CHAPTER 8

VEIN PATTERN RECOGNITION

Hand vein technology is relatively a new biometric technology and still under research. Hence public database for hand veins are still not available. After a detailed study on the methods used for vein recognition, an acquisition setup is designed for capturing veins in the dorsal region of the hand. A database of vein patterns is created. The vein pattern recognition system is implemented as seen in Figure 8.1

![Vein Pattern Recognition Diagram](image)

**Figure 8.1 Vein Pattern Recognition**

8.1 IMAGE ACQUISITION

8.1.1 Imaging Wavelength

Vein patterns cannot be observed using normal, visible light since they are beneath the skin’s surface. Moreover, features, such as moles, warts, scars, pigmentation, and hair usually cover the vein pattern. In addition, subcutaneous fat may also obscure the visibility of the vein pattern.

Two Infrared imaging techniques are generally used to capture the vein pattern. If the sensitive spectrum of an IR camera is 3–5 or 8–14 µm, the captured images will be absolutely independent of visible light which is with
a spectrum at 0.4–0.7 \( \mu m \). Thus, the effects of unwanted skin surface features
caused by visible light can be avoided to reduce the complexity of thermal
images. In addition, the IR images are robust under a wide range of lighting
conditions and exhibit high contrast.

Far-Infrared technique (wavelength range 3-5 \( \mu m \)) is based on the
fact that all objects emit infrared radiation when they are heated. The
superficial human vein has higher temperature than the surrounding tissues
and emits far infrared radiation, which can be captured by an IR camera of 3-5
\( \mu m \) wavelength. Vein patterns can also be viewed through an image sensor
which is sensitive to near-infrared light (wavelength range 8-14 \( \mu m \)). The
near-infrared light passes through human body tissues; the reduced
hemoglobin in venous blood absorbs more of the incident IR radiation than
the surrounding tissue thus appearing darker in the near-infrared image.

Far-Infrared imaging technology is very sensitive to both external
and body conditions. The images have low levels of contrast, which makes it
difficult to separate the veins from the background. Also, due to heat
radiation, the tissue near the blood vessels may have similar temperature (and
hence similar gray level in the image) as the vein. This makes it difficult to
locate the exact position of a vein. On the other hand, near-infrared imaging
produces good quality images Yu and Leedham (2006) and is more tolerant to
changes in environmental and body conditions. Since FIR imaging does not
provide a stable image quality, NIR technique is adopted for capturing the
vein pattern.

8.1.2 Experimental Setup

A Charge-Coupled Device (CCD) camera (WAT-902H) is used to
capture the vein images. Sometimes, naturally emitted near IR radiation can
be weak and cannot be detected by the camera’s CCD imager. So IR lighting
is provided by an array of 24 IR LEDs (Light Emitting Diodes) [160] [161]. The diodes are mounted in a square shape, 6 LEDs on each side, of a designed and assembled PCB (printed circuit board). It is mounted in such a way that the LEDs appear attached around the CCD lens. A 7V-DC supply is given to the LED array. The intensity of IR light is good enough to capture the vein patterns, when the voltage of power supply is maintained around 7V. The camera senses the image through a photographic negative film which is used as IR Filter. The intensity of the LED radiation is 100 watts per sq m, which is only 0.019% of the maximum acceptable exposure of 5,100 watts per sq m. Therefore, the LED strength is within a safe level. The CCD camera outputs an analog image signal. Since computers do not accept analog signals, a frame grabber is needed to capture the images for computer processing. Thus the camera is connected to a computer to capture the images using a frame grabber. The entire setup is outlined in Figure 8.2.

Figure 8.2 Outline of the Image Acquisition Setup

8.2 DATABASE CREATION AND ANALYSIS

The volunteer crew consisted of 75 individuals from different age groups. 10 vein images are taken for each individual. Users were asked to always use their right hand. Without this consistency, it would be difficult to observe and prevent use of the wrong hand at enrolment or verification. The “failure to enroll” rate which measures the proportion of individuals for
whom the system is unable to generate repeatable templates was observed to be 0.1% i.e., 1 in 75 individuals. Thus the database consists of 740 images of vein pattern. The age and gender distribution of the volunteer crew is shown in Figure 8.3.

![Figure 8.3 Gender and Age distribution of the volunteer crew](image)

8.2.1 Database Analysis

A brief analysis and few special cases are discussed about the captured vein images.

Case 1:

The clarity of vein pattern is not based on the color of the skin. As shown in the Figure 8.4, the vein pattern is clear for fair skin, medium skin and dark skin.
Figure 8.4 Vein patterns of person with different skin color

Case 2:

For certain persons, the vein pattern is clear in any one hand and not in the other hand as shown in the Figure 8.5.

Figure 8.5 Left and right hand vein patterns of same person

Case 3:

This is highly exceptional case where the vein patterns are not visible for both the hands as shown in Figure 8.6. For such cases, the other biometric traits, such as the finger prints may be useful.
Figure 8.6 Vein images of same person with poor trace of vein patterns

8.3 VEIN IMAGE PROCESSING

The acquired vein images are processed as shown in Figure 8.7

![Vein Image Processing Diagram](image)

Figure 8.7 Vein Image Processing

8.3.1 Smoothing

Noise introduces high frequency components in the image. An anisotropic diffusion process similar to the physical diffusion process where the concentration balance between the molecules depends on the density gradient, is proposed to remove noise. In anisotropic diffusion, for the given image \( u \), the diffusivity ‘\( g \)’ depends on the gradient as shown in Equation (8.1).

\[
\begin{align*}
g & \rightarrow 0 \ for \ \nabla^2 u \rightarrow \infty \\
g & \rightarrow 1 \ for \ \nabla^2 u \rightarrow 0
\end{align*}
\]

(8.1)
The gray value of each pixel is calculated iteratively depending on the gray value gradient in a 4-pixel neighborhood surrounding the pixel. The gradient is calculated using the non-linear diffusion function ‘g’ so that the smoothing is more over the homogenous regions rather than the edges, so that the edges remain sharp. The noisy and noiseless images are shown in Figure 8.8.

