OPTIMIZED FRAMEWORK FOR HAND VEIN RECOGNITION

A Dissertation

SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE AWARD OF DEGREE OF

MASTER OF TECHNOLOGY

IN

SIGNAL PROCESSING AND DIGITAL DESIGN

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2016-2018

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I, (Shalabh Varma), 2K16/SPD/15 of M.Tech. (Signal Processing & Digital Design), hereby declare that the project dissertation titled "OPTIMIZED FRAMEWORK FOR HAND VEIN RECOGNITION" which is submitted by me to the department of Electronics & Communication, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is original & not copied from any source without paper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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ACKNOWLEDGEMENT

I owe my gratitude to all the people who have helped me in this dissertation work & who have made my postgraduate college experience one of the most special periods of my life.

Firstly, I would like to express my deepest gratitude to my supervisor Mr. Ajai Kumar Gautam, Assistant Professor (ECE) for his invaluable support, guidance, motivation & encouragement throughout the period during which this work was carried out. I am deeply grateful to Dr. S. Indu, H.O.D. (Department. of ECE) for her support & encouragement in carrying out this project.

I also wish to express my heart full thanks to all faculties at Department of Electronics & Communication Engineering of Delhi Technological University for their goodwill & support that helped me a lot in successful completion of this project.

Finally, I want to thank my parents, family & friends for always believing in my abilities & showering their invaluable love & support.

SHALABH VARMA

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ABSTRACT

This project explores the domain of palm vein recognition-the authentication of individuals based on their unique vein patterns in palm. Biometrics is the field of using an individual's biological characteristics for the process of authentication and identification. The aim of this project is to design a biometric authentication system based on hand veins. A vein map with vein bifurcation points and end points from the palm region is used as a feature. This feature is used in boosted tree classifier which classifies the hand vein image of being authentic or not. Comparison with other classifiers is also done in the report. The advantages and disadvantages of using machine learning in the field of biometrics is also explored.

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List of Abbreviations

IR	Infrared
ROI	Region of Interest
CLAHE	Contrast Limited Adaptive Histogram Equalization
NIR	Near Infrared
LBP	Local Binary Pattern
ML	Machine Learning
NN	Nearest Neighbour

CHAPTER 1

INTRODUCTION

Security of data, assets or area against non-authorized persons is very important. For authentication password based systems are very common. But passwords are prone to compromise. Passwords need to be unique and hard to guess. If these requirements are satisfied then the password itself becomes complex to remember. Using biometrics for authentication solves these problems. Biometrics are biological characteristics present in humans. The advantage with biometrics is that they do not need to be remembered and are always present with the authentic person.

Biometric systems uses different type of biometrics like iris, fingerprints, face etc. In vascular biometrics the information of blood vessels present in a human hand are used.

Palm vein recognition is a secure and reliable method in contrast to the traditional password based security systems. The hand veins provide the opportunity for a biometric authentication system that uses the vein pattern as it differs in all individuals and remains constant. This is a type of vascular recognition system which has several advantages over the nonvascular ones like fingerprints, eye based, face recognition, etc. This does not requires physical contact making it a more hygienic system and avoids the anomalies that occur with varied levels of pressure applied by individuals. Moreover it's an internal detection rather than external which makes it difficult to copy it or gain stealthily. It also is capable of discovering whether the person is alive or not based on haemoglobin absorption of infrared [1].

Not being on surface it's robust and more reliable. It requires NIR which is absorbed by the veins and when processed it appears as black lines or dark grey over a grey background. The issues faced with this biometric system is extraction of features from the captured image and processing the vein structure [2].

A couple of things to be kept in mind while designing a biometric based system are that it's something that should be possessed by the majority of people and it should be unique and permanent. Apart from that it should be something quantifiable [3]. The palm vein recognition system fulfils all these criteria and even though it's a complex process, it's excellent qualities when it comes to security and accurateness makes it a perfect identification arrangement for vulnerable information.

