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1 Introduction

A wide variety of systems and situations require reliable personal recognition schemes to either confirm or determine the identity of an individual. The purpose of such schemes is to ensure that the systems are accessed only by a legitimate user and no one else. Secure access to buildings, computer systems, laptops, cellular phones, and ATMs are some of the examples of such applications. Biometric recognition or, simply, biometrics refers to the automatic recognition of individuals based on their physiological and/or behavioral characteristics. By using biometrics, it is possible to confirm or establish an individual's identity. Unlike conventional recognition techniques such as passwords or ID cards, which are based on 'what we know' or 'what we have', biometric recognition is based on 'who we are'. Anatomical features such as face, fingerprint or iris, or behavioral traits such as signature or gait can define "who we are". Unlike passwords or ID cards, it is extremely difficult to guess, share, misplace, copy or forge biometric identifiers. This makes biometric technologies much more difficult to abuse than traditional methods of identification.

Traditional methods of identification used in forensics, for example, analysis of DNA, hair and fiber samples, are not fully automated either and take a long time (hours to days) to make the identification. This may be acceptable for criminal investigations, but not for many commercial applications. On the other hand, the recent advent of compact and cheap sensors and systems allow fully automatic and 'real-time' identification (typically within a second). Even traditional methods of capturing finger prints have been updated with electronic sensors based on optical, solid-state, thermal, ultrasound and multispectral technologies. Many of these sensors are extremely compact and cheap, enabling them to be embedded in consumer electronic products such as mobile phones, personal digital assistants and laptops.

Although biometrics emerged from its extensive use in law enforcement to identify criminals (e.g., illegal aliens, security clearance for employees for sensitive jobs, fatherhood determination, forensics, and positive identification of convicts and prisoners), it is being increasingly used today to establish person recognition in a large number of civilian applications. There are increase in demands of biometrics because of growing concerns about security threats and fraud.

Biometrics can be used in positive and negative recognitions. Positive recognitions aim to prevent multiple people from using the same identity (Wayman, 2001). An example of positive recognition is, say we want to log in to our laptop with a built-in fingerprint reader. Instead of entering our password, we place our finger on the sensor. If the features extracted from our fingerprint match the fingerprint template associated with our ID in the laptop's enrolment database, access is granted. Positive recognition is easy. Negative recognition is more challenging. The purpose of negative recognition is to prevent a single person from using multiple identities (Wayman, 2001). An example of negative recognition is, say you want a new driver's license. Typically, you have to produce one or more forms of paper identification such as a birth certificate or a passport. But these can be relatively easily forged. How does the licensing authority know that you do not already have a license under a different name? A biometric database allows the license issuer to find this out by matching a biometric trait (your face, for example) with that of all the individuals in the database who have already been issued with a license. There are many such examples in which 'multiple enrolments' by the same person need to be detected — issuing passports and disbursing welfare payments, for example. We use the generic term "recognition" for both positive and negative recognitions.

2 Biometric Systems

A biometric system is essentially a pattern recognition system that operates by acquiring biometric data from an individual, extracting a feature set from the acquired data, and comparing this feature set against the template set in the database.

A typical biometric recognition system has four modules. First, there is the sensor, to capture or read the biometric trait — a fingerprint, iris, signature, voice trait or similar. Then there's the feature extractor, to extract some salient characteristics of the trait for recognition; the enrolment database, where the biometric features (also called templates) of all the enrolled users of the system are stored; and the matcher, which compares an input biometric sample with the templates in the database.

Depending on the application, a biometric system may operate either in verification mode or identification mode (Figure 1).

- In the ***verification mode***, the system validates a person's identity by comparing the captured biometric data with her own biometric template(s) stored in the system database. The system conducts a one-to-one comparison to determine whether the claim is true or not. Identity verification is typically used for positive recognition.
- In the ***identification mode***, the system recognizes an individual by searching the templates of all the users in the database for a match. Therefore, the system conducts a one-to-many comparison to establish an individual's identity (or fails if the subject is not enrolled in the system database) without the subject having to claim an identity (e.g., "Whose biometric data is this?"). Identification is a critical component in negative recognition; however, it can also be used in positive recognition.

