1 INTRODUCTION

Nowadays a very large number of identification systems exist that are based on different types of biometrics. This includes iris, fingerprint, retina, voice, face, palm and vascular pattern recognition. This last one is quite a new emerging technology in the biometric field, and has been gradually adopted over the world. The idea of using the hand vascular pattern as a biometric was first considered in the early 2000s but it wasn't until 2015 that a commercial product was developed. In 2016 it finally became popular when an application was created for personal identification based on the vein pattern on the back of the hand.

Since its introduction, hand vein pattern technology has expanded to fingers and palm based systems and was adopted in 2017 by the International Standard Organization (ISO) where the storage and transmission of vascular biometric images was standardized.

The demand for secure identification systems has increased exponentially over the last ten years. These systems are required to be very reliable but also easy to use since their application is no longer restricted to high-security facilities. The advantages of hand vein pattern recognition are due to the fact that veins lie underneath the skin, which makes them easily accessible for the system but also hard to alter. In this perspective, the accessibility of vein pattern compared with other biometrics and its ease of use have made it a very interesting alternative for applications where a high level of security is required. It is also a good alternative to biometric systems that require physical contact in order to identify the individual, especially in environments such as hospitals where hygiene has high priority.

An identification system should be fast, simple and secure and due to its desirable advantages, vein pattern technology is being considered into various authentication solutions for use in public places (access control, time and attendance, security, hospitals). The market for hand vascular pattern technology is growing rapidly and today it is an area of ongoing research that draws a lot of attention.

1.1 Scope of the Project

As the ability to verify the identity of individuals has become increasingly important in many areas of modern life, the need of cheap biometric recognition systems becomes greater. Knowing this, it would be appropriate to build an application, based on the use of a cheap set up, which identifies an individual by extracting his hand vascular pattern using a Near Infra-Red (NIR) image.

Such a system could be used in different areas, mainly for physical access control and time attendance, as for example in schools, libraries, airports, hospitals and banks.

LITERATURE SURVEY

T Zhang and C Suen presented fast parallel algorithm for thinning digital pattern. which is emerged in 1984. : A fast parallel thinning algorithm is proposed in this paper. It consists of two sub iterations: one aimed at deleting the south-east boundary points and the north-west corner points while the other one is aimed at deleting the north-west boundary points and the south-east corner points. End points and pixel connectivity are preserved. Each pattern is thinned down to a "skeleton" of unitary thickness. Experimental results show that this method is very effective. It is well known that the general problem of pattern recognition lies in the effectiveness and efficiency of extracting the distinctive features from the patterns. The stroke analysis method is a powerful approach to recognizing certain types of digital patterns such as alphanumeric characters and ideographs. It should be noted that the strokes thinned by hardware or software are accompanied by different kinds of distortion. Differ- ent thinning algorithms produce different degrees of distortion. There is no general agreement in the literature on an exact definition of thinness. Pavlidis describes a thinning algorithm that determines skeletal pixels by local operations. At the same time, the pixels are labelled so that the original image can be reconstructed from its skeleton. The goal of this paper is to find a faster and more efficient parallel thinning algorithm. The distortion should be as little as possible. Experimental results indicate that this method can be used to thin a variety of digital patterns. Our method for extracting the skeleton of a picture consists of removing all the contour points of the picture except those points that belong to the skeleton. In order to preserve the connectivity of the skeleton, we divide each iteration into two sub iterations.

K. Zuiderveld,developed Contrast Limited Adaptive Histogram Equalization, which emerged in 1994. This paper describes a contrast enhancement technique called adaptive histogram equalization, AHE for short, and an improved version of AHE, named contrast limited adaptive histogram equalization, CLAHE, that both overcome the limitations of standard histogram equalization. CLAHE was originally developed for medical imaging and has proven to be successful for enhancement of low contrast images such as portal films. When an image has poor contrast, the use of an appropriate mapping function (usually a linear ramp) often results in an improved image. The mapping function can also be nonlinear; a well-known example is gamma correction. Another non-linear technique is histogram equalization; it is based on the assumption that a good gray-level assignment scheme should depend on the frequency distribution (histogram) of image gray levels. As the number of pixels in a certain class of gray levels increases, one likes to assign a larger part of the available output gray ranges to the corresponding pixels. This condition is met when cumulative histograms are used as a gray-level transform

The histogram of the resulting image is approximately flat, which suggests an optimal distribution of the gray values. Large peaks in the histogram can also be caused by uninteresting areas (especially background noise); in this case, histogram equalization mainly leads to an improved visibility of image noise. The technique does also not adapt to local contrast requirements; minor contrast differences can be entirely missed when the number of pixels falling in a particular gray range is small.

In the case of Adaptive Histogram Equalization our eyes adapt to the local context of images to evaluate their contents, it makes sense to optimize local image contrast. To accomplish this, the image is divided in a grid of rectangular contextual regions in which the optimal contrast must be calculated. The optimal number of contextual regions depends on the type of input image, and its determination requires some experimentation. Division of the image into 8x8 contextual regions usually gives good results; this implies 64 contextual regions of size 64 x 64 when AHE is performed ona512x512 image. For each of these contextual regions, the histogram of the contained pixels is calculated. Calculation of the corresponding cumulative histograms results in a graylevel assignment table that optimizes contrast in each of the contextual regions, essentially a histogram equalization based on local image data.

In the case of CLAHE, The noise problem associated with AHE can be reduced by limiting contrast enhancement specifically in homogeneous areas. These areas can be characterized by a high peak in the histogram associated with the contextual regions since many pixels fall inside the same gray range. With CLAHE, the slope associated with the gray-level assignment scheme is limited; this can be accomplished by allowing only a maximum number of pixels in each of the bins associated with local histograms. After clipping the histogram, the pixels that were clipped are equally redistributed over the whole histogram to keep the total histogram count identical. The clip limit (or contrast factor) is defined as a multiple of the average histogram contents. With a low factor, the maximum slope of local histograms will be low and therefore result in limited contrast enhancement. A factor of one prohibits contrast enhancement (giving the original image) redistribution of histogram bin values can be avoided by using a very high clip limit (one thousand or higher), which is equivalent to the AHE technique.The main advantages of the CLAHE transform as presented in this Gem are the modest computational requirements, its ease of use (requiring only one parameter: the clip limit), and its excellent results on most images. CLAHE does have disadvantages. Since the method is aimed at optimizing contrast, there is no 1 to 1 relationship between the gray values of the original image and the CLAHE processed result; consequently, CLAHE images are not suited for quantitative measurements that rely on a physical meaning of image intensity. A more serious problem are artifacts that sometimes occur when high-intensity gradients are present. Since CLAHE has its roots in medical imaging, the earlier CLAHE implementations assumed 16-bit image pixels, since medical scanners often generate 12-bit images. This implementation is a rewrite of a K&R C version written more than five years ago; it is now Ansi-C as well as C++ compliant and can also process 8-bit images.

A. K. Jain, A. Ross, and S. Prabhakar have presented an introduction to biometric recognition. which is emerged in 2004. A wide variety of systems requires reliable personal recognition schemes to either confirm or determine the identity of an individual requesting their services. The purpose of such schemes is to ensure that the rendered services are accessed only by a legitimate user and no one else. Examples of such applications include secure access to buildings, computer systems, laptops, cellular phones, and ATMs. In the absence of robust personal recognition schemes, these systems are vulnerable to the wiles of an impostor. Biometric recognition or, simply, biometrics refers to the automatic recognition of individuals based on their physiological and/or behavioural characteristics. By using biometrics, it is

possible to confirm or establish an individual‟s identity based on "who she is," rather than by "what she possesses" (e.g., an ID card) or "what she remembers" (e.g., a password). Humans have used body characteristics such as face, voice, and gait for thousands of years to recognize each other. Alphonse Bertillon, chief of the criminal identification division of the police department in Paris, developed and then practiced the idea of using a number of body measurements to identify criminals in the mid-19th century. Just as his idea was gaining popularity, it was obscured by a far more significant and practical discovery of the distinctiveness of the human fingerprints in the late 19th century. Soon after this discovery, many major law enforcement departments embraced the idea of first "booking" the fingerprints of criminals and storing it in a database (actually, a card file). Later, the leftover (typically, fragmentary) fingerprints (commonly referred to as latents) at the scene of crime could be “lifted” and matched with fingerprints in the database to determine the identity of the criminals.

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. Depending on the application context, a biometric system may operate either in verification mode or identification mode. Human factors dictate the success of a biometric-based identification system to a large extent. The case and comfort in interaction with a biometric system contribute to its acceptance. For example ,if a biometric system is able to measure the characteristic of an individual without contact, such as those using face, voice, or iris, it may be perceived to be more user-friendly and hygienic. Additionally, biometric technologies requiring very little cooperation or participation from the users (e.g., face and face thermograms) may be perceived as being more convenient to users. On the other hand, biometric characteristics that do not require user participation can be captured without the knowledge of the user, and this is perceived as a threat to privacy by many individuals.

S Choras, developed Image feature extraction techniques and their applications for CBIR and biometrics systems. which is emerged in 2007.In CBIR (Content-Based Image Retrieval), visual features such as shape, color and texture are extracted to characterize images. Each of the features is represented using one or more feature descriptors. During the retrieval, features and descriptors of the query are compared to those of the images in the database in order to rank each indexed image according to its distance to the query. In biometrics systems images used as patterns (e.g. fingerprint, iris, hand etc.) are also represented by feature vectors. The candidates patterns are then retrieved from database by comparing the distance of their feature vector. In various computer vision applications widely used is the process of retrieving desired images from a large collection on the basis of features that can be automatically extracted from the images themselves. These systems called CBIR have received intensive attention in the literature of image information retrieval since this area was started years ago, and consequently a broad range of techniques has been proposed. The extraction task transforms rich content of images into various content features. Feature extraction is the process of generating features to be used in the selection and classification tasks. Feature selection reduces the number of features provided to the classification task. Those features which are likely to assist in discrimination are selected and used in the classification task. Of these three activities, feature extraction is most critical because the particular features made available for discrimination directly influence the efficacy of the classification task. The end result of the extraction task is a set of features, commonly called a feature vector, which constitutes a representation of the image. First generation CBIR systems were based on manual textual annotation to represent image content. This technique can only be applied to small data volumes and, to be truly effective, annotation must be limited to very narrow visual domains. In contentbased image retrieval, images are automatically indexed by generating a feature vector (stored as an index in feature databases) describing the content of the image. The similarity of the feature vectors of the query and database images is measured to retrieve the image.

As the feature are extracted, a suitable classifier must be chosen. A number of classifiers are used and each classifier is found suitable to classify a particular kind of feature vectors depending upon their characteristics. The classifiers used commonly is Nearest Neighbour classifier. The nearest neighbour classifier is used to compare the feature vector of the prototype with image feature vectors stored in the database. It is obtained by finding the distance between the prototype image and the database. The main contributions of this work are the identification of the problems existing in CBIR and Biometrics systems describing image content and image feature extraction. We have described a possible approach to mapping image content onto lowlevel features. This paper investigated the use of a number of different colour, texture and shape features for image retrieval in CBIR and Biometrics systems

L. Wang, G.Leedham, S.Y. Cho, have designed and implemented Infrared imaging of hand vein patterns for biometric purpose. which is emerged in 2007.A novel non-invasive imaging technique to image the vein patterns in parts of the hand for biometric purposes is evaluated. Two imaging methods are investigated: far-infrared (FIR) thermography and nearinfrared(NIR)imaging. Experiments involving data acquisition from various parts of the hand, palm and wrist where carried out using both imaging techniques. Analysis of the data collected shows that FIR thermography is less successful at capturing veins in the palm and wrist. FIR thermography is less successful at capturing vein in the palm and wrist. FIR thermography can capture the large veins in the back of the hand ,but it is sensitive to ambient temperature and humidity conditions as well as human body temperature. NIR imaging produces good quality images when capturing vein in the back of the hand, palm and wrist. NIR imaging is good quality images when capturing veins in the back of the hand, palm and wrist. NIR imaging is also more tolerant to changes in the environment and body condition but faces the problem of pattern corruption because of visible skin features being mistaken for veins. This corruption is not present in FIR imaging. An initial biometric system is investigated to test both FIR and NIR images for biometric purposes. The results show all the subjects were correctly identified, which indicates vein pattern biometrics with infrared imaging is a potentially useful biometric. Biometric is the science of identifying a person using their physiological or behavioural features. Recently, vein pattern biometrics has attracted increasing interest from both research communities and industries. A vein pattern is the physical structure of the vast network of blood

vessels underneath a person‟s skin. Anatomically, aside from surgical intervention, the shape of vascular patterns in the same part of the body is distinct for each person, and it is very stable over a long period of time, as a person‟s pattern of blood vessels is believed to be „hardwired‟ in to 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 underneath the skin are invisible to the human eye, vein patterns are much harder for intruders to copy as compared to other biometric features. The properties of uniqueness, stability and strong immunity to forgery of the vein pattern make it potentially good biometric that offers secure and reliable features for person identify verification.