1.1) OUTLINE

The vein image in the hand will be acquired by infrared camera. Then the authentication process would be divided into two parts - feature engineering and classification. In feature engineering process the image will go through various image processing operations so that a unique feature template can be extracted which will be fed to the boosted tree classifier. The boosted tree classifier needs to be trained with image samples of the person so that it can authenticate the identity of a person. The trade off lies between making the feature template more detailed and no. of training samples required for the classifier. Boosted tree is a complex but extremely accurate classifier. If the no. of samples is very high then the classifier can authenticate the identity without even any feature engineering. But in most cases the no. of samples available for a biometric system is limited. So the optimization process in this project would consist of optimizing the details in feature template. A more detailed feature template would be computationally demanding and would require more samples. A less detailed template will not give enough input for the classifier to distinguish between persons.

CHAPTER 2

LITERATURE REVIEW

2.1) BIOMETRIC SYSTEMS

Recognizing patterns is the main feature of a biometric system. It works on a set of features taken from the input data. It then makes comparisons on this set of features based on what features were previously stored in a database. After this comparison, a particular action is taken. Biometrics can be defined by mainly four components [4]. Figure 2.1 shows this interpretation.

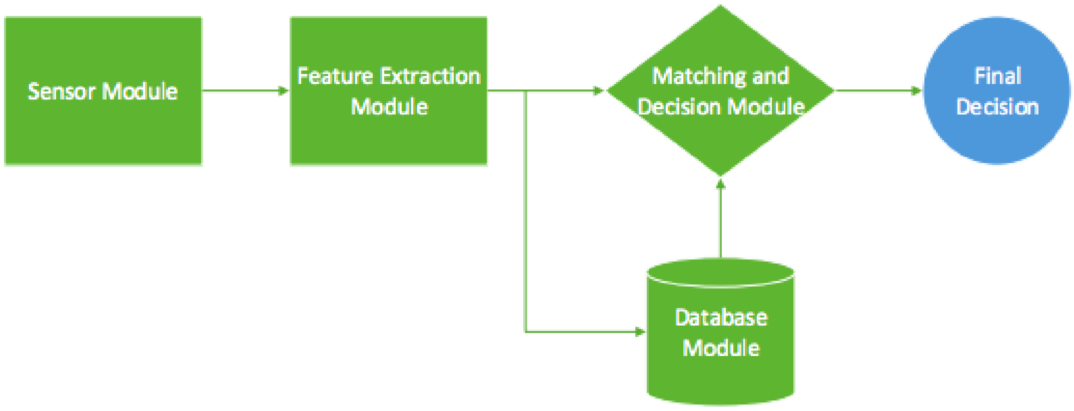

Fig 2.1 Components of a biometric system

2.1.1) Sensor module

Biometric data is extracted from the user with the help of a scanner. This data is raw. When we are working on recognizing veins, the camera used is infrared (IR). The source of illumination is IR too, for example IR LED banks [5].

2.1.2) Feature Extraction module

The work of this module is to extract features to represent the biometric data which is raw, with much accuracy. In the early phase known as enrolment, a database is used to store the extracted features. Feature vectors or templates are what these features are generally called as.

2.1.3 Database module

The decisions required to make in the future by the system are based on the biometric information stored in this module information. This module requires security to prevent the templates from being used maliciously by attackers.

2.1.4) Matching and decision module

This module is responsible for the comparisons. It generates scores based on the degree of matching. A threshold is set to determine whether the image is rejected or matched to the query image.

The two main tasks of a biometric system are to identify or verify a person. Verification can be defined as validating an individual's claims of identity [4]. This claim is made generally by using a password or access card. A comparison is made by the system to determine the validity of the claim [4]. Japan came up with automated teller machines that were finger vein technology emergence applications. This system used a card provided by the bank along with a pin code and verification of fingerprints after scanning for access. Therefore, monetary theft with the possession of just the card and pin was not possible without the owner’s fingerprint.

Identification is harder than verification. Individuals are recognized on the basis of extracted features from input and comparing these with the existing feature vectors in the database. This is known as one-to-many comparison [4]. No claim is made by the user regarding the identity and theoretically, multiple accounts for one user are not possible.