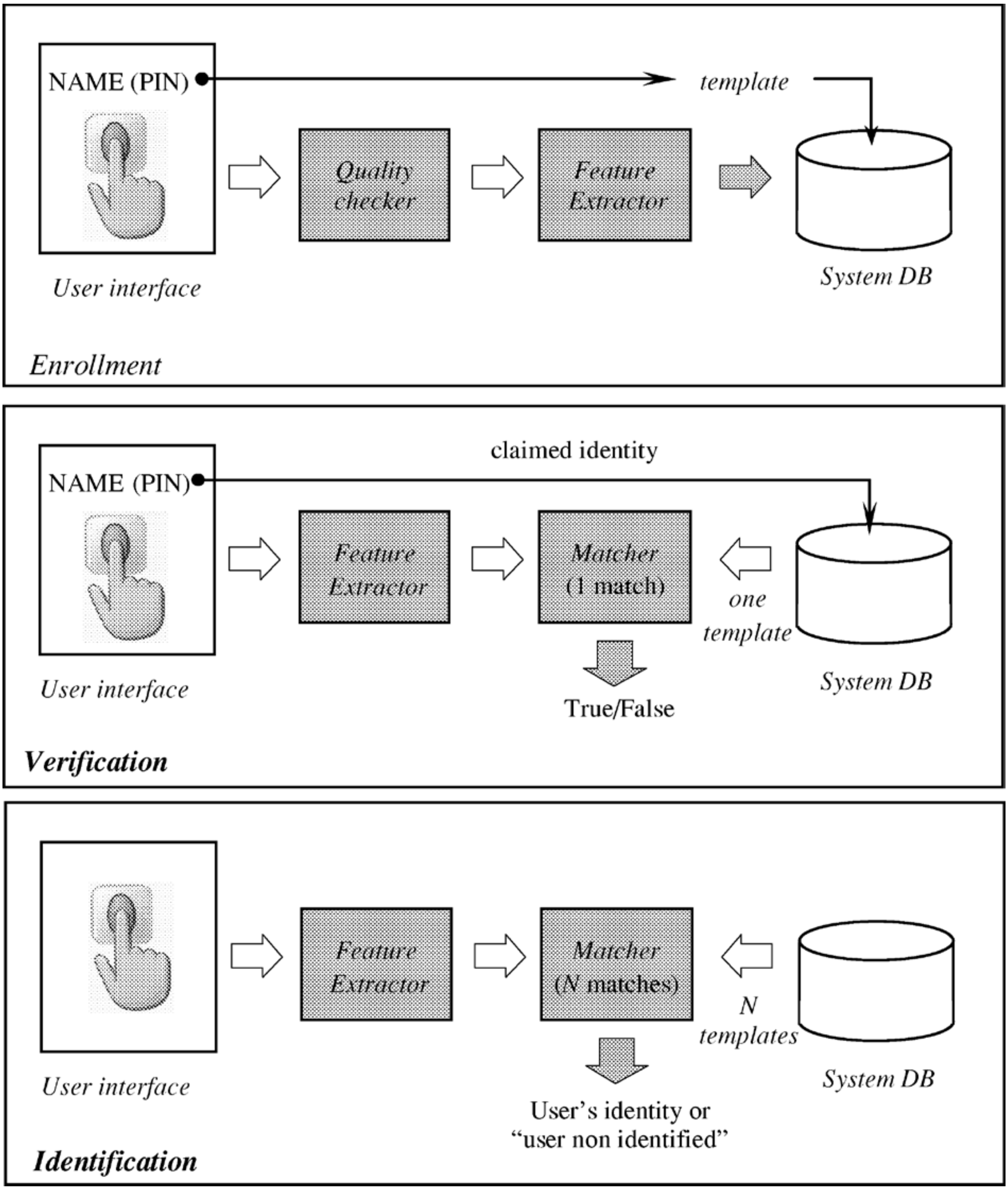

Figure 1 Block diagrams of enrollment, verification, and identification tasks are shown using the four main modules of a biometric system, i.e., sensor, feature (Jain et al., 2004)

3 Types of Biometrics

Various different biological measurements lead to different types of biometrics technologies. Theoretically, any human physiological and/or behavioral characteristic can be used as a biometric characteristic as long as it satisfies the following requirements (Jain et al., 2004):

1. ***Universality***: each person should have the characteristic.

2. ***Distinctiveness***: any two persons should be sufficiently different in terms of the characteristic.
3. ***Permanence***: the characteristic should be sufficiently invariant (with respect to the matching criterion) over a period of time.
4. ***Collectability***: the characteristic can be measured quantitatively.

However, for a biometric system to be practical, there are a number of other issues that should be considered, including:

1. ***Performance***: It refers to the achievable recognition accuracy and speed, the resources required to achieve the desired recognition accuracy and speed, as well as the operational and environmental factors that affect the accuracy and speed;
2. ***Acceptability***: It indicates the extent to which people are willing to accept (from privacy, cultural and religious point of views) the use of a particular biometric identifier (characteristic) in their daily lives;
3. ***Circumvention***: This reflects how easily the system can be fooled using fraudulent methods or be hacked.

No single biometrics is expected to effectively satisfy the needs of all recognition applications. A number of biometrics has been proposed. Each biometrics has its strengths and limitations; and accordingly, each biometrics appeals to a particular recognition application. Some of the biometric technologies that are in use are: voice, thermograms, face, fingerprints, palmprints, hand geometry, gait, iris and vein. We describe these biometrics technologies in the Section 3.1.

3.1 State of the art Biometric Technologies

- ***Voice***: Voice is a characteristic of an individual (Furui, 1997) and hence it is used in some applications in person identification. Features (e.g. cepstral) are extracted from voice signal either in time-domain or frequency domain and they are used in matching. The matching strategy may typically employ approaches based on hidden Markov model, vector quantization, or dynamic time warping. Voice recognition may be text (fixed predetermined phrases) and/or language dependent or independent. Voice capture is unobtrusive and voice print is an acceptable biometric in almost all societies. Voice is only the biometric for identification of a person over telephone.

  The drawback of voice recognition biometrics is that, it is not expected to be sufficiently unique to permit identification of an individual from a large database of identities. Voice may be affected by a person's health (e.g., cold), stress, emotions etc. a voice signal available for authentication is typically degraded in quality by the microphone, communication channel, and digitizer characteristics. Besides, some people seem to be extraordinarily skilled in mimicking others.

- ***Infrared Facial Thermograms***: Human body radiates heat and the pattern of heat radiation is a characteristic of each individual body (Prokoski et al., 1992). An image indicating the heat emanating from different parts of the body can be acquired with an infrared sensor and these images are called thermograms (Figure 2). Infrared facial thermograms can be acquired without any physical contact and as they are non-invasive, they are considered as acceptable biometrics.

Figure 2 Facial thermogram

- ***Infrared Vein Thermograms***: They are similar to facial thermograms, where the images are taken for vein structures of the palm or the back of the hand as shown in Figure 3 and Figure 4. And the structure of the vein is used for the identification as the vein structure is unique to every individual, even among identical twins. Near-infrared (NIR) is, in general, used in this case.

Figure 3 Vein structure of the hand

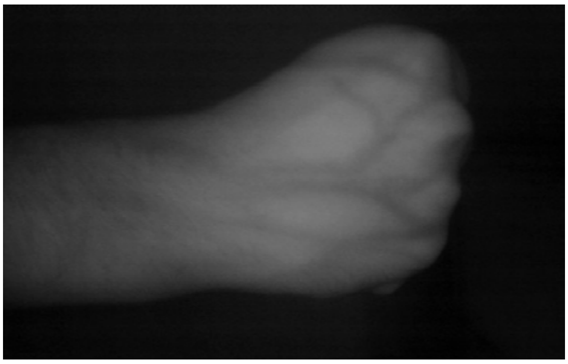

Figure 4 Vein structure of back of the hand

- ***Fingerprints***: Fingerprints are graphical flow-like ridges present on human fingers. A fingerprint is made of a number of ridges and valleys on the surface of the finger. Ridges are the upper skin layer segments of the finger and valleys are the lower segments. The ridges form so-called minutia points: ridge endings (where a ridge end) and ridge bifurcations (where a ridge splits in two). Fingerprints are usually considered to be unique, with no two fingers having the exact same dermal ridge characteristics. The uniqueness of a fingerprint can be determined by the pattern of ridges and furrows as well as the minutiae points. Fingerprints are one of the most mature biometric technologies used in forensic divisions worldwide for criminal investigations. Typically, a fingerprint image is captured in one of two ways: (i) scanning an inked impression of a finger, or (ii) using a live-scan fingerprint scanner (Figure 5).