In future, the research will focus on the NIR imaging and use of these image for vein pattern biometrics. More investigation is needed in all stages of the subsequent processing of the NIR images. This includes preprocessing to enhance the images and better extract the vein lines from the images while filtering out other non-vein lines. Further research is needed to determine and select an appropriate feature set that can be extracted which best represent the uniqueness of vein patterns. Lastly, as the details of vein are limited to the larger veins, the amount of detail is limited in each image. It is likely that hand vein pattern biometrics will most effectively be used in conjunction with other biometrics such as palm prints, finger prints and hand geometry in a multimodal biometric system.

SYSTEM STUDY

3.1 EXISTING SYSTEM

PERSONAL IDENTIFICATION USING FINGERPRINTS

Fingerprint-based identification is one of the most important biometric technologies which have drawn a substantial amount of attention recently. Fingerprints are believed to be unique across individuals and across fingers of same individual. Even identical twins having similar DNA, are believed to have different fingerprints .A fingerprint is the pattern of ridges and valleys on the surface of a fingertip. Fingerprint recognition can be categorized into identification and verification. Fingerprint identification is the process of determining which registered individual provides a given fingerprint. Fingerprint verification, on the other hand, is the process of accepting and rejecting the identity claim of a person using his fingerprint. Fingerprint recognition can also be categorized into minutiae extraction based and spectral features of the image based. All technologies of fingerprint recognition, identification and verification, minutiae extraction based and spectral features based, each has its own advantages and disadvantages and it may requires different treatments and techniques. The choice of witch technologies to use is application specific.

HOW FINGERPRINT IDENTIFICATION WORKS

At the highest level, all fingerprint recognition systems contain two main modules feature extraction and feature matching. Feature extraction is the process that detects singular and all other minutiae points which are ridge ending and ridge bifurcation which differentiate one fingerprint from another which impart individuality to each fingerprint from the original image that can later be used to represent each fingerprint. Feature matching involves the actual procedure to identify the unknown person by comparing extracted features from his/her fingerprint with the ones from a set of known persons.

FINGERPRINT RECOGNITION

In less than few seconds, even on a database of hundreds of records, the matrix of pixels generated from an image of fingerprint is compared to previously enrolled ones to see if it matches any of them. The decision threshold is automatically adjusted for the size of the search database to ensure that no false matches occur even when huge numbers of matrixes of fingerprints are being compared with the live one. Some of the bits in a matrix signify if some data is corrupted (e.g. the image of fingerprint has degraded by noise), so that it does not influence the process, and only valid data is compared. Decision thresholds take account of the amount of data, and the matching operation compensates for any tilt of the image of fingerprint. A key advantage of fingerprint recognition is its ability to perform identification using a one-to-all search of a database, with no limitation on the number of fingerprint records and no requirement for a user first to claim an identity, for example with a card. For our method we use and experiment a recent neural network called a spike neural network. The neural network is used for matching and performs recognition using a one-to-all search of a database.

PERSONAL IDENTIFICATION USING FACE AND HAND GEOMETRY FUSION AND SUPPORT VECTOR MACHINES

Automated personal authentication based on anatomical or behavioral characteristics of a person from two or more sources is known as multimodal biometric authentication. Several biometrics have been investigated including face, iris, hand geometry, fingerprint, voice, signature and gait. Recently, multimodal biometric has become one of the most attractive authentication solutions and received gradually more research attention. This is due to its potential to alleviate a number of limitations of traditional single biometric technologies. These limitations include: noisy sensor data, susceptibility to spoofing attacks, non-universality, and unacceptable error rates due to the inter-class similarity and intra-class variability .Incorporating more than one biometric boosts the capability of the system to complement the lack of evidence of each biometric with the information in the other biometric. For instance, face technology can be affected by face expressions such as smiling whereas hand shape biometric is not sensitive to such emotions. Hence, by consolidating the information from hand shape, the system can compensate this deficiency when using the face alone. The inconvenience of using pegged platforms for capturing hand images has encouraged researchers to relax the constraints applied to end users by proposing new techniques with peg-free or contactless designs.

The proposed bimodal identification system is based on the integration of face and hand geometry biometrics. Similar to the traditional multimodal biometric system, the proposed system has two stages: enrollment and identification (matching/classification). In the enrollment stage, the system captures several hand and face images for each potential user of the system. Then, the system carries out pre-processing and feature extraction to represent each image by a feature vector. Two optional procedures can be used separately or together; these are feature normalization (FN) and feature selection (FS). The location of these procedures can be performed before or after the fusion of features. We perform feature-level fusion by simply concatenating the two biometric features to generate one fused feature vector. The combination of a feature vector with PID for a specific person is known as his/her template. Templates are stored in a database and will be used later to construct an identification model.

3.1.1 EXISTING SYSTEM DISADVANTAGES

3.1.1.1 DISADVANTAGES OF FINGERPRINT

Biometric systems—surfacing during the latter half of the 20th century—really haven't become common place until the early 21st century. They are now available for many uses, including security purposes, as well as employee management. There are many advantages to biometric systems, as well as a few notable disadvantages as well.

SECURITY

Biometric fingerprint readers offer a way to capture an identity point that is very difficult to fake—making the technology extremely secure. **As many as half of smart phone owners do not utilize a password to lock their hardware , This can present a considerable threat to endpoint data protection , as if the individual’s unlocked device is lost or stolen , The hackers have easy access to any sensitive content contained there .While locking the smart phone with the fingerprint may serve to ward off these kinds of attacks , The security experts have showed that such protection measures can be hacked , The process is not an easy one & it requires the correct , clean fingerprint of the device owner which is copied with transparency film and used to unlock the phone .If not**

performed correctly , the cyber-criminal may not be successful as the users only have a set number of attempts before they are asked to utilize a four-digit or patterned pass-code .

COSTLY

Biometric systems can be costly to implement, which might exclude many companies or organizations from implementing it. **Having a high security system may require expensive computer hardware and software , Certain fingerprint scanners can be quite expensive , Many employees are working with their hands , their fingers may get rough or scratched which could lead to a miss-reading.**

TIME

Since fingerprint recognition software only reads one section of a person's finger—it is prone to error. Manually repositioning fingers to get the right reading can be time-consuming.

FALSE READINGS

Biometric systems—especially lower cost systems—are prone to errors, including failing to identify an authorized person and incorrectly identifying unauthorized people.

3.1.1.2 DISADVANTAGES OF FACE RECOGNITION

With facial recognition becoming ever more prevalent in day-to-day life, there is a big concern about the impact it could have on personal privacy.

Exposure: Insiders speculate about potential situations like using facial recognition to determine who around you belongs to a certain cultural or religious group, or who has a criminal record. This application might make the user feel safer or better informed, but it would be invasive to those on the receiving end.

Safety: In an era where online bullying has become prevalent, this type of technology could also leave more people vulnerable to stalking and harassment in the real world.

Legislation: There are concerns that biometrics are progressing too rapidly for regulators, legislators, and the judicial system to set up standardised rules and precedents around their use. For example, in the USA, the Fifth Amendment protects people from giving up information that could incriminate them. This would include information like a password or PI

3.2 PROPOSED SYSTEM

PERSONAL IDENTIFICATION USING FOREARM VEIN PATTERN

Images play an important role in the identification process of people. The core of all biometrics system have five key modules: sensors, feature extractor, biometric database, matcher and decision maker. The sensor reads the biometric information from the user. Feature extractor module extracts features from the biometric data. Matcher module indicates the similarity between extracted features from the user sample and an enrolled template. Biometric database maintains the templates of the enrolled users. Decision maker interprets the result.

The two types of biometric categories are:

(1)identification systems

(2)verification systems

Feature extraction is the process which analysis images to extract features that are important inputs to stage selection. Features are automatically extracted from the images. All features can be coarsely classified into low level features and high level features. Low level features can be extracted directed from the original images, whereas high level feature extraction must be based on low level features.

The feature extraction algorithm extracts significant components from the biometric sample and converts it into biometric data so that it can be matched to a reference template in the database. The number of features are reduces and used in the classification task.

The matcher component of the system compares feature vector obtained from the feature extraction algorithm to produce a similarity score. This score indicates the degree of similarity between a pair of biometrics data under consideration. In this project we use matcher for template matching

Vein recognition is a method of biometric, that uses pattern recognition techniques based on images of blood vessel. Blood vessel patterns are unique to each individual. Vein recognition does not require contact during registering and authentication and is a strong immunity to forgery.

In the field of forearm recognition for medical imaging applications, near infrared band in the electromagnetic spectrum is typically accepted technique. Visibility human vein patterns in the visible light is low, but in the biometric applications, current trends show more expensive approach where image captured is performed without any touching. It is found that tins with the same DNA sequence have different vein patterns biometrics based on the veins is efficacious method to identify user. Human forearm vein recognition is a new biometric technology. In this paper a recognition method used a feature derived from a firearm vein image is presented.

The forearm recognition is considered to be more secured than other biometric traits because veins are inside the human body. The forearm recognition has been developed using the characteristic points based technique where the image is first normalized, binarized and thinned, is then a crossing number is used to extract properties of the veins e.g. bifurcation.

Image acquisition is defined as the action of retrieving an image from some source, usually a hardware-based source for processing. It is the first step in the workflow sequence because, without an image, no processing is possible.

Steps in vein image processing:

1)**IMAGE ENHANCEMENT**

The forearm vein image usually has poor contrast, non uniform gray level and noise. Contrast enhancement improves the image . For contrast enhancement of image we use CLAHE(Contrast limited adaptive histogram equalisation). This technique divides the image into equal sized blocks and then performs contrast limited histogram equalisation on each block. The contrast limiting is done by clipping the histogram before histogram equalisation.

2)IMAGE BINARIZATION

It is used to convert the pixel image into binary image. Let the initial global threshold be th. Using th we produce two groups of pixels: first with all pixels intensity values>th, second with pixels with values<th. Net compute the mean intensity values mean1 and mean2 for the pixels with first and second groups respectively. Finally a new threshold value is defined by T=mean1+mean2/2.

3)NOISE ELIMINATION

Median filtering is a non linear method based on statistics used to remove the noise from images. The noisy value of the digital image is replaced by the median value of the neighbourhood pixels. The pixels of the mask are ranked in the order of their gray levels and the median value of the group is stored to replace the neighbourhood pixels.

4)THINNING

It is used to remove the selected foreground pixels from the binary image . Used in various applications but most widely used in skeletalization.

After this methods the image is then given to bifurcation point matching.

5)BIFURCATION POINT MATCHING

The feature vector is created as follows:

F VX = {bif1, bif2, . . . , bifK}

where:

X indicate on the input forearm image and/or on the template forearm image.

K = u is the number of bifurcation points in the input forearm image and K = v is the number of bifurcation points in the template forearm image.

bifK = {xK, yK, θK1, θK2, θK3}. (xK, yK) are position of bifurcation points, (θK1, θK2, θK3) are the bifurcation angles with respect to the horizontal axis.

Two bifurcation points bifu and bifv are considered to match, if their position and orientation are close [2]:

D(bifu, bifv) = p(xu − xv)2 + (yu − yv)2 < T h1

A(bifu, bifv) = (10)= min(|θu1 − θv1|, |θu2 − θv2|, |θu3 − θv3|) < Θ

If S is higher than a threshold value, then the input forearm image is matched with the template forearm image, otherwise it doesn't match. S is defined as follows

S =Huv √uv

where the number of matched bifurcation is Huv.

The correspondence between the vessel in an input image and the vessel templates is based on the their characteristic points. These characteristic points are then compared and we calculate the total number of matching points and obtain the matching results.

The number of matching pairs (threshold T) is used to measure the similarity of two forearm vein images. Two fore arm vein images will be classified as the same class if the number of matching pairs is bigger than T, otherwise these two forearm vein images will be classified as different classes.

3.2.1 PROPOSED SYSTEM ADVANTAGES

Some of the advantages the forearm vein pattern recognition provides are:

- The vein patterns are unique to each individual. Apart from size, the pattern does not change over time. This feature makes it suitable for one-to-many matching, for which hand geometry and face recognition may not be suitable. Vein recognition technology has a False Rejection Rate (FRR) of 0.01% and a False Acceptance Rate (FAR) of 0.0001%, hence making it suitable for high-security applications.
- Veins are located underneath the skin surface and are not prone to external distortion the way fingerprints are. This reduces the high failure to enroll (FTE) rate caused by bad samples. Vein patterns are difficult to replicate because they lie under the skin

surface. Fingerprints can be duplicated using gummy fingers. Additionally, some vein recognition models come with ‘liveness’ detection that senses flow of blood in veins.

