes three layers: the epidermis, dermis and hypodermis. Skin thickness differs from person to person, and it also depends on the location on the body, but blood vessels can be captured below the epidermis (Gray, 1981).

Imaging of Blood Vessels

Knowledge of the interior of the human body is important for diagnosis and medical science. The Egyptians, around 1000 B.C., were the first group to visualise and make discoveries about the inside of the human body and understand the importance of the cardiovascular system for health (Seigworth, 1980). The World Health Organisation (WHO) has announced that disease related to the cardiovascular system is one of the main causes of death in the world (WHO, 2004). Hence, blood image processing is receiving much interest these days.

By using new technologies, it is possible to investigate inside the human body and gather valuable information without doing specific surgery. Rontgen discovered the X-ray in 1895 and he created in vivo images of bone structures (Egas Moniz, 1940). With the development of cerebral angiography (angio = vessel, graphy = imaging) by Antonio Egas Moniz in 1927-28, it became possible to create in vivo images of the brain by injecting a contrast agent absorbing X-ray into the brain in order to recognise abnormalities through visualising the blood vessels (Egas Moniz, 1940). Angiography refers to medical imaging techniques and it is used for visualising internal organs such as veins and vessels. In 1991 it became possible to use vein patterns for biometric purposes by developing and using near-infrared (NIR) images (MacGregor & Welford, 1991). To follow, we will discuss the history and features of the most common medical-imaging technologies.

X-RAY

High-density materials such as bones are revealed by X-ray, as its wavelength is between 10 nanometers and 1 picometer. The Beer-Lambert law describes the absorbance of X-ray and is defined as (Momose, Takeda, & Itai, 2000):

$$E_\lambda = \log(I_0/I_1) = \epsilon_\lambda * c * d, \tag{1}$$

where E_λ is a relationship between I_0 (the intensity of radiation) and I_1 (the measured intensity) after passing through the medium. d is the length of the passage, c is the molar concentration (the ratio between density and molar mass), and ϵ is the specific absorbance coefficient. By making the radiation into X-ray tubes, the bones can be captured on X-ray-sensitive film as they are able to absorb high amounts of the rays (appear bright) and the rest of the parts appear dark (Momose et al., 2000).

By using fluoroscopy as one of the imaging techniques, it is possible to acquire live image sequences of the internal body. A fluorescent screen or an image intensifier is placed in front of the X-ray source and can transform the radiation into visible light. This visible light is captured by a common charge-coupled device (CCD) and it helps to visualise the vessel or cardiovascular patterns (Momose et al., 2000).

According to a WHO report (Caro, Trindade, & McGregor, 1991), the use of X-ray can affect human health and it is classified as a carcinogen. In addition, the capturing devices are very expensive. Therefore, using X-ray is unsuitable for biometric identification purposes.

MAGNETIC RESONANCE IMAGING (MRI)

With the aid of nuclear magnetic resonance, magnetic resonance imaging (MRI) is used for visualising internal organs and tissues, and was developed in the 1980s. Paul Lauterbur and Peter Mansfield won the Nobel Prize in Physiology or Medicine in 2003 for their achievement (Widmaier, Raff, & Strang, 2006). MRI can be used for visualising the blood vessels in the human body. Capturing images from a blood vessel largely depends on the oxygen level, therefore it is known as susceptibility-weighted imaging (SWI) (Widmaier et al., 2006).

MRI is known for providing high soft-tissue contrast. Unlike X-ray, MRI does not depend on ionising radiation; however, it can damage electronic devices by causing metal components to heat up. In addition, MRI devices are expensive, noisy and large scanners with a long scanning time (Widmaier et al., 2006).

ULTRASOUND

Ultrasound (US) is a technique used to capture internal imaging. US waves, like sound waves, have a specific frequency (above 20 KHz), but for medical ultrasonography, ultra-high-frequency is used, which is usually 2-18 MHz (Maltoni, Maio, Jain, & Prabhakar, 2009).

US works based on the echo (reflection) of sound. US sensors are transceivers that send sound waves and record the echo. This is usually done using piezoelectric crystals and the piezoelectric effect: if the crystal is activated with an electric signal it emits sound waves. The reflected echo produces an electric signal at the crystal, which can be measured (Maltoni et al., 2009). There are different patterns in echogenicity of tissue, and these can affect the reflectance of the sound waves.

US is popular to use in fingerprint recognition. It measures the difference in the echo between fingerprint ridges and valleys, which have trapped air (Narayanasamy, 2009). By using grey-scale US, the structure of human fingerprints can be captured.

The equipment used in US, such as sensors, is cheaper than that used in MRI, but US is not suitable for biometric purposes because water-based gels need to be applied to the skin, which can mitigate the reflection from the air between sensor and body (Narayanasamy, 2009).

FAR-INFRARED

Far Infrared (FIR) is one of the sub-divisions of Infrared that is a region in the infrared spectrum of electromagnetic radiation with a wavelength of 15 micrometers (μm) to 1 mm (Dodel, 1999). FIR has been used since the early 19th century for measuring the temperatures of the various colours of the visible light spectrum, and has been used in the manufacture of products since the Industrial Revolution. In China and Japan in the mid-20th century they began to use FIR to treat the body, make products and heat homes in winter, using FIR-emitting heat lamps (Dodel, 1999).