Figure 5 Fingerprint image

- ***Palmprints***: Palm print is similar to fingerprint but based on the image of the whole palm area of the hand (Figure 6). The palm itself consists of principal lines, wrinkles (secondary lines) and ridges. Palm identification, just like fingerprint identification, is based on the aggregate of information presented in a friction ridge impression. It differs to a fingerprint in that it also contains other information such as texture, indents and marks which can be used when comparing one palm to another. A comprehensive introduction to palmprint technologies has been provided in the book by Zhang, 2004.

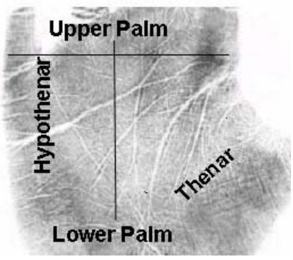

Figure 6 Palmprint image

- ***Hand and Finger geometry:*** Hand geometry is a biometric that identifies users by the shape of their hands (Figure 7). Hand geometry readers measure a user's hand along many dimensions and compare those measurements to measurements stored in a file.

  

  Figure 7 Hand geometry

  Viable hand geometry devices have been manufactured since the early 1980s, making hand geometry the first biometric to find widespread computerized use. It remains popular; common applications include access control and time-and-attendance operations.

  Since hand geometry is not thought to be as unique, it is not suitable for so-called one-to-many applications, in which a user is identified from his biometric without any other identification. However, hand geometry is very reliable when combined with other forms of identification, such as identification cards or personal identification numbers.

  Finger geometry is a variant of hand geometry and is a relatively new technology which relies only on geometrical invariants of fingers (index and middle) (Biomet, 1997).

- ***Face***: Facial biometrics is one of the fastest growing areas of biometrics. The method of acquiring face images is non-intrusive There are primarily two approaches to the identification based on face recognition:

  (i) **Transform approach**: In this approach, the universe of face image domain is represented using a set of orthonormal basis vectors. Currently, the most popular basis vectors are eigenfaces (Turk and Pentland, 1991): each eigenface (Figure 8) is derived from the covariance analysis of the face image population. Two faces are considered to be identical, if they are sufficiently "close" in the eigenface feature space. A number of variants of such an approach exist, e.g. fisherfaces (Jing et al., 2006), laplacianfaces (He et al., 2005).

  

  Figure 8 Illustration of Eigenface

  (ii) **Attribute-based approach**: This approach reads the peaks and valleys of an individual's facial features; these peaks and valleys are known as nodal points (Figure 9). There are 80 nodal points in a human face, but the software needs only 15-20 to make identification. These features extracted from the face image and the invariance of geometric properties among the face landmark features is used for recognizing features (Atick et al., 1996). More concentration is given on the golden triangle region between the temples and the lips. This area of the face remains the same even if hair and a beard is grown, weight is gained, aging occurs, or glasses are put on.

  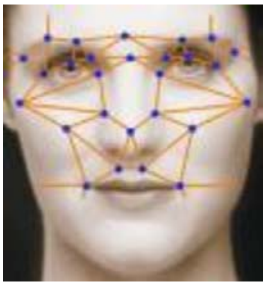

  Figure 9 Attribute based face recognition

  It is very challenging to develop face recognition techniques which can tolerate the effects of aging, facial expressions, slight variations in the imaging environment and variations in the pose of face with respect to camera (2D and 3D rotations) (Phillips et al., 1998).

- ***Ear***: Ear-shape analysis could also be for automatically identifying people. The ear recognition approaches are based on matching vectors of distances of salient points on the pinna from a landmark location (Figure 10) on the ear (Burge and Burger, 2000).

  Ear recognition can be easily captured from a distance without a fully cooperative subject, although sometimes it may be hidden with hair, scarf and jewelry. Also, unlike a face, the ear is a relatively stable structure that does not change much with the age and facial expressions.

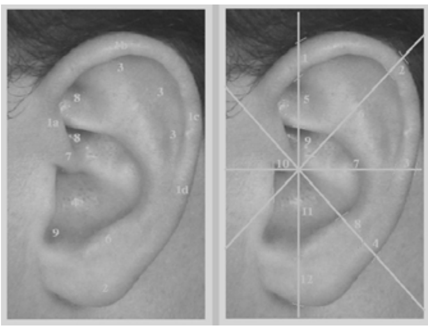

Figure 10 Ear features used for identification (Burge and Burger, 2000)

- ***Gait***: Gait is the peculiar way one walks and is a complex spatio-temporal behavioral biometrics. Gait biometrics identifies a person by the way the walk, run, or any other type of motion of the legs (Figure 11). A person's gait is the way in which they move on their feet. There are two ways of doing gait analysis: from video-sequence images (Lee and Grimson, 2002) and from the measurement of gait with accelerometer (Gafurov et al., 2006).

  Gait biometrics would be particularly beneficial in identifying criminal suspects. Police could scan a large crowd for a suspect without them knowing they were on to them.

  Gait is not supposed to be unique to each individual, but is sufficiently characteristic to allow identity authentication. Gait is a behavioral biometric and may not stay invariant especially over a large period of time, due to large fluctuations of body weight, major shift in the body weight (e.g., waddling gait during pregnancy, major injuries involving joints or brain (e.g., cerebellar lesions in Parkinson disease), or due to inebriety (e.g., drunken gait) (Julian et al., 1995). Besides, a gait system can easily be deceived because walking patterns can sometimes be altered.