2.2) Evolution of biometrics

Biometrics have revolutionized the identification process of individuals. The benefits are grand in terms of security, accuracy, convenience and more. The identification process can be broadly categorized into two types. First is materialistic, for example with identification objects like ID cards, certificates, etc. The second type is through knowledge of the individual. For example passwords and sequence numbers. These methods included the use of static passwords, set by user which ensure nobody except those with the password would have access. Smart cards are also used which are nothing but ICs with user data. Further SMS is also used for one time passwords. This is a form of dynamic authentication system. These methods are not much reliable because they are vulnerable to deception, theft, or being misplaced. Moreover the objects for identification may wear over time and would need reinvestment for replacement [6]. Biometric identification offers a more sophisticated method to authenticate an entity. Biometric systems work with the physical and behavioural aspects of a being. This method involves the capturing, categorizing, feature extraction of images captured in form of digital data. This data is compared to some stored data to determine the identity of a person [7]. There are two kinds of biometrics, namely physical and behavioural. The physical ones include unique to an individual body parts like irises, fingernails, palm patterns, etc. while the behavioural ones are more subtle like voice, handwriting, signature, etc. [6].

2.3) Palm vein recognition

The finger recognition systems came to the picture in earlier years, but palm vein recognition is a relatively new concept and much more refined and complex to implement. It has many variations depending on which feature is focused on like the veins, the lines, bifurcations, etc. [7]. It has the advantage of being a no contact method which promotes hygiene and is better for longevity of biometric systems due to reduction of frictional damages. Moreover it provides higher amount of information than the small area of finger impression which supports diversity of identification systems. Like all other biometric based systems, this too involves two sample sets, the training samples and the test samples. The training samples create a database by collecting the information in earlier stages. Then when the identification is to be carried out, the test sample is compared to the stored samples and a decision is made based on some set algorithms to determine the validity of the person. The basic palm vein biometric system consist of five stages as described in fig. 2.2

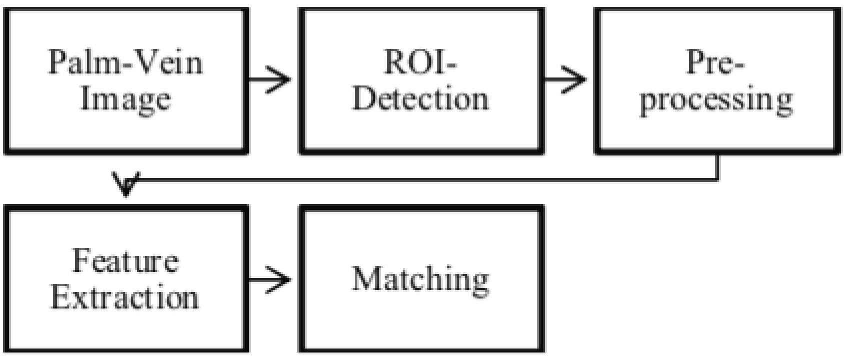

Fig 2.2 Stages of a basic palm vein biometric system

2.4) CASIA Database- Multi-Spectral Palm-print

The database used here is a widely used one with 7200 images. A group of 100 people were taken for creating it. It stores JPEG files for palm images and all the images are grey level images, 8 bit in size. The image for each particular hand is taken twice with a gap of a month between capturing them and both times three samples are taken. The database contains six images for one person which is close to the number of samples available in a real world scenario. Moreover, the three samples contain six images taken using separate electromagnetic spectrums. These spectrums range over 460 nm to 940 nm. Another possibility is taken into account by varying the hand postures slightly for every image to promote diversity and make the system more practical.

A CCD camera is used in the device at the bottom of it to capture the hand image and pegs are not used for free movement over the device. The adjusting of spectrums is automatic using control circuitry [8].

2.5) Classifiers

Machine learning involves creating algorithms that work with past data and train themselves to be capable of solving future issues. Classifier is a type of machine learning algorithm, supervised in nature. Samples to train the system are given and the system learns to generalize the data with some set standards and classify them accordingly. This classification may be into two classes or more [9]. There are various kinds of classifiers, namely, linear, boosted tree, decision trees, support vector machines, neural networks, etc. [10]

Here we have used the Boosted Tree algorithm. In this type of classifier, the machine learns iteratively. It supports supervised learning and probability of miscalculations is pretty low with the use of many classifiers.

CHAPTER 3

METHODOLOGY

3.1) IMAGE ACQUISITION

Acquisition process is of two types basically, namely far and near infrared approach. Using near infrared approach, veins are recognized utilizing the distinction observed in absorbed light by the deoxygenated blood in the veins to that of the tissues surrounding the veins. The darker, tube like structures in the images represent veins. The amount of NIR light from LEDs absorbed by them is more compared to the tissue. Whereas, when it comes to the far-infrared approach, the body's heat radiation is measurable, ie., the warm blood in the veins have a different temperature gradient than to the tissues. So this spectrum makes it measurable.