- User friendliness: This technology overcomes aversion to fingerprinting and related privacy concerns since its traditional association to criminal activity is non-existent. In countries such as Japan, where there is strong opposition to fingerprinting, vein recognition has become the biometric technology of choice. It is relatively quick as it takes less than 2 seconds to authenticate. Some noncontact models are more hygienic than fingerprint readers.
- Potential fusion with other biometric technologies: With the popularity of multimodal biometrics, vein recognition technology could be used in conjunction with hand or fingerprint biometrics. Vein recognition can provide one-to-many matching, and hand geometry can be used for one-to-one matching, thereby enhancing security.

SYSTEM CONFIGURATION

4.1 HARDWARE REQUIREMENT

4.1.1 CAMERA

A **webcam** is a video camera that feeds or streams its image in real time to or through a computer to a computer network The term "webcam" (a clipped compound) may also be used in its original sense of a video camera connected to the Web continuously for an indefinite time, rather than for a particular session, generally supplying a view for anyone who visits its web page over the Internet. Some of them, for example, those used as online traffic cameras, are expensive, rugged professional video

Image sensors can be CMOS or CCD the former being dominant for low-cost cameras, but CCD cameras do not necessarily outperform CMOS-based cameras in the low-price range. Most consumer webcams are capable of providing VGA resolution video at a frame rate of 30 frames per second. Many newer devices can produce video in multi megapixel resolutions, and a few can run at high frame rates such as the PlayStation Eye which can produce 320×240 video at 120 frames per second. The Wii Remote contains an image sensor with a resolution of 1024×768 pixels.

Various lenses are available, the most common in consumer-grade webcams being a plastic lens that can be manually moved in and out to focus the camera. Fixed-focus lenses which have no provision for adjustment, are also available. As a camera system's depth of field is greater for small image formats and is greater for lenses with a large f-number (small aperture), the systems used in webcams have a sufficiently large depth of field that the use of a fixed-focus lens does not impact image sharpness to a great extent Most models use simple, focal-free optics (fixed focus, factory-set for the usual distance from the monitor to which it is fastened to the user) or manual focus.

Digital video streams are represented by huge amounts of data, burdening its transmission (from the image sensor, where the data is continuously created) and storage alike .Most if not all cheap webcams come with built-it ASIC to do video compression in real-time. Support electronics read the image from the sensor and transmit it to the host computer. The camera pictured to the right, for example, uses a SonixSN9C101 to transmit its image over USB. Typically, each frame is transmitted uncompressed in RGB or YUV or compressed as JPEG. Some cameras, such as mobile-phone cameras, use a CMOS sensor with supporting electronics "on die", i.e. the sensor and the support electronics are built on a single silicon chip to save space and manufacturing costs. Most webcams feature built-in microphones to make video calling and videoconferencing more convenient

Typical interfaces used by articles marketed" webcam" are USB, Ethernet and IEEE 802.11 (denominated as IP camera. Further interfaces such as e.g. Composite video or S-Video are also available .The USB video device class (UVC) specification allows inter-connectivity of webcams to computers without the need for proprietary device drivers.

4.1.2 IR LED

Infrared radiation (**IR**), sometimes called **infrared light**, is electromagnetic radiation (EMR) with longer wavelengths than those of visible light and is therefore generally invisible to the human eye, although IR at wavelengths up to 1050 nano meters (nm)s from specially pulsed lasers can be seen by humans under certain conditions. IR wavelengths extend from the nominal red edge of the visible spectrum at 700 nano meters frequency 430 THz to 1 millimeter (300 GHz Most of the thermal radiation emitted by objects near room temperature is infrared. As with all EMR, IR carries radiant energy and behaves both like a wave and like its quantum particle, the photon

Infrared radiation was discovered in 1800 by astronomer Sir William Herschel who discovered a type of invisible radiation in the spectrum lower in energy than red light, by means of its effect on a thermometer. Slightly more than half of the total energy from the Sun was eventually found to arrive on Earth in the form of infrared. The balance between absorbed and emitted infrared radiation has a critical effect on Earth's climate.

Infrared radiation is emitted or absorbed by molecules when they change their rotational-vibrational movements. It excites vibration modes in a molecule through a change in the dipole moment, making it a useful frequency range for study of these energy states for molecules of the proper symmetry. Infrared spectroscopy examines absorption and transmission of photons in the infrared range. Infrared radiation is used in industrial, scientific, military, law enforcement, and medical applications. Night-vision devices using active near-infrared illumination allow people or animals to be observed without the observer being detected. Infrared astronomy uses sensor-equipped telescopes to penetrate dusty regions of space such as molecular clouds, detect objects such as planets and to view highly red-shifted objects from the early days of the universe Infrared thermal-imaging cameras are used to detect heat loss in insulated systems, to observe changing blood flow in the skin, and to detect overheating of electrical apparatus.

Extensive uses for military and civilian applications include target acquisition, surveillance, night vision, homing and tracking. Humans at normal body temperature radiate chiefly at wavelengths around 10 µm (micrometers). Non-military uses include thermal efficiency analysis, environmental monitoring, industrial facility inspections, detection of grow-ops, remote temperature sensing, short-range wireless communication , spectroscopy and weather forecasting

4.1.3 LAPTOP

A laptop computer (also shortened to just **laptop**; or called a **notebook** or **notebook computer**) is a small, portable personal computer (PC) with a clamshell form factor, typically having a thin LCD or LED computer screen mounted on the inside of the upper lid of the clamshell and an alphanumeric keyboard on the inside of the lower lid. The clamshell is opened up to use the computer. Laptops are folded shut for transportation, and thus are suitable for mobile use Its name comes from lap, as it was deemed to be placed on a person's lap when being used. Software required for our project is installed in the lap top

4.2 SOFTWARE REQUIREMENT

4.2.1 OPEN CV-PYTHON

Open CV (Open Source Computer Vision Library) is an open source computer vision and machine learning software library. Open CV was built to provide a common infrastructure for computer vision applications and to accelerate the use of machine perception in the commercial products. Being a BSD-licensed product, Open CV makes it easy for businesses to utilize and modify the code.

The library has more than 2500 optimized algorithms, which includes a comprehensive set of both classic and state-of-the-art computer vision and machine learning algorithms. These algorithms can be used to detect and recognize faces, identify objects, classify human actions in videos, track camera movements, track moving objects, extract 3D models of objects, produce 3D point clouds from stereo cameras, stitch images together to produce a high resolution image of an entire scene, find similar images from an image database, remove red eyes from images taken using flash, follow eye movements, recognize scenery and establish markers to overlay it with augmented reality, etc. Open CV has more than 47 thousand people of user community and estimated number of downloads exceeding 18 million The library is used extensively in companies, research groups and by governmental bodies.

Along with well-established companies like Google, Yahoo, Microsoft, Intel, IBM, Sony, Honda, Toyota that employ the library, there are many start ups such as Applied Minds, Video Surf and Zeitera, that make extensive use of Open CV. Open CV's deployed uses span the range from stitching street view images together, detecting intrusions in surveillance video in Israel, monitoring mine equipment in China, helping robots navigate and pick up objects at Willow Garage, detection of swimming pool drowning accidents in Europe, running interactive art in Spain and New York, checking runways for debris in Turkey, inspecting labels on products in factories around the world on to rapid face detection in Japan.

It has C++, Python, Java and MATLAB interfaces and supports Windows, Linux, Android and Mac OS. Open CV leans mostly towards real-time vision applications and takes advantage of MMX and SSE instructions when available. A full-featured CUDA and Open CL interfaces are being actively developed right now. There are over 500 algorithms and about 10 times as many functions that compose or support those algorithms. Open CV is written natively in C++ and has a templated interface that works seamlessly with STL containers.

Python is a general purpose programming language started by **Guido van Rossum** which became very popular in short time mainly because of its simplicity and code readability. It enables the programmer to express his ideas in fewer lines of code without reducing any readability. Compared to other languages like C/C++, Python is slower. But another important feature of Python is that it can be easily extended with C/C++. This feature helps us to write computationally intensive codes in C/C++ and create a Python wrapper for it so that we can use these wrappers as Python modules

This gives us two advantages: first, our code is as fast as original C/C++ code (since it is the actual C++ code working in background) and second, it is very easy to code in Python. This is how Open CV-Python works, it is a Python wrapper around original C++ implementation.And the support of Numpy makes the task more easier. **Numpy** is a highly optimized library for numerical operations. It gives a MATLAB-style syntax. All the Open CV array structures are converted to-and-from Numpy arrays. So whatever operations you can do in Numpy, you can combine it with Open CV, which increases number of weapons in your arsenal. Besides that, several other libraries like SciPy, Matplotlib which supports Numpy can be used with this.

Open CV is used for all sorts of image and video analysis, like facial recognition and detection, license plate reading, photo editing, advanced robotic vision, optical character recognition, and a whole lot more. There are some operations for Open CV that you will not be able to do without a full installation of OpenCV (about 3GB in size), but you can actually do quite a bit with the fairly minimal installation of python-Open CV.

code is fairly simple and straight forward as well. We make a function that sets the width and height of the video capture 'cap' to the desired resolution values. For a resolution of 480p, the height will be equal to 480 and the width will be equal to 640. Similarly for the resolutions of 720p and 1080p the heights and widths will be equal to 720 & 1280 and 1080 & 1920 respectively. One thing here to note is that as the resolution of the video increases, the size of the video will increase as well. There will be some cases when you can set an even bigger resolution than the camera hardware can support but this will only result in a very lagged and choppy video

Smoothing and Blurring techniques help us in eliminating noises from our image. There are various types of smoothing and blurring techniques available at direct disposal from open-cv. Let's explore some of them to get adept with them. Keep in mind that each and every technique has its own advantages as well as disadvantages

After having a clear idea on the concept of Smoothing and Blurring we move towards our next topic. Canny edge detection does exactly as it sounds. It basically detects the edges from any given image. We are going to detect the edges from the live video input from the primary webcam.

This introductory part of the OPEN-CV series will be enough to get the basic understanding of how the Open-CV library, combined with python, works and it will also provide the grounds of understanding the field of Computer Vision itself

Along with well-established companies like Google, Yahoo, Microsoft, Intel, IBM, Sony, Honda, Toyota that employ the library, there are many startups such as Applied Minds, VideoSurf, and Zeitera, that make extensive use of OpenCV. OpenCV's deployed uses span the range from stitching streetview images together, detecting intrusions in surveillance video in Israel, monitoring mine equipment in China, helping robots navigate and pick up objects at Willow Garage, detection of swimming pool drowning accidents in Europe, running interactive art in Spain and New York, checking runways for debris in Turkey, inspecting labels on products in factories around the world on to rapid face detection in Japan.

4.3 <u>SYSTEM DISCREPTION</u>

4.3.1.HARDWARE DISCREPTION

4.3.1.1 CAMERA

The purpose of this project, is to create a capture setup that is efficient and has a low cost. A cheap webcam (Logitech Webcam pro 9000 shown in Figure 4.1) was chosen to be used for taking the pictures of the hand. The camera has been modified so it can capture NIR images. A captured image of a hand in the NIR spectrum shows the veins in black and the skin in white as explained in subsection

Most webcams have a CMOS image sensor, which is sensitive to both visible light and NIR light as shown in figure 4.2. Most are also sold with a filter which blocks all NIR light in order to improve quality of the image in the visible spectrum. However the camera used for this project had this filter removed, and was thus already sensitive to both visible and NIR light. So in order to capture only images in the NIR spectrum, visible light must be blocked otherwise it would reduce contrast between veins and background. This would reduce usability of the image.

The easiest and cheapest way to block the visible light is to use pieces of a color photographic negative as filter. For the project setup the film negative Kodak Gold ISO 200 was used as it blocks most of the visible light while being very transparent to NIR light. The figure shows the response curve for a filter made from an exposed Kodak color film. It shows that the film negative is a very good filter for this purpose. After developing the film, it is cut into small pieces, fitting the size of the webcam lens and fixed on it. Such a modified webcam produces pictures in NIR spectrum.