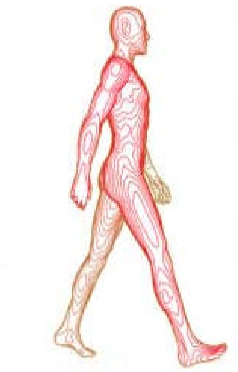

Figure 11 Gait recognition

- ***Keystroke Dynamics***: This is a behavioral biometric based on the assumption that the manner and rhythm in which an individual types characters on a keyboard or keypad are distinctive. The keystroke rhythms of a user are measured to develop a unique biometric template of the users typing pattern for future authentication. Raw measurements available from most every keyboard can be recorded to determine Dwell time (the time a key pressed) and Flight time (the time between "key down" and the next "key down" and the time between "key up" and the next "key up"). The recorded keystroke timing data is then processed through a unique neural algorithm, which determines a primary pattern for future comparison.

Figure 12 Keystroke dynamics

- ***Iris recognition***: Iris recognition is based on the analysis of unique and stable texture patterns that are visible within the iris (the colored portion) of the human eye (Figure 13). Camera technology is used to record an image of the eye, and the iris region is localized after digitally removing the pupil, eyelids and eyelashes. Iris recognition uses subtle IR illumination to reduce specular reflection from the convex cornea to create images of the detail-rich, intricate structures of the iris. These unique structures converted into digital templates, provide mathematical representations of the iris that yield unambiguous positive identification of an individual. The phase information of the digitally filtered iris image (which represents the unique wavy pattern of each iris), is computed and stored as a string of bits. Recognition is performed by comparing two such bit sequences.

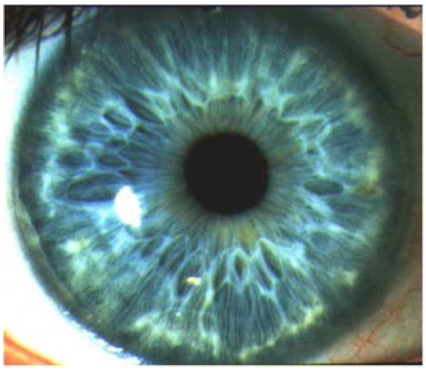

Figure 13 Image of an Iris

  Iris recognition is not much affected by glasses or contact. Iris technology has the smallest outlier (those who cannot use/enroll) group of all biometric technologies. A key advantage of iris recognition is its stability, or template longevity as, barring trauma, a single enrollment can last a lifetime.

- ***Vein recognition***: The pattern of blood veins is unique to every individual, even among identical twins. Palms have a broad and complicated vascular pattern and thus contain a wealth of differentiating features for personal identification. Furthermore, it will not vary during the person's lifetime. It is a very secure method of authentication because this blood vein pattern lies under the skin. This makes it almost impossible for others to read or copy.

  An individual's vein pattern image is captured by radiating his/her hand with near-infrared rays (Figure 14). The reflection method illuminates the palm using an infrared ray and captures the light given off by the region after diffusion through the palm. The deoxidized hemoglobin in the in the vein vessels absorbs the infrared ray, thereby reducing the reflection rate and causing the veins to appear as a black pattern. This vein pattern is then verified against a preregistered pattern to authenticate the individual.

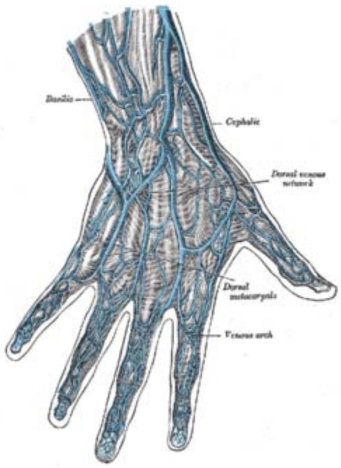

Figure 14 Palm vein structure

  As veins are internal in the body and have a wealth of differentiating features, attempts to forge an identity are extremely difficult, thereby enabling a high level of security. In addition, the sensor of the palm vein device can only recognize the pattern if the deoxidized hemoglobin is actively flowing within the individual's veins. Yuhang et al., 2005 presented a hand vein recognition method. Hao Luo, 2010 studied different techniques of vein recognition in his survey.

This system is not dangerous; a near infrared is a component of sunlight: there is no more exposure when scanning the hand than by walking outside in the sun.

A commercial vein recognition system from Hitachi, Vein ID (Figure 15) scanner uses sub-dermal vein patterns – themselves unique and normally invisible - to identify users. Vein ID works by projecting high-intensity light through the finger, which creates a high-contrast image of the vein structure. That is then compared to records to ascertain identity. Since it relies on what's going on under the surface, cuts, scrapes or sores will not get in the way, and even dirt or sweat present no problem.

Figure 15 Hitachi VeinID technology

Besides these, there are some other biometrics technologies that are in use and/or under investigation including human signature identification, sear canal recognition, odor identification, retinal scan, and DNA identification.

4 Use of Multispectral Imaging

Conventional biometrics technologies use either one channel gray level or 3 channel color images. These biometrics may be subject to breaching. An example is employing a spoof biometric trait (an artificial or dead finger, or a face mask, for example). This is a serious concern. Multispectral imaging can help detect breaching of a biometric system. New fingerprint sensors can detect whether the finger placed at the sensor is living or not by using, for example, a multispectral imaging technique to measure how much light the finger absorbs, or by measuring the finger's electrical conduction properties using electric-field sensors.

Multispectral imaging captures image data at specific wavelengths across the electromagnetic spectrum. This is unlike conventional imaging which captures three channel values: red, green and blue. A gray scale image is a one channel image and an RGB image is a three channel image (Figure 16). A multispectral image is a multi-channel (more than three) images which can be seen as a stack of images, each representing the intensity image at a given wavelength (Figure 17). Number of channels in multispectral image, is in general, between 4 and 20.