Embryonic vasculogenesis generate patterns of veins. A lot of random factors influence the end structure. Not much research is done on vein patterns. Its claimed by many sources that pattern of veins are different in all individuals. The position of veins remain same throughout life too. These systems promote hygiene being contactless and are hence best suited for public application.

This is quite spoof proof too, being present below skin. It's difficult to forge and hidden prints are avoided too. This has emerged as a highly convenient technology for controlling access because it is hard to forge and has the same convenience of fingerprints. As good as this is for protecting privacy, it also poses some concerns for privacy because of the possibility of recognition of disease patterns reference images. Measures are being taken to prevent sensitive data from being misused from biometric references. Between databases, Linkability is overcome and secondly, enabling capacity of revocation, this enables us to construct multiple identifiers taken from the similar traits of biometric. Encrypting biometric simply is sometimes not sufficient using functions that are cryptographically classic. It is because comparing them in the encrypted domain is not possible. We try to use identifiers that are pseudonymous since they can't be tracked to the data input. Simultaneously, it is important to deny profiling, which means that for same data, different pseudonymous identifiers must be unlinkable.

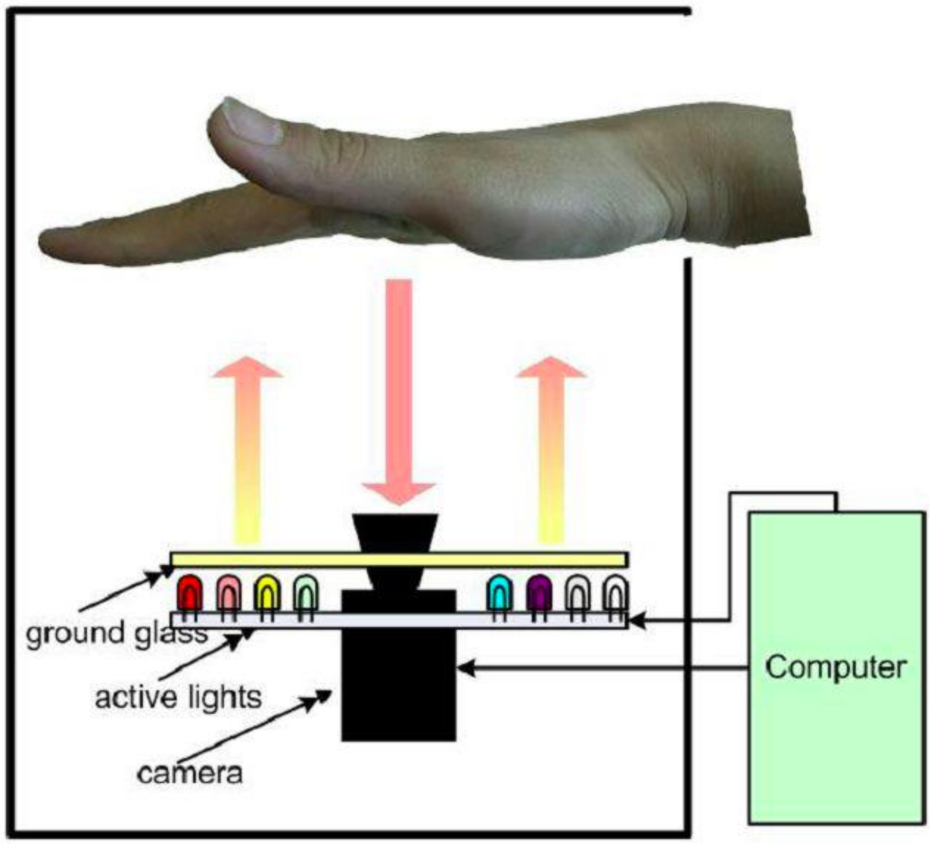

Fig 3.1 Palm image acquisition system

In visible light, it is difficult to observe the vein-pattern. But there's the fact that the temperature is different from the temperature of the surrounding skin which also has a temperature gradient. Taking into account the above two properties and also the law for heat radiation, the Stefan-Boltzmann law, and the vein patterns can be generated thermally with images. Assuming the sensitivity of spectrum of a camera based on IR is 8~14µm or 3~5µm, the thermal images that are captured are completely independent of light in visible region that is with 0.4~0.7µm spectrum. Hence, we successfully avoid the effects of the unwanted features on the surface of skin because of visible light. Avoiding these reduces the complexity and variability of thermal images. Also, these images are tough under a huge range of conditions for lighting.