As described previously, thermal regulation is one of the important functions of the vascular system. The human body can be warm or cold in different situations and the vascular system needs to adjust the blood temperature. If the body is too cold, this system heats the blood and distributes it to the whole body (Lin & Fan, 2004). In addition, this system can cool down the blood using the superficial veins. As long as this temperature can be measured and the heated object can emit electromagnetic radiation, we can capture human body-heat using far-infrared (FIR) radiation (Lin & Fan, 2004).

FIR is already used for biometric systems such as ear recognition and 2D face recognition (Yoshitomi, Miyawaki, Tomita, & Kimura, 1997; Watne, 2008).

FIR is not practical in all situations and it has several limitations (Fan & Lin, 2004; L. Wang & Leedham, 2006; Lin & Fan, 2004):

– There are fewer studies on FIR for vein-pattern recognition
– Low image resolution
– Difficulty of capturing the fine structure because of the spread of heat in the tissue
– Poor contrast between veins and tissue in high temperatures (between 30˚ and 34˚ C) and humidity over 80%
– High cost of FIR sensors

Nevertheless, FIR can achieve high recognition accuracy under controlled lab conditions.

NEAR-INFRARED

This frequency range of the electromagnetic spectrum from below 1 hertz to 1025 hertz can be divided into different bands. The portion of the electromagnetic spectrum able to be realised by the human visual system is typically called ‘visible spectrum,’ and has a range from near 380 to 700 nanometers in wavelength, while this range is from almost 700 to 1100 nanometers for infrared and 750 to 2500 nanometers for NIR (Fredembach & Süsstrunk, 2008).

NIR is used in scientific, industrial and medical applications such as infrared-astronomy used in the sensor of a telescope (Manohar, 2015), or infrared thermal-imaging cameras used to observe changing blood flow in the skin (Girardot, 1990). The human visual system is unable to see the NIR range and needs specific cameras that can capture NIR images. Uncovering vein patterns from colour images that are taken from consumer digital cameras is extremely challenging because the veins are behind the muscles, fat and skin surface, and they are almost invisible to the naked eye. Most digital cameras have a ‘hot-mirror’ lens, which is sensitive to the NIR range and only visible light is able to pass (Manohar, 2015). The hot-mirror lens must be removed and replaced with a clear glass or visible-blocking filter in order to capture an NIR image (Fredembach & Süsstrunk, 2008). Currently, there are some types of technical cameras that can capture an NIR image from subjects in order to uncover vein patterns.

LASER

Laser is another tool that can be used for uncovering vein patterns. The laser was developed in 1960 by Theodore H. Maiman at Hughes Research Laboratories, based on theoretical work by C. H. Towns and A. L. Schawlow (Kang, Rabie, & Wong, 2014). Laser imaging technologies have improved over time, and can now be used to observe veins. With laser imaging technology, valuable information about the location and structure of veins can be extracted, which is useful for identification purposes and medical science (Kang et al., 2014).

In recent decades, some companies have tried to build a novel tool that is able to read vein patterns. One of the successful companies that has worked in uncovering vein pattern is Christie Medical Holdings, Inc. in Japan. It has built a machine called a VeinViewer, which is able to show veins with high accuracy (Worster, Crane, Hansen, Fairley, & Lee, 1995). The NIR technique can be established as a de facto standard for VPR in comparison to other approaches. In order to prove VPR as a reliable biometric system, the NIR images can be used as ground truth (reference dataset) for the mapping/matching process. However, NIR and laser-imaging technologies are inapplicable for forensic investigation, because we need the subject present in order to extract features using devices. Nonetheless, other approaches can be used for improving liveness detection or three-dimensional imaging.

Recently, researchers have tried to extract vein patterns using visible-light cameras for forensic investigation purposes (Varastehpour, Sharifzadeh, Ardekani, & Francis, 2019b). By inverting the process of skin-colour formation, they can visualise the vein pattern. This technique could be used in the near future in order to simplify the design of the sensors for vein capturing. In the next section, we review the methods that have been developed based on a computational approach.

Computational Methods

Visualising vein patterns from colour photographic or video images for criminal and victim identification is a very new research direction. Recently, computational methods such as Optical-Based Vein Uncovering (OBVU) based on the Kubelka-Munk (K-M) theory (Sharifzadeh et al., 2014), Independent Component Analysis (ICA) (Tsumura, Haneishi, & Miyake, 1999), Pigmented Skin Lesions (Claridge, Cotton, Hall, & Moncrieff, 2003) and neural network algorithms (Sharifzadeh et al., 2014) have been developed for this purpose. In this section, we review related work based on computational methods.

RELATED WORKS BASED ON THE KUBELKA-MUNK (K-M) THEORY

Kubelka and Munk performed a simplified analysis of the action and reaction of input light with a layer of material such as paint (Kubelka, 1948). As Kubelka and Munk said, “the material is assumed to be uniform, isotropic, non-fluorescent, non-glossy and the sample has to be illuminated by diffuse, monochromatic light" (Kubelka, 1948, p. 12). According to Kubelka and Munk, the radiation passing through a scattering medium can be in two diffuse fluxes (Kubelka, 1948):

- Forward direction
- Backward direction

As shown in Figure 4 (Tang, Kong, & Craft, 2011, p. 2), these two diffuse fluxes are respectively defined as *I* and *J* (Parrish & Anderson, 1981).