Figure 16 RGB layers of an image

Multispectral image can avoid the metamerism problem of RGB image, at the same time provides more information than just color, and improves the accuracy of the color (Pratt and Mancill, 1976; Hill and Vorhagen, 1994; Burns and Berns, 1996; Tominaga, 1996; Yamaguchi et al., 1997). It is not limited to visual range, rather can also be used in near infrared, infrared and ultraviolet spectrum as well (Horman, 1976; Ellrod et al., 2003; Huang, 2004; Ononye et al., 2007). These features help construct more effective biometric systems with the use of multispectral imaging. Some of the biometric systems that use multispectral imaging has been studied here below.

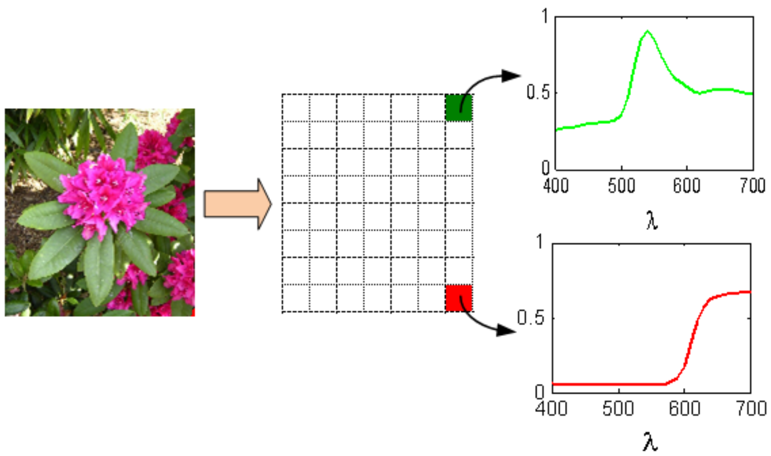

Figure 17 Illustration of pixels in a multispectral image

4.1 Face Recognition

Multispectral imaging in the visible and near infrared spectra helps reduce color variations in the face due to changes in illumination source types and directions. **Buddharaju and Pavlidis, 2007** presented a novel multi-spectral approach for face recognition using visual imagery as well as the physiological information extracted from thermal facial imagery. Figure 18 illustrates the proposed multispectral face recognition methodology. For each subject in the database, facial images collected simultaneously in the visual and thermal bands.

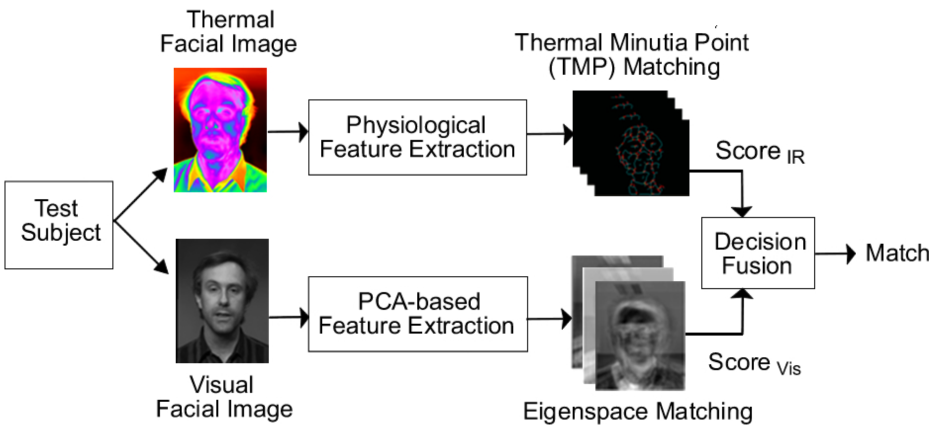

Figure 18 Multispectral face recognition methodology (Buddharaju and Pavlidis, 2007)

For each of the thermal images, the human face is delineated from the background using the Bayesian framework. The blood vessels present on the segmented facial tissue are extracted using image morphology. The extracted vascular network produces contour shapes that are unique to each individual. The branching points of the skeletonized vascular network, referred to as thermal minutia points (TMPs), are an effective feature abstraction. During the classification stage, the local and global structures of TMPs extracted from the test image are matched with those of the corresponding images in the database. The recognition results from their thermal imaging algorithm are fused with those of a popular visual imaging algorithm. From the experimental results on a large database of co-registered visual and thermal facial images, they claimed that the proposed fusion approach has merit and promise.

Hong et al., 2008 introduced the use of multispectral imaging and thermal infrared imaging as alternative means to conventional broadband monochrome or color imaging sensors in order to enhance the performance of face recognition in uncontrolled illumination conditions. They showed that multispectral imaging in the visible and near IR spectra improves performance of face recognition in various types of illumination. A subset of spectral band images are fused using the weight values determined based on the filter transmittance, spectral response of imaging sensor, illumination distribution, and skin reflectance. Thermal IR imaging can be used to identify faces when there is little or no control over lighting conditions. The light in the thermal IR range is emitted rather than reflected from the object. Thermal emission from skin is independent of illumination. Therefore the face images captured using thermal IR sensors would be nearly invariant to changes in ambient illumination. The within-class variability is also significantly lower than that observed in visible imagery.

Bendada and Akhloufi, 2010 introduced the use of local binary pattern (LBP) like texture descriptors for efficient multispectral face recognition. They also introduced a simple differential local tertiary pattern (LTP). The claimed that the proposed texture space is less sensitive to noise, illumination change and facial expressions which make it a good candidate for efficient multispectral face recognition. Linear and non linear dimensionality reduction techniques were introduced and used for performance evaluation of multispectral face recognition in the texture space. Their results showed that the use of the proposed texture descriptors permit to achieve high recognition rates in multispectral face recognition.