3.2) Region of interest detection

The extraction of ROI is basically carrying out a sequence of key points and adjustments on different locations for of vein images of palm, then the central effective area nominated for extracting features, and finally comparison takes place for identification. The ROI is the aforementioned central region, for both the palm vein image and palm print and of a particular palm, the ROI location must be unchanged. This location of ROI and selection is does the normalization for feature area of the separate palm vein and palm print, so the adverse factors stop influencing the process, and the information rich sub image of palm vein or palm print is acquired, this makes the subsequent feature matching and extraction convenient. There are large number of methods for extraction of ROI presently [6-9]. The methods for extracting ROI of palm vein and palm print depend on the inscribed circle, maximum in circumference [8] and methods for calculating centroid are often studied. The method of maximum inscribed circle can be described as the determination of radius and centre for the palm of a hand, and the inscribed circle with largest circumference on the whole area of palm is acquired, this is followed by the correction of angle rotation of the palm. Then the inscribed square with maximum area inside the inscribed circle I cut and is then regularised to 128×128 size of ROI image. This method that depends on extracting the centroid is based on the centroid obtained from the image of the palm, and the interception of rectangle sub image with 256×256 size would taking the centre as the centroid of the palm. The CASIA database based results explain that this method has excellent prospects in terms of applications.

Since the size of palm differs for every individual and the position also varies when patterns for pal are collected, a location based method depending on the inscribed circle with maximum area is used. In this method the characteristics of contours of the shape of hand are taken to advantage. The steps involved are:

1) A binary image of palm is obtained after pre-processing with the central point of the inscribed circle with maximum area on the palm area. For increasing the efficiency of the calculations involved, the centre point and centroid may coincide. The centroid is taken as the origin for defining a certain length rectangle. Based to the previous experiments, usually the rectangles of sizes 100 x100 are determined. Efficiency can be greatly increased by looking for the centre of the circle.
2) A centre point is taken in the rectangle and slowly the radius of circle is changed. As soon as the edge of the circle coincides with the palm print edge, the search for the radius is stopped and radius of that particular circle is recorded.

3) The centre point of the circle is changed and the search is continued for determining the circle radius. At the end, a record is made for the centre point and that of the biggest circle too. This circle, for the palm area, is the inscribed circle of maximum area.

The position of rotation of the palm is beyond limits while the image is collected, hence we must correct the rotation of palm before intercepting ROI.

Apart from the centre of the circle, O, a point of reference, L, is also set. The radius of the maximum inscribed circle is given by R, then the centre of the circle is taken as origin, consequently drawing the circle using KR (K>1). This circle intersects the fingers of the hand. The intersection point of ring and middle fingers, A and B is found and a central point L is taken. OL is connected and taken as a new x axis. The palm is rotated taking this new axis as reference

The centre point O and radius R, Rx R is taken as the size of the previous sub image of the non-fixed size. Therefore, the maximum inscribed square, intercepted as ROI is in the maximum inscribed circle. Then the normalized size is 128x128.