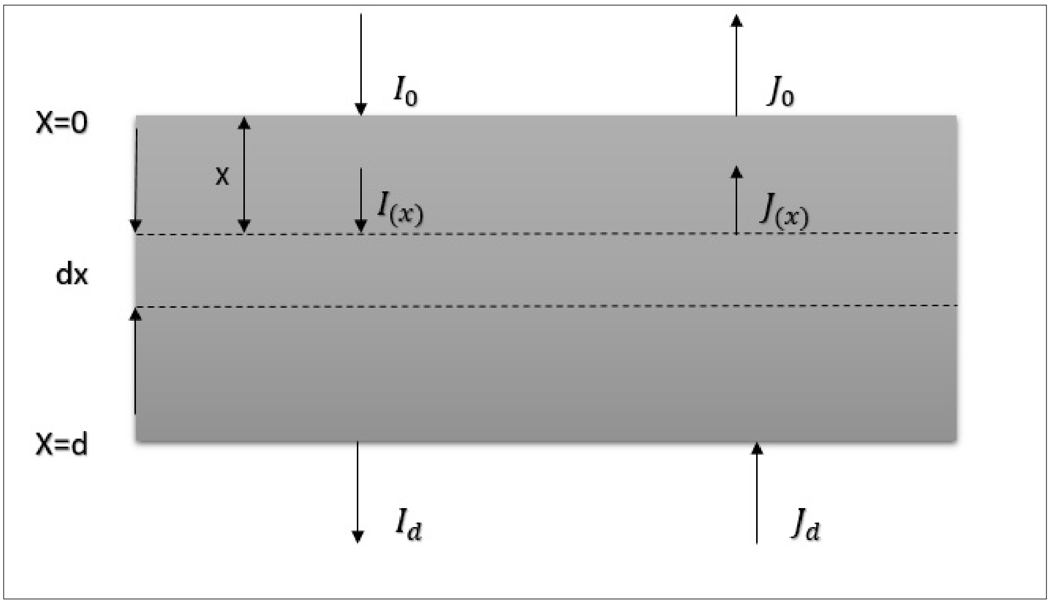

Figure 4. Light transport based on the K-M theory.

The distance from surface for *x*, the variation in flux an infinitesimal distance *dx* for *I* and *J* are:

$$dI = -KIdx + S(-Idx + Jdx), \tag{2}$$
$$dJ = KJdx + S(Idx - Jdx), \tag{3}$$

where $K = 2\mu a$ and $S = 2\mu s$ $.\mu a$ is the scattering coefficient of the medium at a particular wavelength. I is diffuse fluxes in the forward direction and J is used for backward direction.

The K-M theory has been popular and frequently used in skin optic models. In terms of skin optics, Anderson, Hu and Parrish (Parrish & Anderson, 1981; Anderson, Hu, & Parrish, 1981) were the first, in 1981, to try using the K-M theory as the model for optical properties of dermal tissue. This model was developed by Wan et al. to compute the absorption and scattering coefficients of the epidermis, taking into account both collimated and diffuse incident irradiance (Parrish & Anderson, 1981). Based on the K-M theory, Diffey proposed a model that is able to measure change in the refractive index at the skin interferences by considering forward and backward scattering (Diffey, 1983). Furthermore, Van Gemert et al. worked on dominant absorption and scattering using the K-M theory (Van Gemert, Jacques, Sterenborg, & Star, 1989).

The categorisation of pigmented skin lesions was developed through the K-M theory for colour images by Cotton and Claridge (1996). Furthermore, they introduced important factors from the composition of pigmented skin lesions (Claridge et al., 2003). Doi and Tominaga proposed a model based on the K-M theory to estimate the reflectance of human skin (2003). In addition, the K-M theory was used by Donner and Jensen (2005) to model light diffusion in multi-layered translucent materials. It was also used to predict skin optics for laser surgery (Parrish & Anderson, 1981; Anderson et al., 1981).

Claridge et al. (2003) proposed a method using colour images to recognise pigmented skin lesions that could uncover the distribution of melanin, the depth of dermis and haemoglobin. Their target was for medical applications, where the colour images were collected in a controlled environment with white incident light. This method did not work for images taken under uncontrolled illumination conditions (Claridge et al., 2003).

Tsumura et al. (1999) presented an Independent Component Analysis (ICA)-based method to evaluate and synthesise the colour and texture of human skin. The first aim of their method was for computer-graphic applications. Though this method could reveal veins, it could not uncover vein patterns in parts of a body that had a high concentration of melanin or hairy skin (Tsumura et al., 1999).

However, these methods based on the K-M theory focus on different directions, such as medical or graphic applications, and are not designed for forensic purposes.

RELATED WORKS BASED ON OPTICAL-BASED VEIN UNCOVERING (OBVU)

Using OBVU based on the K-M theory and neural network algorithms is a very new research direction for VPR. Tang et al. proposed a method based on optics and skin biophysics to uncover vein patterns hidden in colour images (Tang, Zhang, & Kong, 2016). This method was different from those of Tsumura et al. and Claridge et al., and aimed to use vein patterns for forensic investigations (Zhang, Tang, Kong, & Craft, 2012). The OBVU method used the K-M theory to model the skin-colour formation in an image, i.e.,

$$[R,G,B] = f(I(\lambda), \vartheta_m, \vartheta_p, d^{der}, S_R(\lambda), S_G(\lambda), S_B(\lambda)), \qquad (4)$$

where $I(\lambda)$ is an illuminant; λ represents wavelengths; ϑ_m, ϑ_p, d^{der} are respectively the volume fraction (%) of the epidermis occupied by melanosomes, the volume fraction (%) of the dermis occupied by blood, and the depth of the dermis; and $S_R(\lambda)$, $S_G(\lambda)$ and $S_B(\lambda)$ are respectively the red, green, and blue spectral response functions of a camera (Tang et al., 2011; Varastehpour et al., 2019b). They used these correspondences to train a neural network that takes RGB values as inputs to find the skin parameters. Vein patterns can be extracted through this method where blood in veins has a higher concentration of haemoglobin. In Tang et al.'s experiments, vein patterns could also be seen in other parameter maps, i.e., the concentration of melanin and the depth of dermis. Figure 5 illustrates the OBVU method that was proposed by Tang et al. (2016).