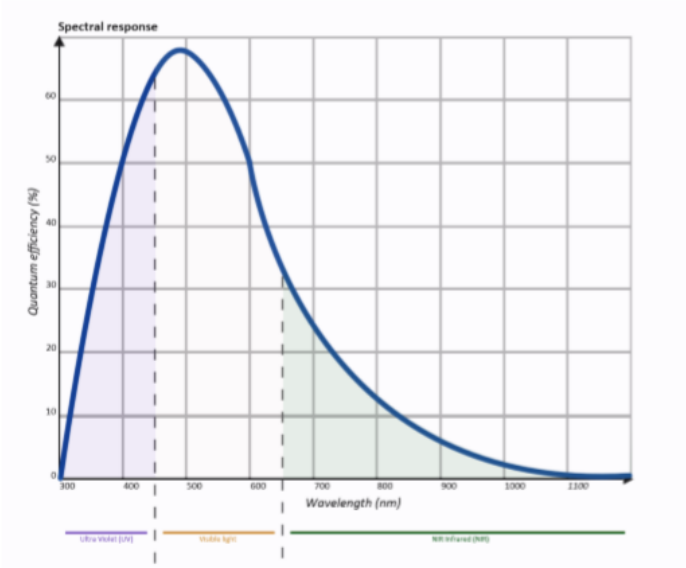


Illustration of the spectral response of a web cam with CMOS component

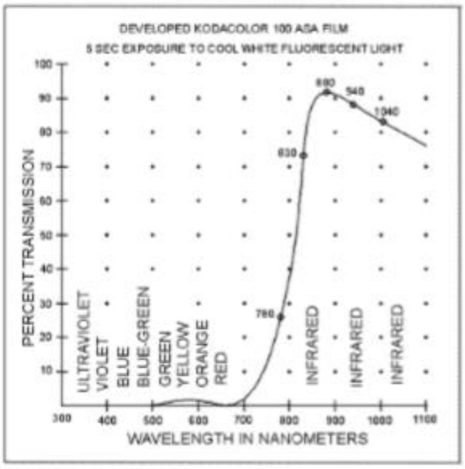


Illustration of the spectral response of a Kodak film negative

Different factors influences the image quality and an important one is the lighting conditions. Hence Infra-Red (IR) Light Emitting Diodes (LEDs) were added to the setup. The position of these LEDs are very important to get an uniform illumination. It has been suggested that a convex surface such as the back of the hand, can be optimally lit at an angle of 55 degrees. The LEDs should be positioned on both sides of the hand with this angle in order to reduce shadows caused by small level differences on the hand’s surface. Moreover, the LEDs should be positioned higher than the camera to keep the light from entering the camera lens directly. Based on these spatial requirements. Some LEDs are added on both sides of the camera in order to improve the quality of the illumination

In this project we remove the IR filter of the webcam.During the day, a day/night camera uses an IR-cut filter. IR light is filtered out so that it does not distort the colours of images as the human eye sees them. When the camera is in night mode, the IR-Cut filter is removed, which allows the camera's light sensitivity to reach down to **low** lux levels!. During the day, the **IR filter** is switched on. It will block infrared and only allow visible light to pass through. This ensures it **does** not distort the image colors, generating true color representation – exactly as the human eye sees them. **Infrared** light is all around us. We **can**'t **see** it, but our **cameras can**. The problem is that **IR** light effects the **camera's** ability to record the visible light correctly. Most manufacturers put **IR** blocking filters over the **digital camera's** sensor to prevent the**IR** light from causing a problem..

In contrast to the naming convention of optical fiber where the name of the filter denotes the wavelengths that are blocked, and in line with the convention for air filters and oil filters, photographic filters are named for the color of light they *pass*. Thus a blue filter makes the picture look blue. A *blue filter* marginally allows more light in the blue wavelength to pass resulting in a slight shift of the color temperature of the photo to a cooler color. Because of this, the term "IR filters" is commonly used to refer to filters that pass infrared light while completely blocking other wavelengths. However, in some applications the term "IR filter" still can be used as a synonym of infrared cut-off filter.

Unlike the eye, sensors based on silicon (including CCDs and CMOS sensors) have sensitivities extending into the near-infrared. Such sensors may extend to 1000 nm. Digital cameras are usually equipped with IR-blocking filters to prevent unnatural-looking images. IR-transmitting (passing) filters, or removal of factory IR-blocking filters, are commonly used in infrared photography to *pass* infrared light and *block* visibleand ultraviolet light. Such filters appear black to the eye, but are transparent when viewed with an IR sensitive device.since the dyes in processed film block various part of visible light but are all fairly transparent to infrared, dark black sections of any processed film (where all visible colors are blocked) pass only infrared light and are commonly used (layering one over another if necessary for better visual light filtering) as a cheap alternative to expensive glass-backed filters. Such filters can be used both over color camera lenses, and to filter visible light from

IR illumination sources. Such filter stock is most easily made available most simply by having any commercial color negative film developed after being fully exposed to light. The leaders of 35mm film are ideal for this, without wasting an entire roll of film. (Some special communication may be necessary in such submission, to ensure that all of the "black" negative film thus produced is indeed returned, and that there is no need to print the color-negative results on photographic paper). In the same way, visually opaque "black" color-positive film emulsions mounted in cardboard, as for routine slide projection, provide inexpensive cardboard-mounted infrared filters. Film sizes larger than 35 mm may be handled in the same way for larger filter production.

4.3.1.2 IRLED

Infrared radiation is popularly known as "heat radiation but light and electromagnetic waves of any frequency will heat surfaces that absorb them. Infrared light from the Sun accounts for 49 of the heating of Earth, with the rest being caused by visible light that is absorbed then re-radiated at longer wavelengths. Visible light or ultraviolet-emitting lasers can char paper and incandescently hot objects emit visible radiation. Objects at room temperature will emit radiation concentrated mostly in the 8 to 25 μm band, but this is not distinct from the emission of visible light by incandescent objects and ultraviolet by even hotter objects (see black body and Wien's displacement law

Heat is energy in transit that flows due to a temperature difference. Unlike heat transmitted by thermal conduction or thermal convection thermal radiation can propagate through a vacuum Thermal radiation is characterized by a particular spectrum of many wavelengths that are associated with emission from an object, due to the vibration of its molecules at a given temperature. Thermal radiation can be emitted from objects at any wavelength, and at very high temperatures such radiation is associated with spectra far above the infrared, extending into visible, ultraviolet, and even X-ray regions (e.g. the solar corona. Thus, the popular association of infrared radiation with thermal radiation is only a coincidence based on typical (comparatively low) temperatures often found near the surface of planet Earth.

The concept of emissivity is important in understanding the infrared emissions of objects. This is a property of a surface that describes how its thermal emissions deviate from the idea of a black body To further explain, two objects at the same physical temperature will not show the same infrared image if they have differing emissivity. For example, for any pre-set emissivity value, objects with higher emissivity will appear hotter, and those with a lower emissivity will appear cooler. For that reason, incorrect selection of emissivity will give inaccurate results when using infrared cameras and pyrometers.

Near-infrared is the region closest in wavelength to the radiation detectable by the human eye. mid- and far-infrared are progressively further from the visible spectrum. Other definitions follow different physical mechanisms (emission peaks, vs. bands, water absorption) and the newest follow technical reasons (the common silicon detectors are sensitive to about 1,050 nm, while InGaAs s sensitivity starts around 950 nm and ends between 1,700 and 2,600 nm, depending on the specific configuration). No international standards for these specifications are currently available.

The onset of infrared is defined (according to different standards) at various values typically between 700 nm and 800 nm, but the boundary between visible and infrared light is not precisely defined. The human eye is markedly less sensitive to light above 700 nm wavelength, so longer wavelengths make insignificant contributions to scenes illuminated by common light sources. However, particularly intense near-IR light (e.g., from IR lasers, IR LED sources, or from bright daylight with the visible light removed by colored gels) can be detected up to approximately 780 nm, and will be perceived as red light. Intense light sources providing wavelengths as long as 1050 nm can be seen as a dull red glow, causing some difficulty in near-IR illumination of scenes in the dark (usually this practical problem is solved by indirect illumination). Leaves are particularly bright in the near IR, and if all visible light leaks from around an IR-filter are blocked, and the eye is given a moment to adjust to the extremely dim image coming through a visually opaque IR-passing photographic filter, it is possible to see the Wood effect that consists of IR-glowing foliage.

Infrared radiation is popularly known as "heat radiation" but light and electromagnetic waves of any frequency will heat surfaces that absorb them. Infrared light from the Sun accounts for 49%of the heating of Earth, with the rest being caused by visible light that is absorbed then re-radiated at longer wavelengths. Visible light or ultraviolet emitting lasers can char paper and incandescently hot objects emit visible radiation. Objects at room temperature will emit radiation concentrated mostly in the 8 to 25 μm band, but this is not distinct from the emission of visible light by incandescent objects and ultraviolet by even hotter objects (see black body and Wien'sdisplacement law

4.3.1.3 LAPTOP

Laptops combine all the input/output components and capabilities of a desktop computer, including the display screen, small speakers, a keyboard, hard disk drive, optical disc drive, pointing devices (such as a touchpad or trackpad), a processor, and memory into a single unit. Most modern laptops feature integrated webcams and built-in microphones, while many also have touchscreens. Laptops can be powered either from an internal battery or by an external power supply from an AC adapter. Hardware specifications, such as the processor speed and memory capacity, significantly vary between different types, makes, models and price points.

Design elements, form factor and construction can also vary significantly between models depending on intended use. Examples of specialized models of laptops include rugged notebooks for use in construction or military applications, as well as low production cost laptops such as those from the One Laptop per Child (OLPC) organization, which incorporate features like solar charging and semi-flexible components not found on most laptop computers. Portable computers, which later developed into modern laptops, were originally considered to be a small niche market, mostly for specialized field applications, such as in the military, for accountants, or for traveling sales representatives. As the portable computers evolved into the modern laptop, they became widely used for a variety of purposes

Python does not come pre-installed with Windows. It needs to be manually downloaded and installed. You can get Python from the following: http://python.org/download/. Simply download the Python installer and follow the instructions. Make sure to remember the directory you used to install Python. You may need this information at the top of each of your Python scripts depending on what type of environment you are using to execute the scripts.

Python programs can be created using any text editor such as EditRocket Python programs and scripts typically end with the .py extension. EditRocket will automatically recognize files with the .py extension as Python programs, and will color the syntax accordingly.

- Some operating systems, notably Linux, provide a **package manager** that can be run to install Python.
- On macOS, the best way to install Python 3 involves installing a package manager called **Homebrew**. You'll see how to do this in the relevant section in the tutorial.
- On mobile operating systems like Android and iOS, you can install apps that provide a Python programming environment. This can be a great way to practice your coding skills on the go.

4.3.2 SOFTWARE DISCREPTION

4.3.2.1 PYTHON

Python is an interpreted, high-level, general-purpose programming language. Created by Guido van Rossum and first released in 1991, **Python** has a design philosophy that emphasizes code readability, notably using significant whitespace. It provides constructs that enable clear programming on both small and large scales.

Python is a powerful modern computer programming language. It bears some similarities to Fortran, one of the earliest programming languages, but it is much more powerful than Fortran. Python allows you to use variables without declaring them (i.e., it determines types implicitly), and it relies on indentation as a control structure. You are not forced to define classes in Python (unlike Java) but you are free to do so when convenient. Python was developed by Guido van Rossum, and it is free software. Free as in "free beer," in that you can obtain Python without spending any money. But Python is also free in other important ways, for example you are free to copy it as many times as you like, and free to study the source code, and make changes to it. There is a worldwide movement behind the idea of free software, initiated in 1983 by Richard Stallman.1 This document focuses on learning Python for the purpose of doing mathematical calculations. We assume the reader has some knowledge of basic mathematics, but we try not to assume any previous exposure to computer programming, although some such exposure would certainly be helpful. Python is a good choice for mathematical calculations, since we can write code quickly, test it easily, and its syntax is similar to the way mathematical ideas are expressed in the mathematical literature. By learning Python you will also be learning a major tool used by many web developers.

5 SYSTEM ANALYSIS

5.1 SYSTEM OVERVIEW

Pattern recognition is based on identifying a pattern and confirms the pattern whether it is correct or not. Basically, a pattern could be of any type be a fingerprint image, vein pattern, a handwritten cursive word, a human face, a speech signal, a bar code, or a web page on the Internet.
Each individual has different patterns and are grouped into various categories depending on their properties. If the individual has the pattern which has the same properties that are grouped together, then the resultant group is also will have the same pattern, which is called as pattern class.

Pattern recognition is the science which deals in observing, distinguishing the patterns of interest, and find out the correct decisions about the patterns or pattern classes. Hence, the biometric system considers pattern recognition to identify and classify the individuals, in order to compare it with the stored templates.

Pattern recognition technique draws a random pattern of human trait into a compact digital signature, which is served as a biological identifier. The biometric systems use pattern recognition techniques to classify the users and identify them separately in order to compare it with the stored template. Here are the components below-
1)Data acquisition
2)Pre-processing
3)Feature extraction
4)Evaluation
5)Decision maker

Data acquisition is the process of sampling signals that measure real world physical conditions and converting the resulting samples into digital numeric values that can be manipulated by a computer. Data acquisition systems, abbreviated by the acronyms *DAS* or *DAQ*, typically convert analog waveforms into digital values for processing. The components of data acquisition systems include:

- Sensors, to convert physical parameters to electrical signals.

- Signal conditioning circuitry, to convert sensor signals into a form that can be converted to digital values.
- Analog-to-digital converters, to convert conditioned sensor signals to digital values.

Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which input is an image and output may be image or characteristics/features associated with that image.