4.2 Fingerprint and Hand Recognition

Rowe et al., 2008 proposed multispectral fingerprint image acquisition. An optical fingerprint sensor based on multispectral imaging had been developed that is able to work across the range of common operational conditions while also providing strong spoof detection. The sensor is configured to image both the surface and subsurface characteristics of the finger under a variety of optical conditions, the combination ensures that usable biometric data can be taken across a wide range of environmental and physiological conditions like bright ambient lighting, wetness, poor contact between the finger and sensor, dry skin. Multiple raw multispectral images are fused into a single high-quality composite fingerprint image which is used to match other multispectral fingerprint images as well as images collected using other methods. The raw multispectral images are captured using different wavelengths of LED illumination light, different polarization conditions, and different illumination orientations. Figure 19 illustrates the proposed multispectral sensor schematic. The different wavelengths penetrate the skin to different depths and are absorbed and scattered differently by various chemical components and structures in the skin. The different

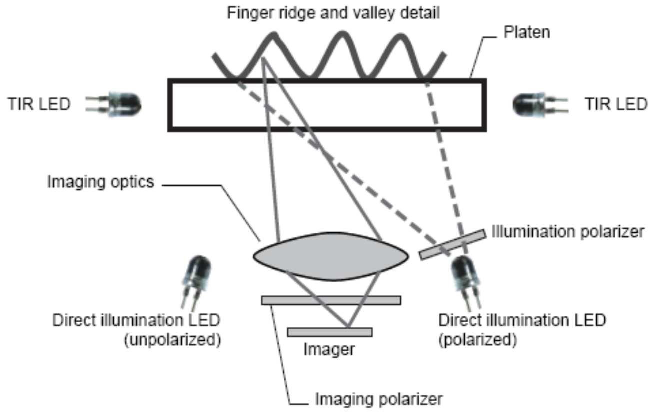

Figure 19 Multispectral sensor schematic (Rowe et al., 2008)

polarization conditions change the degree of contribution of surface and subsurface features to the raw image. Finally, different illumination orientations change the location and degree to which surface features are accentuated.

The raw images are then combined together to produce a single representation of the fingerprint pattern. This fingerprint generation relies on a wavelet-based method of image fusion to extract, combine, and enhance those features that are characteristic of a fingerprint. Figure 20 shows an example a conventional TIR (total internal reflection) image and the compositing image obtained from raw multispectral images. Fine structure such as incipient fingerprint ridges can be seen throughout the image.

Figure 20 Example of TIR and composite multispectral image

Test showed that multispectral fingerprint has multifold advantage over conventional imaging methods: more anatomical features, robust to a broad range of conditions and spoof proof.

Rowe et al., 2007 proposed a multispectral whole-hand biometric authentication system based on the similar technology as the multispectral finger print as discussed above, extending the system to the whole hand. The resulting multispectral data is rich in biometric information providing multiple characteristics of the hand, including: all four fingerprints as well as a partial thumb print, major characteristics of the palm, including principal lines and wrinkles, palm ridges and minutiae, hand shape and skin texture. Each time a hand is placed on the sensor platen (Figure 21), a series of six raw multispectral images (MSI) are collected: four images from the four unpolarized direct LEDs in four different orientations, one image collected with the cross-polarized white-light illumination, and one image collected with the TIR illumination. A single composite image is generated from the raw multispectral images based on a modification of the wavelet fusion technique presented in Jain et al., 1999; Wayman, 2001.

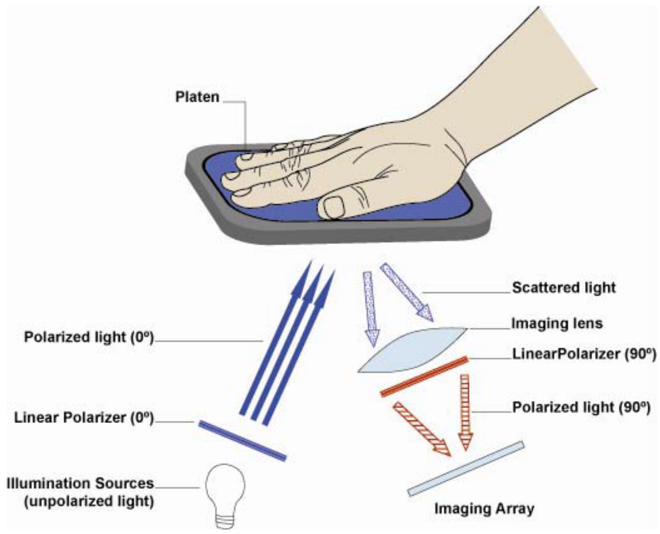

Figure 21 Optical components and layout of the multispectral whole hand imaging system

4.3 Iris Recognition

Boyce et al., 2006 explores the possibility of using multispectral information to enhance the recognition performance of an iris biometric system. Most commercial systems use only the near-IR wavelengths for iris analysis. This paper highlighted the potential of using multispectral (Visible+IR) iris information in recognition systems. They employed Redlake's MS3100 multispectral camera and presents the novel possibility of utilizing user-specific wavelengths for iris image acquisition. The possibility of matching iris images across multiple wavelengths was next studied. It has been found that the cross matching performance decreases as a function of the differences in wavelength of the participating images. The sum rule was used to fuse the match scores generated for each spectral channel. The use of multispectral information enhanced the segmentation and enhancement procedures thereby improving the performance of iris recognition systems.

Park and Kang, 2007 proposed multispectral iris authentication system against counterfeit attack using gradient-based image fusion. Multispectral infrared iris images are taken in order to utilize the spectral features of real iris. The multispectral images are fused into a grayscale image to contain the complementary information among them by a gradient-based image fusion algorithm, and the iris region of the fused image is applied directly to the recognition procedure. Through the fusion process, the images which do not show multispectral variations result in a scrambled image that does not contain the exact features of the original iris. Because of the failure in the fusion process, the fused image of a fake iris does not match the original iris features in the database. Thus, they are simply rejected in the recognition step. Experimental results showed that the proposed scheme successfully localizes the iris position of real irises and prevents possible counterfeit attacks while maintaining the performance of the authentication system.

Ross et al., 2009 suggested (a) the feasibility of acquiring iris images in wavelengths beyond 900nm using InGaAs detectors; (b) the possibility of observing different structures in the iris anatomy at various wavelengths; and (c) the potential of performing cross-spectral matching and multispectral fusion for enhanced iris recognition.