Figure 8.8 Noisy and Noiseless Images

8.3.2 ROI Selection

An iterative method is proposed to extract the ROI. The hand image is binarised to extract its outline as shown in Figure 8.9. A rectangle is generated using predefined coordinates which are fixed based on trial experiments conducted on the existing hand vein database images. The values of these coordinates are changed adaptively based on the input test image. The dimensions of the input test image along the X and Y axes are found using horizontal and vertical scans and using this information the values of the coordinates of the rectangle are changed proportionately. The portion of the hand inside the rectangle is extracted as the region of interest as seen in Figure 8.9. The extraction method can be made more robust by obtaining the
region of interest using certain landmark points on the hand such as the valley between the knuckles Im et al (2001). However it was observed that these points are not reliable as their position changes with different clenching pressure in the fist at different instances. Further, in certain vein images, it was observed that few vein structures were present outside the bounding box created using knuckle tips as reference points since the region between the knuckles was quite narrow in these cases due to the inherent shape of the fist.

![Binarised hand image](image1) ![ROI Selection](image2) ![ROI](image3) ![Skeletonised Image](image4)

(a) Binarised hand image   (b) ROI Selection

(c) ROI   (d) Skeletonised Image

Figure 8.9 Extraction of vein patterns

8.3.3 Thinning

The extracted vein image is skeletonised by a morphological
operation called thinning. Figure 8.9 shows the thinned image, where the veins have shrunk to a minimally connected stroke. Then the operator “spur” is used to remove the end points of lines without allowing objects to break apart.

Now, it is required to extract the so called minutia points which are nothing but the bifurcations and terminations in the vein image. Wang et al (2006) extract the endpoints and cross points from vein images similar to the extraction of minutiae points in a fingerprint image. In this work, it is proposed to extract the corners in the fingerprint image as suggested by Sojka (2002). He defines a corner as an intersection of two straight non-collinear gray value edges. Let ‘Q’ be an image point and let Ω be its neighborhood. Certain isolines of brightness are defined in the neighborhood. Let ‘X’ be a point of approximation in an isoline, which has the same brightness as ‘Q’. Here ‘X’ is assumed to approximate ‘Q’. The probability ‘P’ of ‘Q’ lying on the same curve as ‘X’ is calculated. Let g(X) be the size of the brightness gradient and φ(X) represent the direction of the brightness gradient at ‘X’. Let \( w(r(X)) \) be a weight function that represents the distance between ‘Q’ and ‘X’ as seen in Equation (8.2).

\[
W = \sum_{X_i \in \Omega} P(X_i) w(r(X_i)) \tag{8.2-a}
\]

\[
\mu_\phi = \frac{1}{W} \sum_{X_i \in \Omega} P(X_i) w(r(X_i)) \phi(X_i) \tag{8.2-b}
\]

\[
\sigma_\phi^2 = \frac{1}{W} \sum_{X_i \in \Omega} P(X_i) w(r(X_i)) \left[ \phi(X_i) - \mu_\phi \right]^2 \tag{8.2-c}
\]

The image points for which the size of the gradient of brightness is greater than a predefined threshold (here, fixed as 30) are considered to be the
candidates for the corners. Of the candidates, those points for which Corr (Q) exhibits its local maximum and at which the values of \( \sigma_{\gamma} (Q) \) and Appar (Q) are greater than the chosen thresholds are corners. The minutiae points have a structure as seen in Figure 8.10.

![Figure 8.10 Minutia points of Veins](image)

8.4 CLASSIFICATION USING EUCLIDEAN DISTANCE CLASSIFIER

The weighted Euclidean distance classifier is used for classification. The classification of a given vein image to a particular class ‘k’ is done when the distance \( W(k) \) is a minimum.

\[
W(k) = \sum [(f_{iw} - f_{iw}^k)^2 / (\delta_{iw}^k)^2]
\]

where, \( f_{iw} \) is the ‘i’th feature of the input feature vector and \( f_{iw}^k \) is the ‘i’th feature of the template feature vector in the database, \( \delta_{iw}^k \) is the standard deviation of the template set. If the distance between the input vector and the vectors in class ‘k’ are less than a pre-determined threshold, then the input hand vein is classified as the ‘k’th class.
Euclidean distance classifier uses genuine and imposter score for classification. Euclidean distance is calculated between the testing set and the standard set of the same individual, to generate the genuine score. Same procedure is followed for all the individuals in the database. The distance will be less between the various instances of the same persons.

Imposter score is generated by calculating the Euclidean distance between a person’s testing set and the standard set of all other members. It is repeated for all individuals.

Threshold is set based on the genuine and imposter scores. If the Euclidean distance calculated is less than the threshold, they are recognized as genuine persons. If the score is greater than the threshold, the person is recognized as an imposter. The threshold for the system is fixed based on these scores. The threshold helps to arrive at a suitable compromise between the number of false acceptances that can be allowed and the number of false rejections that can be tolerated. This is very important in practical implementation of a biometric system to ensure security (less false acceptance) as well as to avoid user frustration (less false rejection). An FAR of 0.7 and FRR of 0.46 are obtained.

8.6 CONCLUSION

A vascular biometric authentication system is thus successfully implemented using a near IR camera. The system is tested with a database of 74 individuals and the results obtained are satisfactory. The experiments conducted prove the feasibility of using the dorsal hand veins for biometric authentication, which can be used universally for people of all skin colors and for various age groups.