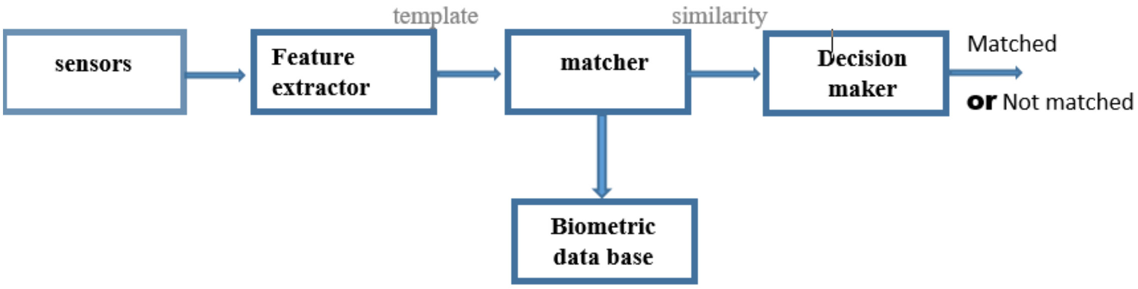
Feature extraction is the process which analysis images to extract features that are important inputs to stage selection. Features are automatically extracted from the images. All features can be coarsely classified into low level features and high level features. Low level features can be extracted directed from the original images, whereas high level feature extraction must be based on low level features.

Evaluation is a systematic determination of a subject's merit, worth and significance, using criteria governed by a set of standards. It can assist an organization, program, design, project or any other intervention or initiative to assess any aim, realisable concept/proposal, or any alternative, to help in decision-making,or to ascertain the degree of achievement or value in regard to the aim and objectives and results of any such action that has been completed. The primary purpose of evaluation, in addition to gaining insight into prior or existing initiatives, is to enable reflection and assist in the identification of future change.

Decision maker: Deployment of biometric systems in the specific environment is not straightforward. Based on pre-deployment performance test results, a decision maker needs to consider the selection of sensors and matching algorithms in terms of the cost, expected false-match and false-non-match failure rates and the underlying quality factors. Which depend on operational scenarios, personnel training, demographics.

Biometrics allows a person to be identified and authenticated based on asset of recognizable and verifiable data, which are unique and specific to them

BLOCK DIAGRAM AND EXPLANATION



The core of all biometrics system have five key modules : sensors (image/data acquisition), feature extractor, biometric database, matcher and decision maker.

The sensor reads the biometric information from the user. Feature extractor module extracts features from the biometric data. Matcher module indicates the similarity between extracted features from the user sample and a enrolled template. Biometric database maintains the templates of the enrolled users. Decision maker interprets the result.

SENSOR

The image sensor or imager is a sensor that detects and conveys information used to make an image. It does so by converting the variable attenuation of light waves (as the pass through or reflect off objects) into signals, small bursts of current that convey the information. The waves can be light or other electromagnetic radiation. Image sensors are used in electrical imaging devices of both analog and digital types, which include digital cameras, camera modules, medical imaging equipment, night vision equipment such as thermal imaging devices radar, sonar, and others. As technology changes, digital imaging tends to replace analog imaging.

An image sensor is an electronic device that converts an optical image into an electronic signal. It is used in digital cameras and imaging devices to convert the light received on the camera or imaging device lens into a digital image.

An image sensor is a device used primarily in standalone or embedded digital cameras and imaging devices. Typically, when light strikes the lens of a camera, the image sensor captures that light, convert it into an electronic signal and then transmits it to the camera or imaging device processor, which transforms the electronic signal into a digital image

In an image sensor, a part of the camera’s hardware that captures light and converts what you see through a view finder or LCD monitor into an image. The soul of digital camera is its sensor-to determine the image size, resolution, low light performance, depth of field, dynamic range, lenses, and even the camera’s physical size, the sensor is key. Think of the sensor as the electronic equipment of film. With film cameras, you could choose from hundreds of film brands, each with its own unique and identifiable characteristics. With digital cameras, much of that technology built into the hardware, and you can apply special filmlike effects later with software. Camera’s sensor determines how good our images look like and how large you can scale them or print them. Image quality depends not only on the size of the sensor, but also on how many millions of pixels (light sensitive photosites) fit on it, and the size of those pixels. The sensor size also effects what you see through the viewfinder-the relationship between what you are shooting and what actually gets recorded in the frame and passed through the memory card. Smaller sensors apply a crop factor to lenses, capturing less of the scene than full frame sensors do. The full frame reference point is always traditional 35mm film.

The most common types of sensors are CCD (charged coupled device) and CMOS (complementary metal oxide semiconductor).

CCD is one of the oldest image capture technologies for digital cameras and has long offered superior image quality compared with CMOS sensors, with better dynamic range and noise control. Although CCD is still prevalent in budget compact models, its basic construction and greater power consumption have for the large part prompted camera manufactures to replace it with CMOS alternatives. CMOS has been considered an inferior competitor to CCD, but today's CMOS sensors have been upgraded to match and even transcend the CCD standard. With more built in functionality than CCDs, CMOS sensors work more efficiently, require less power, and perform better for high speed burst modes.

Here in this project we use Frontech camera as sensor. The driver update utility for Frontech devices is intelligent software which automatically recognizes your computers operating system and camera model and find the most up to date drives for it. The driver update utility downloads and installs your drives quickly and easily.

FEATURE EXTRACTOR

In machine learning, pattern recognition and in image processing feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non redundant, facilitating the subsequent learning and generalization steps and in some cases leading to better human interpretations. Feature extraction is a dimensionality reduction process, where an initial set of raw variables is reduced to more manageable groups (features) for processing while still accurately and completely describing the original data set.

When the input data to an algorithm is too large to be processed and it is suspected to be redundant then it can be transformed into a reduced set of features. Determining the subset of the initial feature is called feature selection. The selected features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data.

In general feature extraction involves reducing the amount of resources required to describe a large set of data. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power, also it may cause a classification algorithm to overfit to training samples and generalize poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy. Many machine learning practitioners believe that properly optimized feature extraction is the key to effective model construction.

Feature extraction is the process which analysis images to extract features that are important inputs to stage selection. Features are automatically extracted from the images. All features can be coarsely classified into low level features and high level features. Low level features can be extracted directed from the original images, whereas high level feature extraction must be based on low level features.

The feature extraction algorithm extracts significant components from the biometric sample and converts it into biometric data so that it can be matched to a reference template in the database. The number of features are reduces and used in the classification task.

Features plays an important role in the area of image processing. Before getting features, various techniques like binarization, thresholding, resizing, normalization etc. are applied on the sampled image. After that, feature extraction techniques are applied to get features that will be useful in classifying and recognition of images. Feature extraction techniques are helpful in various image processing applications e.g.character recognition. As features define the behaviour of an image they shoe its place in terms of storage taken, efficiency in classification and obviously in time consumption also.

All images consist of pixels. Considering each pixel can have 8 bit value, even a 640*480 image will have 640*480*8 bits of information. Too much for a computer to make a computer head or tail out of ot directly. So in feature extraction we figure out what parts of an image are distinctive, like lines, corners, special patches that can uniquely describe the image.

Feature extraction(like how to represent intersecting point which we found to compare with other intersecting point(feature), ex - local orientation of area around the point etc), Feature detection(like to find some intersecting point(feature) in an image, ex - To find corner, layout etc) are often used to solve common computer vision problem like image detection, recognition. When image sizes are large, reduced feature representation require to quickly complete the tasks.

Some common feature extraction technique:

Histogram of Oriented Gradients (HOG) - In HOG, The distribution (histograms) of directions of gradients (oriented gradients) are used as features.

Color histograms - A histogram represents the distribution of colors in an image. It can be visualized as a graph (or plot) that gives a high-level intuition of the intensity (pixel value) distribution.

LBP(Local binary patterns) - LBP is a type of visual descriptor used for classification in computer vision**.** It computes local representation of texture, which is constructed by comparing each pixel with its surrounding neighborhood of pixels.

Some common feature detection technique:

Harris Corner Detection - It basically finds the difference in intensity for a displacement of (u, v) in all directions.

SIFT(Scale- invariant feature transform) -

SURF(Speeded-up robust features) - It is speed-up version of SIFT. SURF is a patented local feature detector and descriptor.

Feature extraction methods encompass, besides the traditional transformed and non transformed signal characteristics and texture, structural and graph descriptors. In general, Feature extraction is an essential processing step in pattern recognition and machine learning tasks. We therefore need to transform the initial data representation to a more suitable one, by extracting audio features that represent the properties of the original signals while reducing the volume of data. The feature is defined as a function of one or more measurements, each of which specifies some quantifiable property of an object, and is computed such that it quantifies some significant characteristics of the object. We classify the various features currently employed as follows:

• General features: Application independent features such as color, texture, and shape. According to the abstraction level, they can be further divided into: -

Pixel-level features: Features calculated at each pixel, e.g. color, location.

Local features: Features calculated over the results of subdivision of the image band on image segmentation or edge detection.

Global features: Features calculated over the entire image or just regular sub-area of an image.

• Domain-specific features: Application dependent features such as human faces, fingerprints, and conceptual features. These features are often a synthesis of low-level features for a specific domain. Other features considered in image are as follows

COLOR FEATURE

The color feature is one of the most widely used visual features in image retrieval. Images characterized by color features have many advantages:

• Robustness. The color histogram is invariant to rotation of the image on the view axis, and changes in small steps when rotated otherwise or scaled. It is also insensitive to changes in image and histogram resolution and occlusion.

• Effectiveness. There is high percentage of relevance between the query image and the extracted matching images.

• Implementation simplicity. The construction of the color histogram is a straightforward process, including scanning the image, assigning color values to the resolution of the histogram, and building the histogram using color components as indices.

• Computational simplicity. The histogram computation has $O(X, Y)$ complexity for images of size $X \times Y$. The complexity for a single image match is linear, $O(n)$, where n represents the number of different colors, or resolution of the histogram.

• Low storage requirements. The color histogram size is significantly smaller than the image itself, assuming color quantisation.

TEXTURE FEATURE

Texture feature is another important property of images. Texture is a powerful regional descriptor that helps in the retrieval process. Texture, on its own does not have the capability of finding similar images, but it can be used to classify textured images from non-textured ones and then be combined with another visual attribute like color to make the retrieval more effective.

Texture has been one of the most important characteristic which has been used to classify and recognize objects and have been used in finding similarities between images in multimedia databases.

In general, feature extraction is an essential processing step in pattern recognition and machine learning tasks. We therefore need to transform the initial data representation to a more suitable one, by extracting audio features that represent the properties of the original signals while reducing the volume of data.

MATCHER

The matcher component of the system compares feature vector obtained from the feature extraction algorithm to produce a similarity score. This score indicates the degree of similarity between a pair of biometrics data under consideration. In this project we use matcher for template matching

Pattern recognition occurs when information from the environment is received and entered into short term memory, causing automatic activation of a specific content of long term memory. An early example of this is learning the alphabet in order. When a carer repeats ‘A, B, C’ multiple times to a child, utilizing the pattern recognition, the child says ‘C’ after he/she hears ‘A, B’ in order. Recognizing patterns allow us to predict and expect what is coming. The process of pattern recognition involves matching the information received with the information already stored in the brain. Making the connection between memories and information perceived is a step of pattern recognition called identification. Pattern recognition requires repetition of experience. Semantic memory, which is used implicitly and subconsciously is the main type of memory involved with recognition.

Pattern recognition is not only crucial to humans, but to other animals as well. Even koalas, who possess less-developed thinking abilities, use pattern recognition to find and consume eucalyptus leaves. The human brain has developed more, but holds similarities to the brains of birds and lower mammals. The development of neural network in the outer layer of the brain in humans has allowed for better processing of visual and auditory patterns. Spatial positioning in the environment, remembering findings, and detecting hazards and resources to increase chances of survival are examples of the application of pattern recognition for humans and animals.

There are six main theories of pattern recognition: template matching, prototype matching, feature analysis, recognition by component theory, bottom-up and top-down processing, and Fourier analysis. The application of these theories in everyday life is not mutually exclusive. Pattern recognition allows us to read words, understand language, recognize friends, and even appreciate music. Each of the theories applies to various activities and domains where pattern recognition is observed. Facial, music and language recognition, and seriation are a few of such domains. Facial recognition and seriation occur through encoding visual patterns, while music and language recognition use the encoding of auditory patterns.

In our project we use template matching, Template matching theory describes the most basic approach to human pattern recognition. It is a theory that assumes every perceived object is stored as a "template" into long-term memory. Incoming information is compared to these templates to find an exact match. In other words, all sensory input is compared to multiple representations of an object to form one single conceptual understanding. The theory defines perception as a fundamentally recognition-based process. It assumes that everything we see, we understand only through past exposure, which then informs our future perception of the external world. For example, A, **A**, and *A* are all recognized as the letter A, but not B. This viewpoint is limited, however, in explaining how new experiences can be understood without being compared to an internal memory template.