Burge and Monaco, 2009 proposed multispectral iris fusion for enhancement, interoperability, and cross wavelength matching. They introduced a novel iris code, Multispectral Enhanced irisCode (MEC), which uses pixel-level fusion algorithms to exploit texture variations elicited by illuminating the iris at different frequencies, to improve iris matcher performance and reduce Failure-To-Enroll (FTE) rates. They also presented a model for approximating an NIR iris image using features derived from the color and structure of a visible light iris image.

Ngo et al., 2009 proposed a design and implementation of a multispectral iris capture system. They used a single camera with spectral response from 400 nm to 1000 nm, multiple narrow band LED illuminators of wavelengths 405 nm, 505 nm, 590 nm, 700 nm, 810 nm, 910 nm, 970 nm,

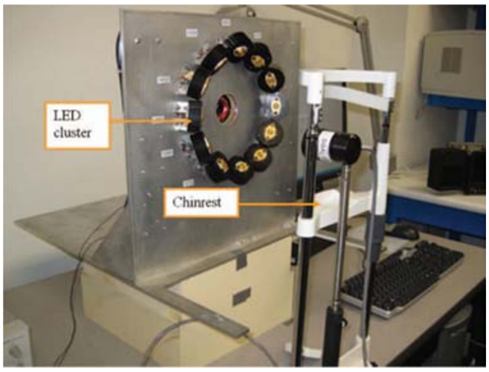

Figure 22 Multispectral iris capture system (Ngo et al., 2009)

1070 nm, 1200 nm, 1300 nm, 1450 nm, 1550 nm mounted circularly around the camera axis as shown in Figure 22. Figure 23 illustrates spectral iris images with different wavelengths. They manually segmented the images and used Daugman algorithm and Hamming distance to calculate similarity between segmented images.

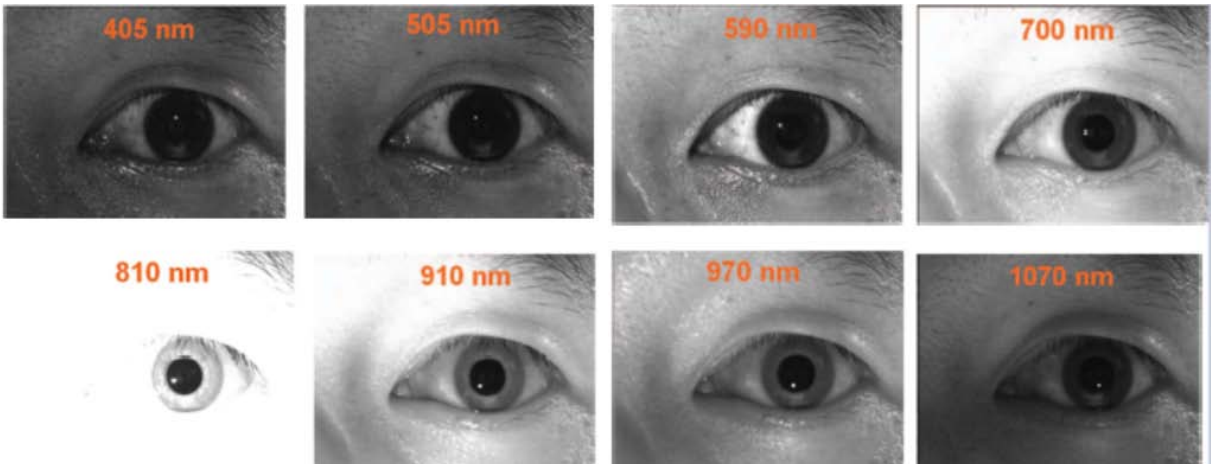

Figure 23 Illustration of multispectral iris images captured with different wavelengths (Ngo et al., 2009)

The system is somewhat slow to be practical. Use of multiple-camera multiple-filter might speeds up the system. Hardware limits the performance of the system. (e.g. camera with 400 – 1000 nm spectral response. There is a need for automated iris segmentation algorithm that works across multispectral eye images.

4.4 Vein Recognition

As discussed above, vein recognition is a fairly recent technological advance in the field of biometrics. Effectiveness of vein recognition could also be improved with the use of multispectral imaging. Instead of using a single infrared band, a number of bands could be used and either a composite image could be generated or separate bands could be used in matching.

Paquit et al., 2009 proposed a 3D and multispectral imaging for subcutaneous veins detection. Images of each subject's arm are captured under every possible combination of illuminants, and the optimal combination of wavelengths for a given subject to maximize vein contrast using linear discriminant analysis (LDA) is determined. A structured lighting system is also coupled to our multispectral system in order to provide 3D information of the patient arm orientation. They presented that the LDA projection of the multispectral images in the NIR and visible spectrum associated with 3D information of the arm topography lead to reliable results for automatic veins detection. Figure 24 shows the comparative results of the vascular centerline detection with different approaches.