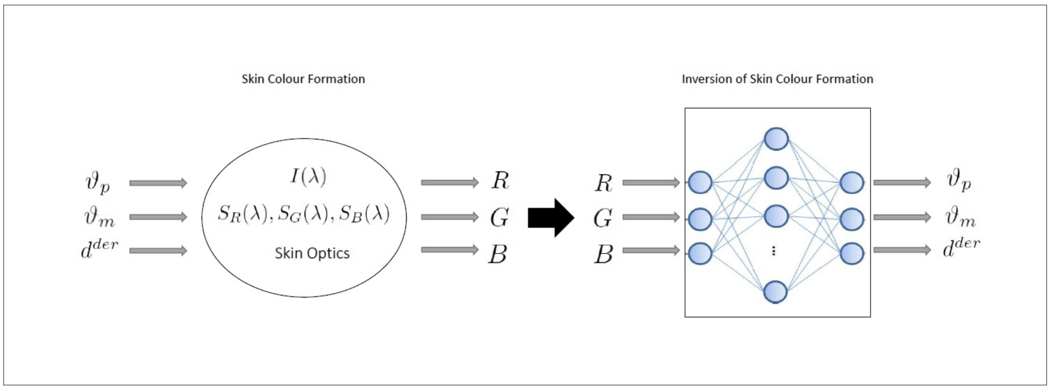

Figure 5. A schematic diagram of the OBVU method to visualise vein patterns. The left block represents the skin-colour formation model and the right block represents the inversion of the skin-colour formation to obtain $[\vartheta_m, \vartheta_p, d^{der}]$ from $[R, G, B]$, where ϑ_m, ϑ_p, d^{der} are respectively the concentration of melanin, haemoglobin, and the depth of dermis (Tang, Kong, & Craft, 2011, p. 4).

Tang et al. (2016) noted that this model is sensitive to noise in the green channel (Zhang et al., 2012) and that different illumination conditions can affect the performance of pattern uncovering. In addition, the data must be collected in a controlled environment (Zhang et al., 2012).

To deal with these limitations, Zhang et al. (2012) proposed a vein-pattern uncovering algorithm that was partially based on OBVU. They added a new scheme to achieve the best results, which is parameter-range optimisation through colour and automatic adjustment for image intensity (Zhang et al., 2012). They introduced a parameter *a* into the trained neural network of the OBVU method. Mathematically, it can be modified as:

$$d_p = f(M_p/a), \tag{5}$$

where M_p is an RGB value of the pixel p in an input colour image, d_p is a skin parameter given by the OBVU method, f represents the trained neural network from the OBVU method and a is a free parameter to handle illumination variation. Combining all d_p from different pixels forms a vein pattern image denoted as d. Zhang et al.'s method has two problems, as outlined below (Zhang et al., 2012):

- They used a single channel such as a green channel for their models, which made their models weak in diverse skin properties (different tones of skin).
- Their parameters did not adapt to fit local image characteristics, which are weak in local illumination and pose variations.

To address these weaknesses, Sharifzadeh et al. proposed a new algorithm composed of a bank of mapping models that transform colour photographic images to NIR images for uncovering vein patterns, and a local parameter estimation scheme for handling different image characteristics in different regions (Sharifzadeh et al., 2014).

Tang et al. proposed three optical models for uncovering vein patterns from colour photographic images: the baseline model, the two optimisation scheme model, and the improved model (Tang et al., 2016). Each model consists of a skin structure, a camera model, illuminant models and method to compute all reflectance from the skin structure. These models can be divided into two categories. In the first category, the baseline model and two optimisation scheme model have used the K-M theory and a three-layered skin structure, which is constituted by the dermis, the melanin and the haemoglobin. In the second category, the improved model has used Reichman's solution instead of the K-M theory, with the same three-layered structure (Tang et al., 2016; Varastehpour et al., 2019b).

LIMITATIONS OF VEIN-PATTERN RECOGNITION

Historically, in the VPR system, it was impossible to see vein patterns with the naked eye, because they are inside the human body and almost invisible to devices taking colour photographic images (Zhang et al., 2012; Varastehpour et al., 2019b). Researchers have argued that vein patterns are unique and do not usually change in a person's lifetime; in addition, they are inside the human body and thus less vulnerable to forgery. Furthermore, arteries and veins are distributed across all of the human body. With this point in mind, VPR devices or applications can uncover vein patterns through the haemoglobin that flows in the veins. However, these devices are all based on NIR or laser-imaging technologies.