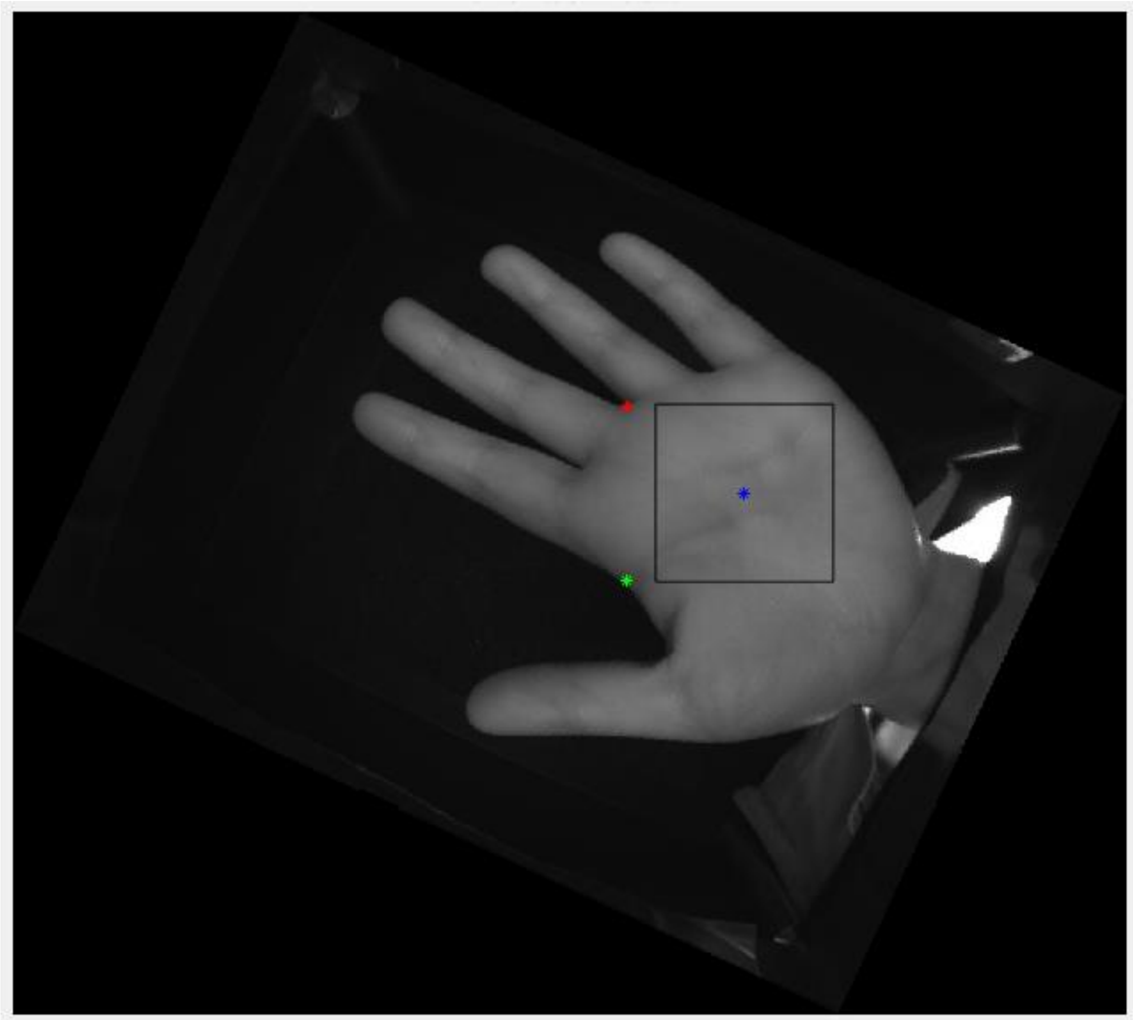

Fig 3.2 Detected region of interest through centroid

3.3) Image Enhancement

To make the veins stand out in images that is make them easier to see and work on, a number of methods are employed.

An image is made up of a large number of pixels and the range for which the intensity values of these pixels differ is known as contrast. Contrast enhancement is relevant since features are easier to extract from images with greater contrast. Moreover, vein images tend to have non-uniform illumination and low contrast. This is not only the fault of the imaging hardware, but also due to the fact that the human veins scatters the near infrared light (NIR) penetrating it similar to the way that visible light is scattered by fog.

3.3.1) Histogram normalisation

Histogram normalisation, is a simple contrast enhancement method which "stretches" the dynamic range of pixel intensity values by linearly scaling the intensities such that light pixels become even lighter and dark pixels even darker. This point-wise operation is computed by

$$'(x, y) = ((Rmax - Rmin) \times (I(x, y) - Imin)) / (Imax - Imin) \ \forall \ x, y \in I \qquad (2.4)$$

where Rmax and Rmin represent the new maximum and minimum grey levels respectively, I is the original image and I′ is the output image. Rmax and Rmin would typically be 255 and 0 respectively.

3.3.2) Adaptive histogram equalisation

An alternative to histogram normalisation is histogram equalisation – a non-linear process which adjusts the grey levels of the image such that the gray level histogram is mapped onto a uniform one [24]. A full derivation of a global histogram equalisation method is provided by both [25] and [24].