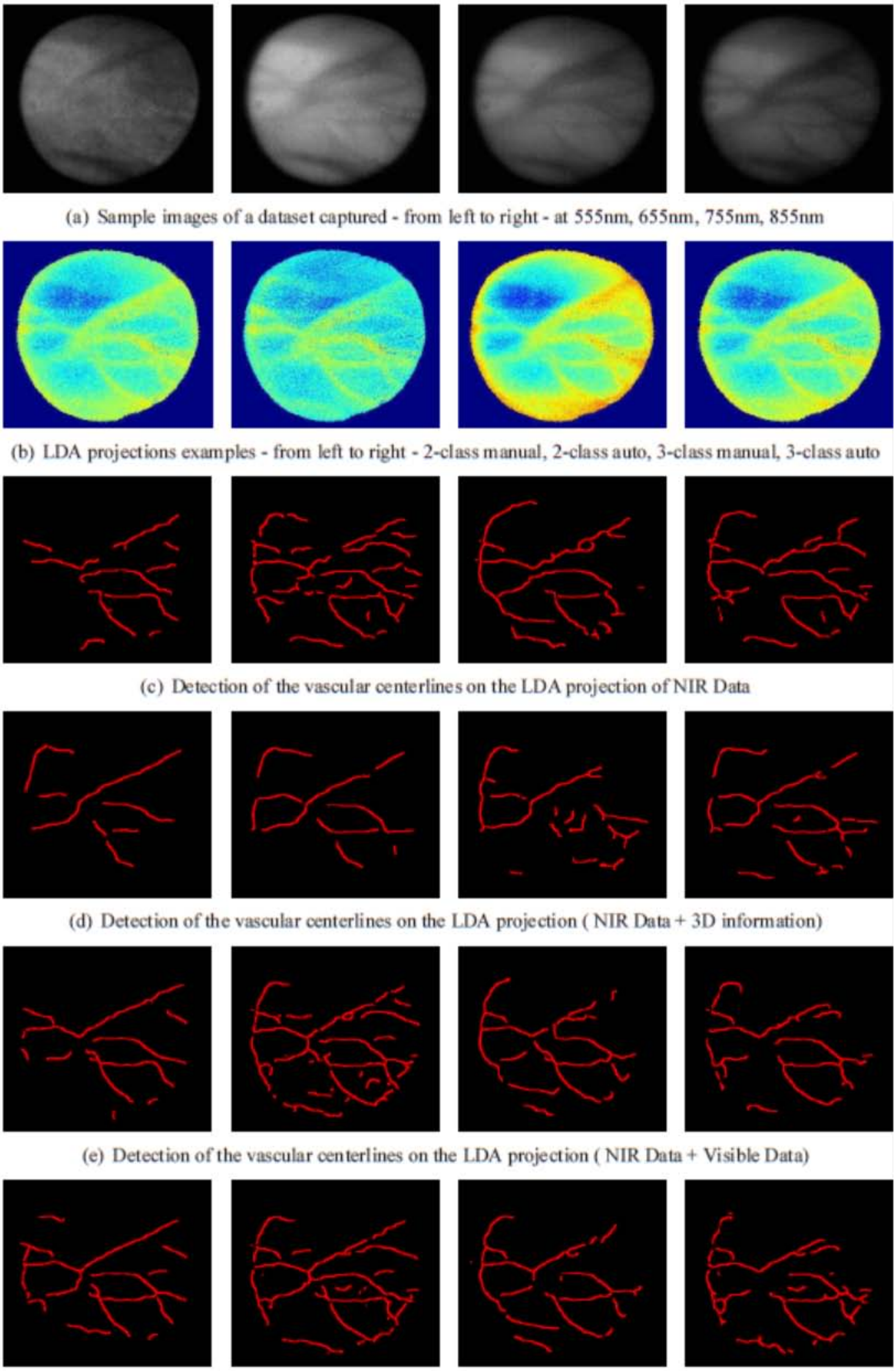

Figure 24 Comparison of the vascular centerline detection using Steger's algorithm for different input features and class masks: (first column) two class problem - vein/not vein - where the mask is manually defined; (second column) two class problem with mask automatically generated from the PCA image; (third column) three class problem - vein/skin/other -with mask manually defined; and (fourth column) three class problem with mask automatically generated from the PCA image ([Paquit et al., 2009](#))

5 Multimodal biometrics

One type of (unimodal) biometrics may not always be sufficient for biometrics authentication. In order to improve the effectiveness, two or more biometrics are combined to form so called, multimodal biometrics. Multimodal biometric technology uses more than one biometric identifier to compare the identity of the person. Therefore in the case of a system using say three technologies i.e. face mimic and voice. If one of the technologies is unable to identify, the system can still use the other two to accurately identify against. Figure 24 illustrates a general schematic of a multimodal biometric system.

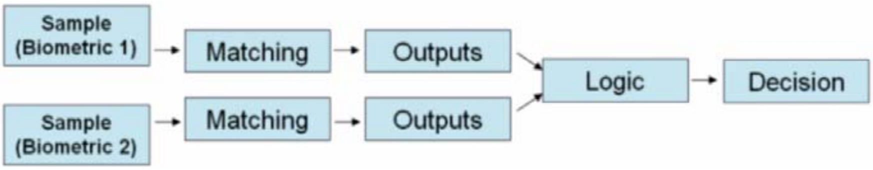

Figure 25 General multimodal system schematic

Some of the benefits of using multimodal biometrics, and for very secure environments the biometrics could include *fingerprint, iris* and *voice*, to allow you to safely reset passwords, process payments, and access control to a secure area. Two typical multimodal biometrics implementations are: face, finger iris and voice modalities are used to identify Afghan detainees with Biometric Automated Toolset; Narita airport uses iris and face based multimodal biometric system.

Shahin et al., 2008 proposed a multimodal hand vein, hand geometry, and fingerprint prototype design for high security biometrics. They presented the design based on whole hands biometrics prototype system that acquires left and right (L/R) index and ring fingerprints (FP), L/R near-infra-red (NIR) dorsal hand vein (HV) patterns, and L/R NIR dorsal hand geometry (HG) shape. They claimed that the proposed system is very hard to spoof attacks on the sensory level and the NIR HV and NIR HG thermal images are good signals for liveness detection.

Runbin and Dewen, 2010 proposed a multimodal biometrics based on multispectral palm and vein recognition. They presented two methods for fusion of the images from multi-sensor imaging system with the objective of establishing some preprocessing algorithms in palm authentication system. The methods derive from opponent-processing and dual-tree complex wavelet transform (DTCWT). Experiments on different fused images showed that their methods are fast enough to be applied in real-time system.

6 Conclusion

Multispectral imaging has been used in many biometrics modalities including fingerprint, whole hand, iris and vein recognition. It not only increases the effectiveness of the biometrics recognition but facilitates detection of breaching and spoofing. There are already many commercial biometrics systems based on multispectral imaging available in the industry. However, one type of biometrics is still not 100% strong enough for full proof biometrics system. Multimodal biometrics have been proposed and also in use for more effectiveness. There is still much scope of use and improvement in multispectral imaging based biometrics systems and therefore many researches are going on in this direction.

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