Recently, researchers have created various methods for uncovering vein pattern from colour photographic (RGB) images (Tang et al., 2011); nevertheless, recognising vein patterns on some subjects is limited, and clear vein patterns are difficult to obtain, with some of these limitations noted below (Zhang, Huang, Wang, & Wang, 2015; Nurhudatiana & Kong, 2015; Varastehpour, Sharifzadeh, Ardekani, & Francis, 2019a):

- Diversity of skin colour
- Hairy bodies
- High concentration of body fat
- Tattoos

In addition, most of these methods are very sensitive to illumination changes and depend heavily on the biophysical parameters being measured in ideal medical conditions (Van Lanh, Chong, Emmanuel, & Kankanhalli, 2007). Furthermore, all datasets must be collected in controlled environments at laboratories with high standards of light, angle, etc.; it is difficult to reveal veins with images that are taken from simple consumer cameras with varying qualities of resolution. All of these issues, in terms of forensic investigation, are very challenging for revealing vein patterns.

Overall, the computational methods used in VPR show some promising results and they might be able to overcome the limitations of VPR systems being used for forensic purposes. However, these vein visualisation methods all have two common weaknesses. Skin images taken under different illumination conditions have varying intensity values, and this can affect the revealing performance, therefore the data must be collected in controlled environments. Furthermore, no current literature focuses on image enhancement as a crucial phase prior to the revealing phase: most of the current VPR systems are focused on the matching/mapping phase. The image enhancement phase can help to improve the quality of input data in order to extract features with higher accuracy.

Discussion

Each human in the world has genuine and unique features that can help researchers and scientists for identification purposes. These features are called biometric traits and are divided into two classes: physiological characteristics including palm print, fingerprint, DNA, face, hand geometry, iris; and behavioural characteristics including typing rhythm, voice, gait, signature. Each of these biometric traits has its own pros and cons in terms of accuracy and reliability, and they can be useful or useless in different conditions. DNA has been used for many decades as the most reliable biometric by law enforcement agencies or police but it takes a long process to get results. Face and iris recognition have high accuracy and fast running processes. Fingerprints and palm prints have been used for decades as a reliable form of personal authentication, using a simple process. However, it is necessary to have access to the subject and special equipment.

Personal identification and authentication are critical processes in forensic science. Law enforcement agents and forensic laboratories around the world use most of the physiological characteristics for criminal and victim identification. However, these biometric traits are not applicable in legal cases in which images are the only evidence available, but the face of the criminal or victim is not visible. These cases might include images from child pornography or of masked gunmen.

To tackle this problem, vein pattern has been introduced as a new biometric trait that provides personal verification and identification based on the vast network of blood vessels under the skin surface. It is considered to be a unique and stable biometric trait that is nearly impossible to forge. The vast network of larger blood vessels is believed to be 'hardwired' into the body at birth, and remains relatively unaffected by ageing, except for predictable growth, as with fingerprints. In addition, as the blood vessels are hidden beneath the skin and are almost invisible, they are much harder to duplicate compared with other biometric traits.

There are various computational methods working in the field of vein patterns that are based on the Kubelka-Munk (K-M) theory and optical-based vein uncovering (OBVU). Nonetheless, the methods based on the K-M theory are not designed for forensic investigation, and are mostly used in graphical applications, medical applications, or skin optics for laser surgery. Methods based on OBVU have been used for forensic investigation; however, these methods suffer from several weaknesses in different cases, ranging from skin diversity and hairy bodies to subjects with a high volume of dermis fat in which the vein pattern cannot be uncovered.

The authors believe that deep-learning algorithms can provide a solution to some of the limitations of current VPR methods. Deep-learning algorithms are a subset of machine-learning algorithms that aim to explore several levels of the distributed representations from the input data. Recently, many deep-learning algorithms have been proposed to solve traditional artificial-intelligence problems. In recent years, deep learning has been extensively studied in the field of computer vision (image processing) and a number of related approaches have been developed. This literature review suggests the need for further investigation into deep-learning algorithms such as convolutional neural network (CNN), auto-encoder (AE), and restricted Boltzmann machine (RBM) to find an efficient deep-learning algorithm for extracting and enhancing the features of an image for recognition purposes.

Conclusion

Recognition plays a key role in today's society, in which it is necessary to authorise individuals to gain access to resources, services, physical locations or information. In this context, biometrics offers the great advantages of unique physical and behavioural features, so researchers can take advantage of these features for recognition purposes.

Crime prevention and identification of perpetrators such as masked gunmen, rioters, sexual abusers of children, etc. are significant issues for governments and police forces. Due to improvements in technology and computer science in recent decades, researchers have been equipped with many different tools that can help recognise criminals.

There are many types of biometric systems and each of them has pros and cons and does not fit all needs. These systems are regularly used by law enforcement agents around the world. However, they are not applicable in cases where only partial non-facial skin of criminals or victims is observable in photographic evidence or digital images. Sex offences against children are among these cases, thus alternative biometric systems and methodologies to detect them are needed. Among these biometric security systems, vein-pattern recognition is one of the newest and most secure, has a high level of accuracy and is less vulnerable to forgery than other systems. The computational methods used in VPR show some promising results and they might be able to overcome the limitations of VPR systems being used for forensic purposes. However, these vein visualisation methods all have two common weaknesses. Skin images taken under different illumination conditions have varying intensity values, and this can affect the revealing performance, therefore the data must be collected in controlled environments. Furthermore, no current literature focuses on image enhancement as a crucial phase prior to the revealing phase.

In terms of overcoming some of the current limitations of VPR methods and possible solutions, the authors believe that more research should be focused on deep-learning algorithms such as CNN, AE and RBM in order to improve the accuracy and performance of the current VPR methods.