Template matching is a technique in digital image processing for finding small parts of an image which match a template image. It can be used in manufacturing as a part of quality control, a way to navigate a mobile robot, or as a way to detect edges in images.

The main challenges in the template matching task are: occlusion, detection of non-rigid transformations, illumination and background changes, background clutter and scale changes.

For templates without strong features, or for when the bulk of the template image constitutes the matching image, a template-based approach may be effective. Since template-based template matching may potentially require sampling of a large number of points, it is possible to reduce the number of sampling points by reducing the resolution of the search and template images by the same factor and performing the operation on the resultant downsized images (multiresolution, or pyramid), providing a search window of data points within the search image so that the template does not have to search every viable data point, or a combination of both

BIOMETRIC DATABASE

Biometrics is the technical term for body measurements and calculations. It refers to metrics related to human characteristics. Biometrics authentication (or realistic authentication) is used in computer science as a form of identification and access control. It is also used to identify individuals in groups that are under surveillance.

Biometric identifiers are the distinctive, measurable characteristics used to label and describe individuals. Biometric identifiers are often categorized as physiological versus behavioural characteristics. Physiological characteristics are related to the shape of the body. Examples include, but are not limited to fingerprint, palm veins, face recognition , DNA, palm print, iris recognition, retina and odour/scent. Behavioural characteristics are related to the pattern of behaviour of a person, including but not limited to typing rhythm, gait , and voice. Some researchers have coined the term behaviometrics to describe the latter class of biometrics.

More traditional means of access control include token-based identification systems, such as a driver's license or passport, and knowledge-based identification systems, such as a password or personal identification number. Since biometric identifiers are unique to individuals, they are more reliable in verifying identity than token and knowledge-based methods; however, the collection of biometric identifiers raises privacy concerns about the ultimate use of this information.

A biometric system is a technological system that uses information about a person (or other biological organism) to identify that person. Biometric systems rely on specific data about unique biological traits in order to work effectively. A biometric system will involve running data through algorithms for a particular result, usually related to a positive identification of a user or other individual.

Biometric data types vary. Here are six.

Face recognition: Measures the unique patterns of a person's face by comparing and analyzing facial contours. It's used in security and law enforcement but also as a way to authenticate identity and unlock devices like smartphones and laptops.

Iris recognition: Identifies the unique patterns of a person's iris, which is the colorful area of the eye surrounding the pupil. Although widely used in security applications, it isn't typically used in the consumer market.

Fingerprint scanner: Captures the unique pattern of ridges and valleys on a finger. Many smartphones and some laptops use this technology as a type of password to unlock a screen.

Voice recognition: Measures the unique sound waves in your voice as you speak to a device. Your bank may use voice recognition to verify your identity when calling about your account, or you'll use it when giving instructions to a smart speaker like Amazon's Alexa.

Hand geometry: Measures and records the length, thickness, width, and surface area of a person's hand. These devices date back to the 1980s and were typically used in security applications.

Behavior characteristics: Analyzes the way you interact with a computerized system. Keystrokes, handwriting, the way you walk, how you use a mouse, and other movements can assess who you are or how familiar you are with the information you're entering.

A biometric system consists of three different components:

Sensor: This is what records your information, as well as reads it when your biometric information needs to be recognized.

Computer: Whether you're using your biometric information to access a computer or something else, there has to be a computer storing the information for comparison.

Software: The software is basically whatever connects the computer hardware to the sensor.

In our project we use vein patterns recognition ,biometric database maintains the templates of the enrolled users. Vein recognition is a method of biometric that uses pattern recognition techniques based on images of blood vessel. Blood vessel patterns are unique to each individual. Vein recognition does not require contact during registering and authentication and is a strong immunity to forgery.

In the biometrics applications we have two approach:

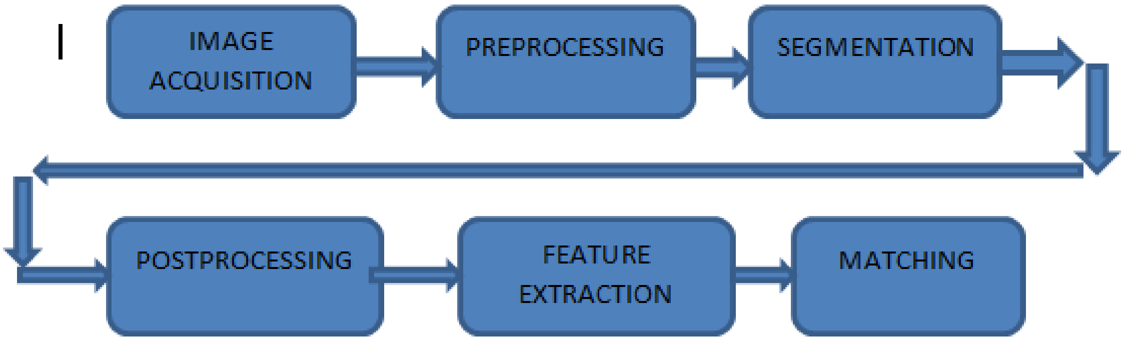
1)in the identification process user is required to cooperate in the image capture.

2)user does not apply in the capture process

IMPLEMENTATION AND RESULT

7.1 SYSTEM OVERVIEW

Pattern recognition systems can exist in endless forms, dealing with problems in many different fields and using different methods to achieve their goals. In spite of this, most, if not all, systems tend to follow the same overall structure.



The hand vein pattern recognition system of this project is designed according to this general structure. It has been implemented in C++ using Armadillo [24], a linear algebra library, and the image library DevIL [25]. The following list explains the purpose of each block.

7.1.1 IMAGE ACQUISITION & PREPROCESSING

The image acquisition and the preprocessing steps are discussed in details. The image of the hand is captured using an ordinary webcam that has been modified to only allow infrared light to reach the image sensor. To normalize the images and limit movement and rotation of the hand, a setup has been built specifically for the purpose. After taking the image and before extraction of the vein pattern, preprocessing is applied to the image. The purpose of this step is to improve the imaging quality so that vein patterns can be more easily detected during the segmentation. This is done by first cropping the image to isolate the ROI, And then applying filters to reduce noise and enhance the contrast

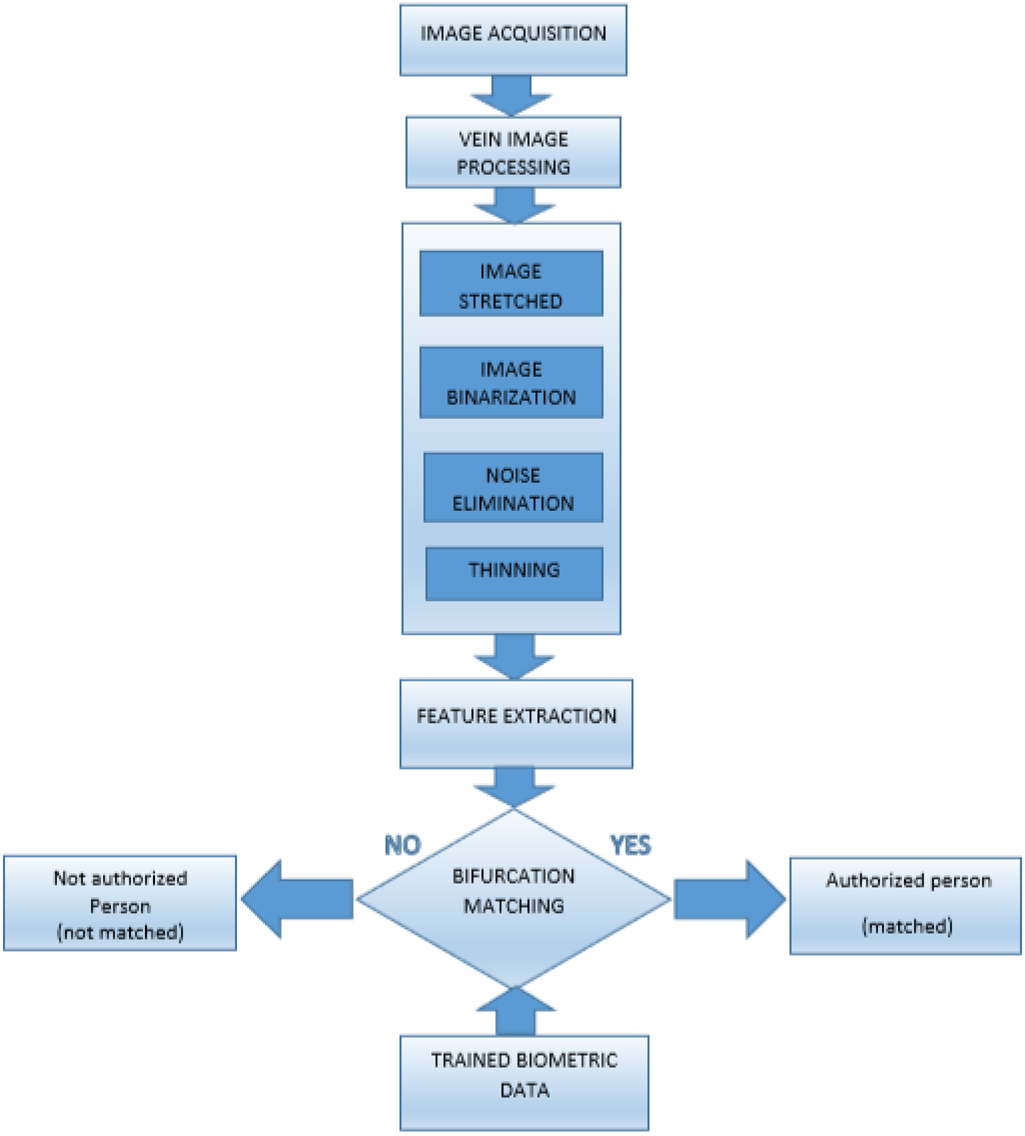
7.1.2 SEGMENTATION & POST-PROCESSING

Once the noise has been reduced and the contrast enhanced, segmentation permits to separate the vein pattern from the background. Indeed, the vein pattern is located and isolated from the rest of the image, thus binarizing it. This is the most crucial step in the entire recognition process. If the veins are not properly detected, the risk of errors increases greatlyThe output image of the segmentation step is a binary image with some unwanted information such as noise, shadows and faint veins. Therefore it is not always a true representation of the actual vein pattern.

7.1.3 FEATURES EXTRACTION & MATCHING

The last two steps of the system, features extraction and matching.. The feature extraction step aims to extract the actual features of the vein pattern, from an image, that then are going to be used for matching. If the image is a enrolled sample, the features are saved in a database for later matching.Once the features are extracted, they are compared with the ones in the database and based on that comparison a decision is taken. Basically the decision comes down to if the input features are similar to a set in the database, the image is identified accordingly, otherwise it is rejected

7.1.3 FLOW CHART



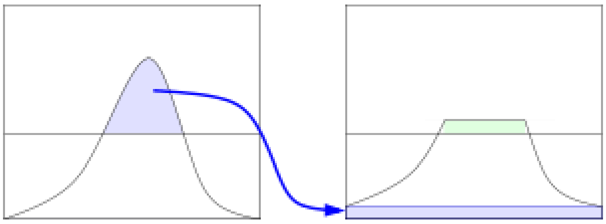
7.1.4 IMAGE ACQUISITION

The forearm vein image usually has poor contrast, non-uniform gray level and noise. Contrast enhancement improves the image. For contrast enhancement of image we used CLAHE (Contrast Limited Adaptive Histogram Equalization) . This technique divides the image into a equal sized blocks and then performs contrast limited histogram equalization on each block. The contrast limiting is done by clipping the histogram before histogram equalization.

Ordinary AHE tends to overamplify the contrast in near-constant regions of the image, since the histogram in such regions is highly concentrated. As a result, AHE may cause noise to be amplified in near-constant regions. Contrast Limited AHE (CLAHE) is a variant of adaptive histogram equalization in which the contrast amplification is limited, so as to reduce this problem of noise amplification.

In CLAHE, the contrast amplification in the vicinity of a given pixel value is given by the slope of the transformation function. This is proportional to the slope of the neighbourhood cumulative distribution function (CDF) and therefore to the value of the histogram at that pixel value. CLAHE limits the amplification by clipping the histogram at a predefined value before computing the CDF. This limits the slope of the CDF and therefore of the transformation function. The value at which the histogram is clipped, the so-called clip limit, depends on the normalization of the histogram and thereby on the size of the neighbourhood region. Common values limit the resulting amplification to between 3 and 4.

It is advantageous not to discard the part of the histogram that exceeds the clip limit but to redistribute it equally among all histogram bins.



The redistribution will push some bins over the clip limit again (region shaded green in the figure), resulting in an effective clip limit that is larger than the prescribed limit and the exact value of which depends on the image. If this is undesirable, the redistribution procedure can be repeated recursively until the excess is negligible.