References

Amin, M. A., & Mohammed, M. K. (2015). Overview of the ImageCLEF Medical Clustering Task. In L. Capellato, N. Ferro, G. J. F. Jones, & E. San Juan (Eds.), *CLEF 2015 Working Notes*. Retrieved from http://ceur-ws.org/Vol-1391/inv-pap1-CR.pdf

Anderson, R., Hu, J., & Parrish, J. (1981). Optical radiation transfer in the human skin and applications in in vivo remittance spectroscopy. In R. Marks & P. A. Payne (Eds.), *Bioengineering and the skin* (pp. 253-265). Dordrecht, Netherlands: Springer.

Bondke Persson, A., & Buschmann, I. R. (2011). Vascular growth in health and disease. *Frontiers in Molecular Neuroscience, 4*(14). https://doi.org/10.3389/fnmol.2011.00014

Caro, J., Trindade, E., & McGregor, M. (1991). The risks of death and of severe nonfatal reactions with high-vs low-osmolality contrast media: A meta-analysis. *American Journal of Roentgenology*, *156*(4), 825-832.

Claridge, E., Cotton, S., Hall, P., & Moncrieff, M. (2003). From colour to tissue histology: Physics-based interpretation of images of pigmented skin lesions. *Medical Image Analysis*, *7*(4), 489-502.

Cotton, S., & Claridge, E. (1996). Developing a predictive model of human skin coloring. *Medical Imaging 1996: Physics of Medical Imaging*, *2708*, 814-826.

Davis, D., Higgins, P., Kormarinski, P., Marques, J., Orlans, N., & Wayman, J. (2008). State of the art biometrics excellence roadmap. *MITRE Corporation*, *1*, 4-14.

Diffey, B. (1983). A mathematical model for ultraviolet optics in skin. *Physics in Medicine & Biology*, *28*(6), 647.

Dodel, G. (1999). On the history of far-infrared (FIR) gas lasers: Thirty-five years of research and application. *Infrared Physics & Technology*, *40*(3), 127-139.

Doi, M., & Tominaga, S. (2003). Spectral estimation of human skin color using the Kubelka-Munk theory. *Color Imaging VIII: Processing, Hardcopy, and Applications*, *5008*, 221-229.

Donner, C., & Jensen, H. W. (2005). Light diffusion in multi-layered translucent materials. *ACM Transactions on Graphics*, *24*(3), 1032-1039.

Egas Moniz, A. (1940). *Die cerebrale arteriographie und phlebographie. Handbuch der neuro*. Berlin: Springer.

Eichmann, A., Yuan, L., Moyon, D., Lenoble, F., Pardanaud, L., & Breant, C. (2003). Vascular development: From precursor cells to branched arterial and venous networks. *International Journal of Developmental Biology*, *49*(2-3), 259-267.

Ellenbogen, J. (2012). *Reasoned and unreasoned images: The photography of Bertillon, Galton, and Marey*. University Park, PA: Penn State University Press.

Fan, K-C., & Lin, C-L. (2004). The use of thermal images of palm-dorsa vein-patterns for biometric verification. *The Proceedings of the IEEE 17th International Conference on Pattern Recognition (ICPR) 2004*. (pp. 450-453).

Fredembach, C., & Süsstrunk, S. (2008). Coloring the near-infrared. *Proceedings of the IS&T/SID Color and Imaging Conference 2008* (1). (pp. 176-182).

Fu, B., Cui, J., & Xiong, X. (2010). A novel adaptive vein image contrast enhancement method based on fuzzy and retinex theory. *The Proceedings of the IEEE International Conference on Information and Automation (ICIA) 2010*. (pp. 2447-2450).

Girardot, J-M. (1990, December 11). *Prevention of prosthesis calcification*. Google Patents. (US Patent 4,976,733).

Gray, H. (1981). *Anatomy descriptive and surgical* [*Gray's anatomy*]. Classics of Medicine Library. Philadelphia, PA: Running Press.

Gray, H., & Standring, S. (2008). *Gray's anatomy: The anatomical basis of clinical practice.* London, UK: Churchill Livingstone, Elsevier Health Science.

Han, C-C. (2004). A hand-based personal authentication using a coarse-to-fine strategy. *Image and Vision Computing*, *22*(11), 909-918.

Jain, A., Bolle, R., & Pankanti, S. (2006). *Biometrics: Personal identification in networked society*. New York: Springer Science and Business Media.

Jain, A., Hong, L., & Pankanti, S. (2000, February). Biometric identification. *Communications of the Association for Computing Machinery (ACM)*, *43*(2), 90-98.

Jain, A. K., Nandakumar, K., & Ross, A. (2016). 50 years of biometric research: Accomplishments, challenges, and opportunities. *Pattern Recognition Letters*, *79*, 80-105.

Jain, A. K., Ross, A., & Prabhakar, S. (2004). An introduction to biometric recognition. *IEEE Transactions on Circuits and Systems for Video Technology*, *14*(1), 4-20.

Kang, Y., Rabie, A. B., & Wong, R. W. (2014). A review of laser applications in orthodontics. *International Journal of Orthodontics*, *25*(1) 47-56.

Kono, M., Ueki, H., & Umemura, S-I. (2000). A new method for the identification of individuals by use of vein pattern matching of a finger. *The Proceedings of the IEEE 5th Symposium on Pattern Measurement*, Yamaguchi, Japan. (pp. 9-12).

Kubelka, P. (1948). New contributions to the optics of intensely light-scattering materials. Part i. *Journal of the Optical Society of America*, *38*(5), 448-457.

Kumar, A., & Prathyusha, K. V. (2009). Personal authentication using hand vein triangulation and knuckle shape. *IEEE Transactions on Image Processing*, *18*(9), 2127-2136.

Ladoux, P-O., Rosenberger, C., & Dorizzi, B. (2009). Palm vein verification system based on sift matching. *The Proceedings of the IEEE International Conference on Biometrics 2009*. (pp. 1290-1298).

Lebovic, N. (2015). Biometrics, or the power of the radical center. *Critical Inquiry*, *41*(4), 853-854.

LG, L. E. U. (2003). *Iris recognition, 2003*. LG Electronics.

Lin, C-L., & Fan, K-C. (2004). Biometric verification using thermal images of palm-dorsa vein patterns. *IEEE Transactions on Circuits and Systems for Video Technology*, *14*(2), 199-213.

MacGregor, P., & Welford, R. (1991). Veincheck: Imaging for security and personnel identification. *Advanced Imaging*, *6*(7), 52-56.

Malki, S., & Spaanenburg, L. (2007). Hand veins feature extraction using dt-cnns. *VLSI Circuits and Systems III*, *6590*, 65900N.

Maltoni, D., Maio, D., Jain, A. K., & Prabhakar, S. (2009). *Handbook of fingerprint recognition*. London, UK: Springer Science & Business Media.

Manohar, S. (2015). *Dynamic obstacle detection*. (Unpublished doctoral dissertation). National Institute of Technology, Rourkela, India.

Masupha, L., Zuva, T., Ngwira, S., & Esan, O. (2015, December). Face recognition techniques, their advantages, disadvantages and performance evaluation. *Proceedings of the IEEE International Conference on Computing, Communication and Security (ICCCS) 2015*. (pp. 1-5).

Matsuda, Y., Miura, N., Nagasaka, A., Kiyomizu, H., & Miyatake, T. (2016). Finger-vein authentication based on deformation-tolerant feature-point matching. *Machine Vision and Applications*, *27*(2), 237-250.

Momose, A., Takeda, T., & Itai, Y. (2000). Blood vessels: Depiction at phase-contrast x-ray imaging without contrast agents in the mouse and rat feasibility study. *Radiology*, *217*(2), 593-596.

Narayanasamy, G. (2009). *Advances in biomedical applications and assessment of ultrasound nonrigid image registration*. (Doctoral dissertation). University of Michigan, Ann Arbor, Michigan.

Nurhudatiana, A., & Kong, A. W-K. (2015). On criminal identification in color skin images using skin marks (rppvsm) and fusion with inferred vein patterns. *IEEE Transactions on Information Forensics and Security*, *10*(5), 916-931.

Parrish, J., & Anderson, R. (1981). The optics of human skin. *Journal of Investigative Surgery*, *7*, 33-37.

Podio, F. L., & Dunn, J. S. (2001). Biometric authentication technology: From the movies to your desktop. *Information Technology Laboratory Bulletin*, May, 1-8.

Santosh, K. C., Xue, Z., Antani, S. K., & Thoma, G. R. (2015). NLM at imageCLEF2015: Biomedical multipanel figure separation. In *CLEF (Working Notes)*. Toulouse, France: Conference and Labs of the Evaluation Forum, 2015.

Sahidullah, M. (2014). *Enhancement of speaker recognition performance using block level, relative and temporal information of subband energies*. (Unpublished doctoral dissertation). Indian Institute of Technology, Kharagpur, India.

Seigworth, G. R. (1980). Bloodletting over the centuries. *New York State Journal of Medicine*, *80*(13), 2022-2028.

Sharifzadeh, H. R., Zhang, H., & Kong, A. W-K. (2014). Vein pattern visualization through multiple mapping models and local parameter estimation for forensic investigation. *The Proceedings of the IEEE 22nd International Conference on Pattern Recognition (ICPR) 2014*. (pp. 160-165).

Shi, Z., & Govindaraju, V. (2009). Robust fingerprint matching using spiral partitioning scheme. In *International Conference on Biometrics*. (pp. 647-655). Berlin, Heidelberg: Springer.

Tang, C., Kong, A. W. K., & Craft, N. (2011). Uncovering vein patterns from color skin images for forensic analysis. *The Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2011*. (pp. 665-672).

Tang, C., Zhang, H., & Kong, A. W-K. (2016). Using multiple models to uncover blood vessel patterns in color images for forensic analysis. *Information Fusion*, *32*, 26-39.

Tsumura, N., Haneishi, H., & Miyake, Y. (1999). Independent-component analysis of skin color image. *Journal of the Optical Society of America*, *16*(9), 2169-2176.

Vacca, J. R. (2004). *Public key infrastructure: Building trusted applications and web services*. Boca Raton, FLA: Chemical Rubber Company Press.

Vacca, J. R. (2006). *Optical networking best practices handbook*. Hoboken, NJ: John Wiley & Sons.

Vacca, J. R. (2007). *Biometric technologies and verification systems*. Cambridge, MA: Elsevier.

Van Gemert, M., Jacques, S. L., Sterenborg, H., & Star, W. (1989). Skin optics. *IEEE Transactions on Biomedical Engineering*, *36*(12), 1146-1154.