Contrast enhancement is an important aspect of vein pattern recognition due to uneven lighting and low contrast across the biometric sample as captured by infrared sensitive devices. The contrast between vein structures and the surrounding tissue is of special interest because the quality of the subsequent feature extraction depends on how well the vein structure can be separated from the rest of the image. Furthermore, the complexity of segmenting the image is lowered if the veins are clearly separated from the surrounding tissue. For the purposes of vein patterns it is desirable that the captured image has a high contrast.

7.1.5 PREPROCESSING

This section describes the methods that are used to preprocess the input images. The preprocessing step serves two main purposes. The first is smoothing and noise removal. Since the images are captured using a modified consumer webcam, considerable noise can occur in the images. Gaussian and median filters are used to remedy the effect of this noise. The second is contrast enhancement. This is necessary as the vein pattern can be faint. Histogram stretching is used to add contrast between the veins and the background.

7.1.5.1MEDIAN.FILTERING

Source of noise in the images is hairs, that show up as very thin dark lines. A way to remove these is to use a median filter. The median filter works by replacing pixel values with the median value of that area. This is done by iterating through every pixel in an image and looking at its neighbours within a specified distance. These pixel values are then gathered and sorted. The value in the middle of the resulting set is then chosen to be the center pixels new value. As an example, consider the following pixel and its neighbours within a radius of 1:

124	124	124
126	$>$**203**$<$	203
128	130	124

The set of surrounding pixel values is thus:

P = {124,124,126,203,128,130,124,203,124}

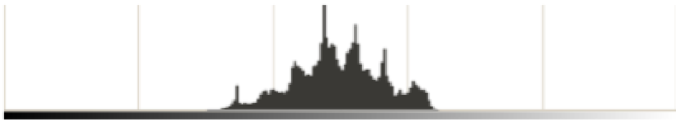
Sorting them according to value yields the following set:

Psorted = {124,124,124,124,126,128,130,203,203}

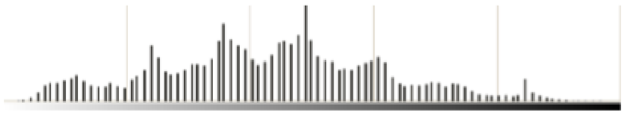
And by choosing the value in the middle, the pixel’s new value is 126.

7.1.6 CONTRAST ENHANCEMENT WITH HISTOGRAM STRETCHING

While the use of IR image capturing makes the veins stand out more clearly, it is often necessary to further improve the contrast before segmenting the image. A simple but very effective method to do this is histogram stretching. This method exploits the fact that most images pixel values don’t span the entire range of possible values from 0 to 255. In the input images, the pixel values tend to be distributed closely together near the middle of the histogram, as shown below



Histoghram of sample image



Stretched histogram of the sample image

In the simplest form, a histogram stretching algorithm uses the lower limit a and the upper limit b to transform the colors in the image. All color values in between a and b will be transformed so they span the entire range from 0 to 255. The colors below a and above b will be set to 0 and 255 respectively. The first step is to find c which is the mean of a and b

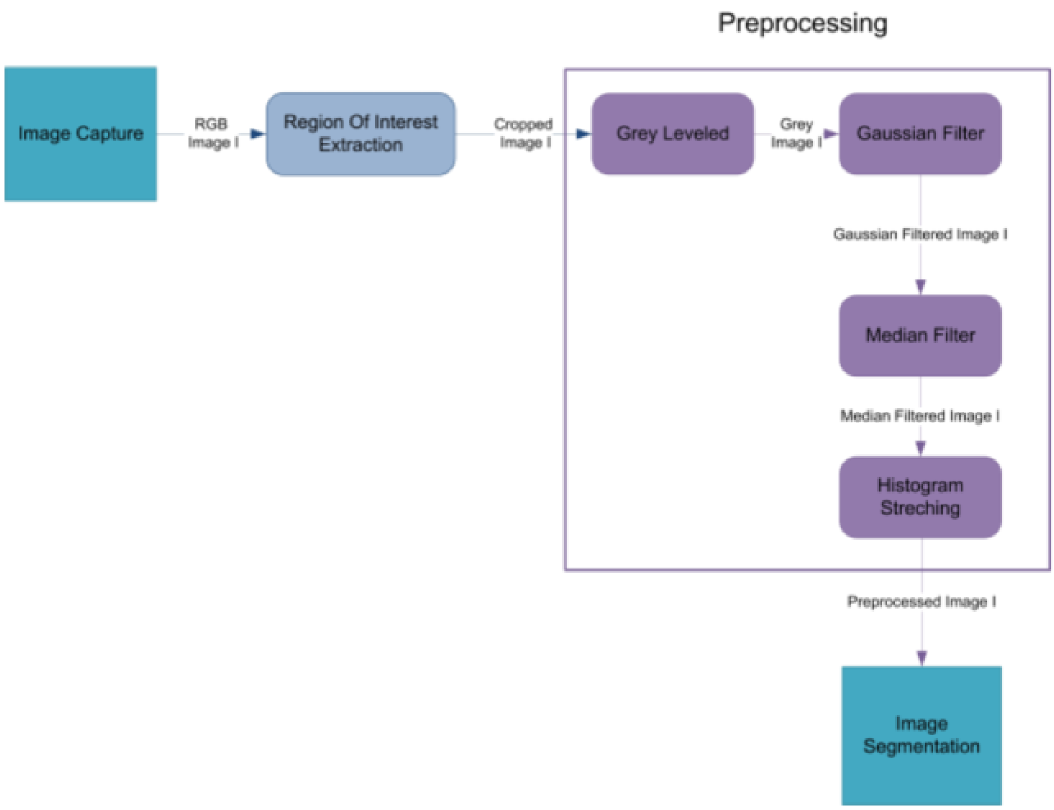
$$c = a + \frac{b-a}{2}$$

Then every pixel in the image is transformed as follows:

$$T(x) = \begin{cases} 128 + \frac{x-c}{b-c} \cdot 127, & b \geq x \geq c \\ \frac{x-a}{c-a} \cdot 127 & a \leq x < c \\ 0 & x < a \\ 255 & x > b \end{cases}$$

Using this method, the color space is stretched equally around the mean of the two limits. An extension is to let c be a variable in between a and b. This allows for uneven stretching around c which is a simple form of gamma correction

After the ROI extraction, the cropped version of the picture is used in the preprocessing. The preprocessing is composed by two low-pass filters. First a smoothing Gaussian low-pass filter is applied to remove noises in the image. And then a median filter is used to reduce noise due to hairs. At the end of the preprocessing a stretching histogram is applied in order to enhance contrast and prepare the image to be segmented.



Flow chart of preprocessing

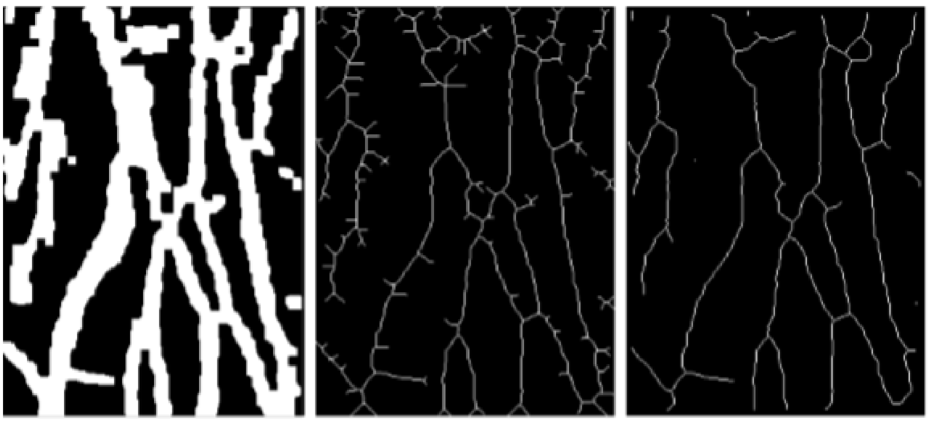
7.1.7 FEATURE EXTRACTION METHODS

This section describes two methods for extracting features from a vein pattern. The first is thinning, which condenses the vein pattern until it is only 1 pixel wide. The next method extracts the end- and crossing points from the thinned vein pattern.

7.1.7.1 THINNING

Depending on different factors such as the ambient temperature, the diameter of veins can vary a lot even for one person. The global shape of the vein pattern needs to be extracted in order to perform an accurate recognition. To obtain a good representation of the shape of a vein pattern, the project focus on the extraction of what is called the skeleton of the vein pattern. The term skeleton describes the representation of a pattern by a collection of thin arcs and curves [30]. Few methods exist to do so including skeletonisation and thinning. The concept of them is to convert binary shapes to 1-pixel wide lines.

Figure shows the results of the skeletonisation and the thinning algorithm. As it can be seen, the thinning algorithm extract only the global shape of the pattern whereas the skeletonisation also extract the size the pattern had on the input binary image. Both methods could be used, however due to its result the thinning algorithm is



a)orginal binary image, b)skeletonisation, c)thinning

7.1.7.2 METHOD

The method used to implement thinning as described in [30] is to obtain the skeleton of a pattern by iteratively remove layers of pixels on the boundary, without shortening it or breaking it apart. Depending on the way the algorithm examines pixels, the thinning algorithm is called either parallel or sequential. In parallel thinning, only the result of the previous iteration is used to examine the deletion or not of pixels, whereas in sequential thinning, contour points are examined for deletion in a predetermined order (this can be accomplished by scans or by contour following). This project focus on parallel algorithm.

The usual parallel thinning algorithm is a succession of iterations. Furthermore, this algorithm divides each iteration into sub-iterations in which are regarded for deletion only a subset of contour pixels.

To decide whether a pixel P should be deleted or preserved, its 8 neighbors in the 3×3 neighborhood need to be observed.

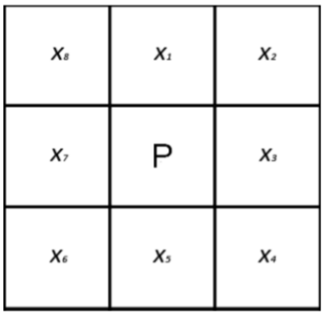


Illustration of the repartition of the pixels for the Thinning.

The algorithm examines the 3×3 local neighbors of a white pixel P. The 8-neighbors of P are the pixels x1, x2,... x8. These pixels are denoted N(P). The 4-neighbors of P are the pixels x1, x3, x5 and x7. Moreover b is defined as the number of white pixel in N(P).

The thinning algorithm is implemented by using the crossing number Xh(P) to examine pixels for deletion in two sub-iterations. The crossing number as defined in equation 6.1 is, most of the time, equal to the number of white pixels in N(P), however Xh(P) = 0 when the 4 neighbors of P are in white.

$$X_h(P) = \sum_{i=0}^{4} b_i$$

$$\text{where } b_i = \begin{cases} 1 \text{ ,if } \ x(2i-1) == 0 \textbf{ and } [\ x(2i) == 1 \textbf{ or } x(2i+1) == 1\ ] \\ 0, \text{ otherwise} \end{cases}$$

A two-part algorithm is implemented. For the first one, if P is a contour pixel with b > 1 and Xh(P) = 1 then P is deleted by each sub-iteration in one of the two distinct subfields of the image. The other part deletes P if and only if the conditions below are fully fulfilled:

Xh(P) = 1

[x1 or x2 or x4] and x3 = 0 in the first sub-iteration and its 180 deg rotation in the second.

2 ≤ min(n1(P),n2(P))<3

$$\text{where } \mathrm{n}_1(P) = \sum_{i=0}^{4} [x(2i-1) \ \textbf{or} \ x(2i)]$$

$$\text{and } \mathrm{n}_2(P) = \sum_{i=0}^{4} [x(2i) \ \textbf{or} \ x(2i+1)]$$

n1(P) and n2(P) represent the number of 4 adjacent pairs of pixel in N(P) containing one or two white pixels.

Even if this algorithm permits to obtain a good skeleton of the vein pattern, the result can be improved by reducing the number of unnecessary small branches. The algorithm used to do so is called pruning.

7.1.7.3 SYSTEM TRAINING & VALIDATION

7.1.7.3.1 ENROLLMENT PROCEDURE

For every individual in the test group, the following steps have been performed to enroll them into the system:

1. The test subject places his/her right hand in the setup so that the thumb and index finger is separated by the left restraining pin. The subject grabs the bar tightly while pushing his/her hand as far to the right as made possible by the right-side restraining pin. The operator verifies that the immediate visual quality of the image is good, then takes a photo.

2. The test subject removes his/her hand from the setup and waits for 5 seconds.

3. The procedure is repeated from point 1, 16 times

It is important to note that this enrollment procedure is solely for collecting training data for the system.