Van Lanh, T., Chong, K. S., Emmanuel, S., & Kankanhalli, M. S. (2007). A survey on digital camera image forensic methods. *The Proceedings of the IEEE International Conference on Multimedia and Expo 2007*. (pp. 16-19).

Van Maanen, J. G. W. (2016). *Biometrics and intelligence: A match made in heaven?* Netherlands: Nederlandse Defensie Academie.

Varastehpour, S., Sharifzadeh, H., Ardekani, I., & Francis, X. (2019a). An adaptive method for vein recognition enhancement using deep learning. *The Proceedings of the IEEE 19th International Symposium on Signal Processing and Information Technology (ISSPIT) 2019*. (pp. 1-5).

Varastehpour, S., Sharifzadeh, H., Ardekani, I., & Francis, X. (2019b). Vein pattern visualisation and feature extraction using sparse auto-encoder for forensic purposes. *The Proceedings of the IEEE 16th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS) 2019*. (pp. 1-8).

Varastehpour, S., Sharifzadeh, H., Ardekani, I., & Sarrafzadeh, A. (2018). A review of biometric traits with insight into vein pattern recognition. *The Proceedings of the IEEE 16th Annual Conference on Privacy, Security and Trust (PST) 2018*. (pp. 1-2).

Wang, L., & Leedham, G. (2005). A thermal hand vein pattern verification system. In *International Conference on Pattern Recognition and Image Analysis*. (pp. 58-65). Berlin, Heidelberg: Springer.

Wang, L., & Leedham, G. (2006). Near- and far-infrared imaging for vein pattern biometrics. *The Proceedings of the IEEE International Conference on Video and Signal Based Surveillance 2006*. (p. 52).

Wang, Y., Li, K., Cui, J., Shark, L-K., & Varley, M. (2010). Study of hand-dorsa vein recognition. *The Proceedings of the IEEE International Conference on Intelligent Computing*. (pp. 490-498).

Watne, K. S. (2008). *Thermal imaging of ear biometrics for authentication purposes.* (Unpublished master's thesis). Gjøvik University College, Norway.

Wen, X-B., & Liang, X-Z. (2010). Research on enhancing human finger vein pattern characteristics based on adjacent node threshold image method. *The Proceedings of the IEEE Fifth International Conference on Frontier of Computer Science and Technology 2010*. (pp. 552-556).

Widmaier, E. P., Raff, H., & Strang, K. T. (2006). *Vander's human physiology* (Vol. 5). New York: McGraw-Hill.

Widmaier, E. P., Raff, H., Strang, K. T., & Vander, A. J. (2008). *Vander's human physiology: The mechanisms of body function*. Boston, MA: McGraw-Hill Higher Education.

Wilson, C. (2010). *Vein pattern recognition: A privacy-enhancing biometric*. Boca Raton, FLA: CRC Press.

World Health Organization. (2004). *The world health report: 2004: Changing history*. Geneva, Switzerland: Author.

Worster, B. W., Crane, D. E., Hansen, H. J., Fairley, C. R., & Lee, K. K. (1995, December 26). Laser imaging system for inspection and analysis of sub-micron particles. Google Patents. (US Patent 5,479,252).

Xueyan, L., & Shuxu, G. (2008). *The fourth biometric – vein recognition*. INTECH Open Access Publisher. doi: 10.5772/6257

Yoshitomi, Y., Miyawaki, N., Tomita, S., & Kimura, S. (1997). Facial expression recognition using thermal image processing and neural network. *Proceedings of the 6th IEEE International Workshop on Robot and Human Communication. RO-MAN '97 SENDAI*. (pp. 380-385).

Yu, C., & Qing, H. (2009). *Biometric identification technology: Finger vein identification technology*. Beijing, China: Tsinghua University Press.

Zhou, B., Lin, X., Jia, H., & Song, R. (2007). Recognition of palm-dorsa vein patterns using multiple feature fusion. *Journal of Tsinghua University*, *47*(2), 194.

Zhao, S., Wang, Y-D., & Wang, Y-H. (2008). *Biometric identification based on low-quality hand vein pattern images. 2008 International Conference on Machine Learning and Cybernetics*, *2*, 1172-1177.

Zhang, Y., Han, X., & Ma, S-l. (2006). Feature extraction of hand-vein patterns based on ridgelet transform and local interconnection structure neural network. *The Proceedings of the IEEE Intelligent Computing in Signal Processing and Pattern Recognition*. (pp. 870-875).

Zhang, H., & Hu, D. (2010). A palm vein recognition system. *2010 International Conference on Intelligent Computation Technology and Automation*, *1*, 285-288.

Zhang, R., Huang, D., Wang, Y., & Wang, Y. (2015). Improving feature-based dorsal hand vein recognition through random keypoint generation and fine-grained matching. *The Proceedings of the IEEE International Conference on Biometrics (ICB)*. (pp. 326-333).

Zhang, H., Tang, C., Li, X., & Kong, A. W. K. (2014). A study of similarity between genetically identical body vein patterns. *2014 IEEE Symposium on Computational Intelligence in Biometrics and Identity Management (CIBIM)*. (pp. 151-159).

Zhang, H., Tang, C., Kong, A. W-K., & Craft, N. (2012). Matching vein patterns from color images for forensic investigation. *The Proceedings of the IEEE Fifth International Conference on Biometrics: Theory, Applications and Systems (BTAS)*. (pp. 77-84).

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