7.1.7.3.2 DETERMINING THE NECESSARY AMOUNT OF MATCHING SAMPLES

This section covers the experimental procedure intended to estimate how much matching data is needed per class, in order for the system to perform correct classification, the matching procedure calculates the average distance between a sample image and all matching samples for a given class. Thus the more matching samples each class has, the more computation time increases. It is therefore desirable to reduce the amount of matching samples in each class as much as possible. The procedure to do so is explained in this section.

The test procedure is as described below:

1. 4 training samples from each class are picked out from the database and used as test images.

2. d(Xj,ωi) is calculated for all i and j.

3. If Xj and ωi are from the same class, the calculated distance is labelled as similar. Otherwise it is labelled as non-similar.

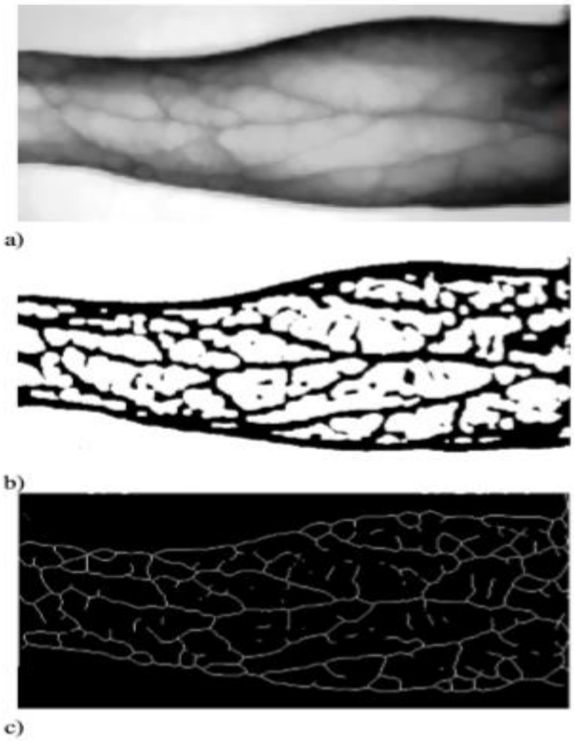
4. A graph is made showing the similar and non-similar distances.

5. A new test setup is generated with one less matching sample per class.

6. These steps are repeated until no more matching sample remains in the database.

After the data is collected, each graph is compared in order to evaluate which number of matching samples is needed.

8.2 SNAP SHOTS

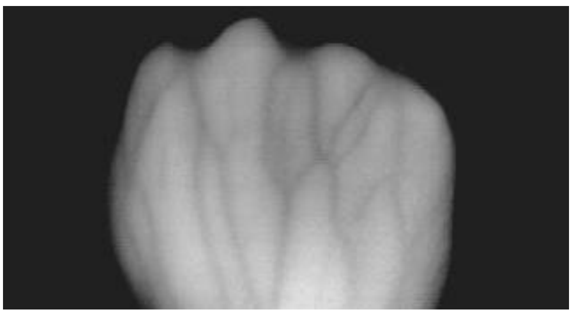


a)Orginal.forearm,veinimage

b)Binarized.image

c)skeleton.image

orginal vein image



NIR image

8. CONCLUSION AND FUTURE ENHANCEMENT

8.1 CONCLUSION

This section covers in details the different methods used in this project. As stated previously, pattern recognition system can exist in many different forms, using various different methods to achieve their goal. This project follows an overall structure that is used by most, if not all, pattern recognition system. This overall structure is composed by first image acquisition followed by preprocessing, segmentation and post-processing, finally feature extraction and recognition are performed. Each step of this structure plays an important role in the whole system and their functions have been studied to best respond to this project aim, which is to create an efficient low cost pattern recognition system based on vein hand pattern.

Image acquisition is done using an cheap consumer webcam, modified to take pictures in the NIR wavelength. A setup has been built to normalize the images and restraint the hand movements (translation and rotation) in order to properly extract a fixed ROI. The image taken is then preprocessed using a Gaussian filter followed by a median filer for a double noise reduction and an histogram stretching to enhance the image contrast.

Among various segmentation algorithm available for vein pattern recognition systems, the segmentation of the image was chosen to be done using local thresholding in conjunction with a direction based vascular pattern algorithm. This algorithm is divided in two filters that extract the abscissa and the ordinate vascular pattern and finally it combines the locally thresholded results of these filters to obtain an image with full vein pattern segmentation and few connectivity losses. This output image is then post-processed using morphological operators (opening, closing) and finally a blob removal is applied to remove blobs that are not part of the vein pattern.

The feature extraction was chosen to be done using a thinning algorithm. This algorithm transforms the binary segmented image, that varies for the same hand according to the variation of the diameter of the veins, into the global shape of the vein pattern, called a skeleton. It is followed by a pruning algorithm, that is used in order to get rid of small unnecessary branches in the skeleton of the vein pattern. Once the skeleton is fully extracted, the recognition is made using MHD. Based on the resulting distance, a decision is made based on the threshold: if the distance is below, the sample is recognized as belonging to an authorized person, otherwise it is rejected.

The system has been trained using images from 5 test participants . It should be noted that this test group has been somewhat narrow, and therefore cannot be considered a general representation of the population. The results showed a True Acceptance Rate (TAR) of 86% on the training data with a False Acceptance Rate (FAR) of only 0.4%. On the new validation data, a true acceptance rate of 65% was achieved with no false acceptances. As the goal was to minimize the FAR while maintaining an acceptable TAR, these results are considered satisfactory, especially in light of the high FTE rate that was observed. This is believed to be caused mainly by problems with the capture setup and is not due to the methods themselves.

8.2 FEATURE ENHANCEMENT

The goal of the author is to develop methods that can be used for forearm feature extracted based on bifurcation characteristic points. In future work, we will develop the use of global knowledge of vein patterns to enhance the matching accuracy and develop a robust preprocessing method to reduce enhancement errors. The system performed with perfect recognition on a little set of forearm images. We used own forearm vein pattern image database contains 56 forearm vein pattern images. As a next step, the performance of the method must be measured in a recognition application. The method needs to be evaluated with images containing artifacts.

The project as new is not of high order security. If the pattern of vein have a similarity to another personnels pattern the system provides authorisation

The use of better algorithm can be very useful identification and detection of personnels,and hence can be used for high security providing system

9. REFERENCES

[1] A. K. Jain, P. Flynn, and A. A. Ross, Handbook of Biometrics. Springer, 2008, pp. 253–270.

[2] (2011, May) Definition of biometry. Internet. [Online]. Available: http: //oxforddictionaries.com/view/entry/m en gb0079020

[3] A. K. Jain, A. Ross, and S. Prabhakar, “An introduction to biometric recognition,” IEEE Transactions on Circuits and Systems for Video Technology, vol. 14, no. 1, pp. 4–20, Jan. 2004. [Online]. Available: http://citeseerx.ist.psu.edu/viewdoc/ download?doi=10.1.1.69.3028&rep=rep1&type=pdf

[4] (2011, May) History of biometrics. Internet. [Online]. Available: http: //www.globalsecurity.org/security/systems/biometrics-history.htm

[5] T. Frank. (2007, May) Face recognition next in terror fight. Internet. [Online]. Available: http://www.usatoday.com/news/washington/ 2007-05-10-facial-recognition-terrorism N.htm

[6] M. Kane. Face recognition grew even before 9/11. [Online]. Available: http://news.cnet.com/2100-1023-883730.html

[7] A. Eichmann, L. Yuan, D. Moyon, F. Lenoble, L. Pardanaud, and C. Breant, "Vascular development: from precursor cells to branched arterial and venous networks," International Journal of Developmental Biology, no. 49, pp. 259–267, 2005.

[8] A.-M. Nadort, "The hand vein pattern used as a biometric feature," Master's thesis, Free University, Amsterdam, 2007.

[9] M. Zamir, "On fractal properties of arterial trees," Journal of Theoretical Biology, vol. 197, no. 4, pp. 517–526, 1999.

[10] G. B.West, J. H. Brown, and B. J. Enquist, "A general model for the origin of allometric scaling laws in biology." Science, no. 276, pp. 122–126, 1997.

[11] W. Schreiner, R. Karch, M. Neumann, F. Neumann, S. M. Roedler, and G. Heinze, "Heterogeneous perfusion is a consequence of uniform shear stress in optimized arterial tree models." Journal of Theoretical Biology, no. 220, pp. 285–301, 2003.

[12] A. Devillard. (2007, July) Des candidats a un examen identifies par les veines de la main. Internet. [Online]. Available: http://www.01net.com/editorial/504337/ des-candidats-a-un-examen-identifies-par-les-veines-de-la-main/

[13] (2011) Federal sensors popular thermal imaging systems. Internet. [Online]. Available: http://www.federalsensors.com/thermal-imager-s/161.htm

[14] L. Wang, G. Leedham, and D. S.-Y. Cho, "Minutiae feature analysis for infrared hand vein pattern biometrics," Pattern Recognition, vol. 41, pp. 920–929, 2008.

[15] A. Kumar and K. V. Prathyusha, "Personal authentification using hand vein triangulation and knuckle shape," IEEE Transactions on Image Processing, no. 38, pp. 2127–2136, 2009.

[16] H.-S. Choi, "Apparatus and method for identifying individuals through their subcutaneaouc vein patterns and integrated system using said apparatus and method," US Patent #006302375B1, 2001, assignees: BK Systems, Seoul and H.S. Choi.

[17] L. Wang and G. Leedham, "A thermal hand vein pattern verification system," Lecture Notes in Computer Science, pp. 58–65, 2005.

[18] Y. Ding, D. Zhuang, and K. Wang, “A study of hand vein recognition method,” in International Conference on Machatronic and Automation. Niagara Falls, Canada: IEEE, 2005.

[19] J. Cross and C. Smith, “Thermographic imaging of the subcutaneous vascular network of the back of the hand for biometric identification,” in Security technology, 1995. Proceedings. Institute of Electrical and Electronics Engineers 29th Annual 1995 International Carnahan Conference on. Sanderstead, UK: IEEE, 1995.

[20] S. K. Im, H. S. Choi, and S.-W. Kim., “A direction-based vascular pattern extraction algorithm for hand vascular pattern verification,” ETRI journal, vol. 5, no. 2, pp. 101–108, 2003.

[21] N. Miura, A. Nagasaka, and T. Miyatake, “Personal identification device and method,” US Patent #2005/0047632A1, 2005.

[22] A. Nagasaka, T. Miyatake, and N. Miura, “Feature extraction of finger-vein patterns based on repeated line tracking and its application to personal identification,” Machine Vision and Applications, vol. 15, pp. 194–203, 2004.

[23] K. Fan, C.-L. Lin, and W.-L. Lee, “A study of hand vein recognition method,” in 16th IPPR Conference on Computer Vision, Graphics and Image Processing. Kinmen, ROC: IPPR, August 2003.

[24] (2011, April) Armadillo: C++ linear algrabra. Internet. [Online]. Available: http://arma.sourceforge.net/

[25] (2010, June) Devil, a full featured cross-platform image labrary. Internet. [Online]. Available: http://openil.sourceforge.net/

[26] L. Inc. (2011) Logitech quickcam pro 9000 webcam description. Internet. [Online]. Available: http://www.logitech.com/en-us/webcam-communications/ webcams/devices/6333

[27] (2011) Cmos technology for scientific imaging. Internet. [Online]. Available: http://spectroscopyonline.findanalytichem.com/spectroscopy/Articles/ CMOS-Technology-for-Scientific-Imaging/ArticleStandard/Article/detail/713402

[28] (2011) Color film negative makes visible light blocking filter. Internet. [Online]. Available: http://www.discovercircuits.com/H-Corner/color%20film%20filter.htm

[29] F. Shafait, D. Keysers, and T. Breuel, “Efficient implementation of local adaptive thresholding techniques using integral images,” Proc. SPIE, 2008. [Online]. Available: http://www.dfki.uni-kl.de/∼shafait/papers/ Shafait-efficient-binarization-SPIE08.pdf

[30] L. Lam, S. Lee, and C. Suen, “Thinning methodologies - a comprehensive survey,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 14, no. 9, pp. 869–879, September 1992.

[31] G. Bebis, T. Deaconu, and M. Georgiopoulos, “Fingerprint identification using delaunay triangulation,” Proceedings 1999 International Conference on Information Intelligence and Systems, pp. 452–459, 1999.

[32] G. Eguchi. (2001, Oct.) Delaunay triangulation. Powerpoint presentation. [Online]. Available: http://groups.csail.mit.edu/graphics/classes/6.838/F01/lectures/ Delaunay/Delaunay2D.ppt

[33] S. Zhao, Y.-D. Wand, and Y.-H. Wang, “Biometric identification based on lowquality hand vein pattern images,” in Seventh International Conference on Machine Learning and Cybermetrics, Kunming, 2008.

[34] (2007, March) Eroding and dilating image objects. Internet. [Online]. Available: http://idlastro.gsfc.nasa.gov/idl html help/Eroding and Dilating Image Objects.html