Global histogram equalisation techniques, however, do not take local details into account and can end up magnifying noise [24]. To overcome this, histogram equalisation can be performed locally, by sliding a two-dimensional window over the image and performing equalisation separately on each region falling within the window. A popular algorithm which implements this is CLAHE – Contrast Limited Adaptive Histogram Equalisation [28] – and is available in the MATLAB Image Processing Toolbox.

3.3.3) The optimal contrast enhancement technique

Olsen et al. [26] conducted a comparison of contrast enhancement techniques for vein recognition due to its importance in the pre-processing stage. CLAHE was found to outperform the normalisation technique proposed by Wang. The amplification of contrast in CLAHE for a particular pixel vicinity can be described by transform function slope. The cumulative distribution function (CDF) slope is also proportional to the same and hence it is proportional to the histogram value for that particular pixel. The amplification is limited by CLAHE by clipping of histogram at a value defined earlier. Then CDF is calculated. The slope of the CDF is limited by this and hence the transformation function. The clip limit is the value defined for limiting histogram. It depends on histogram normalization and so on neighbouring region size too. Three and four define the amplification limit due to common values.

It is beneficial to save the histogram part exceeding the chip limit but we should distribute it amongst all histogram bins equally. This puts the bins in a position where they exceed the limit again 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.

3.4) Segmentation

Segmentation involves partitioning an image into regions which share common attributes or properties. In the context of vein recognition, we are interested in segmenting the veins from the rest of the image. But normal thresholding techniques cannot be done because of non-uniform illumination. So canny edge detector is used. The merits of canny edge detection operator: high SNR criterion, accurate positioning criterion, and single-edge sole response criterion.

The process of canny edge detection is as follows:

1. The Gaussian filter is applied which removes noise. In vein recognition it removes the noise due to skin.
2. Use sobel or prewitt filter in x and y direction and take its magnitude
3. Then for removing spurious edges non maxima suppression is applied
4. Then by using hysteresis the weak linked edges removed.

3.5) Feature Extraction

In Computer Vision, a feature refers to “interest points” on an image [35]. It captures the most important information in an image, and hence can be considered to be a form of dimensionality reduction. When the data input to a pattern recognition system is too large to be processed, it makes sense to extract the key features and process those.

In addition to dimensionality reduction, a more robust method of comparing two images is to compare their features rather than their individual pixels. This is because changes in image size, translation or rotation can cause a pixel-wise comparison to fail. On the other hand, features which possess geometric invariance will not be affected at all [35].

Furthermore, features with photometric invariance are not affected by differences in brightness or exposure between images [35]. Various features like Fourier descriptors, LBP (local binary pattern), minutiae are discussed which can be extracted from vein image.

3.6) Type of features

3.6.1) Fourier Descriptors

Fourier descriptors are commonly used in describing shapes; the method described here represents shapes in terms of complex numbers.

The contour, or outline, of a shape is described as a closed curve using a set of N vertices on the boundary of the shape [19]. In an image, this can be represented by the set of pixels on the boundary of the shape of interest represented by (x0, y0), (x1, y1) ... (xN−1, yN−1). We can rewrite this as x (k) = xk and y (k) = yk fork=0, 1, 2...N−1.

This notation allows us to represent the coordinates of the shape boundary as complex numbers where s (k) = x (k) + j · y (k). Finally, we compute the Discrete Fourier Transform. The DFT assumes that the function is periodic and this is true for this scenario since we are dealing with a closed curve.

The coefficients of the DFT, au, are known as Fourier Descriptors. Shapes can be compared by comparing subsets of Fourier descriptors, beginning with lower order coefficients. The first coefficient is the centre of gravity of the shape. Subsequent components describe the shape in terms of circles, since the basis function ejn describes a circle in the complex plane and the original boundary was expressed in terms of complex numbers. Fourier descriptors are also invariant to rotation if we only consider the magnitudes of the Fourier coefficients, au, as well as invariant to translation if we normalise each term by dividing by the first coefficient, a0 [23]. The rotation invariance follows directly from the shift property of the DFT described in [37].

3.6.2) Minutiae

Minutiae are features commonly used in fingerprint recognition [1]. Minutiae refer to the various ways in which fingerprint ridges (the darker parts of a fingerprint image) can be discontinuous. Although there are several categories of minutiae, the most common are bifurcations – the point where one ridge divides into two – and terminations – the points where a ridge comes to an abrupt end [1].

Minutiae can easily be extended from hand vein images. The segmented vein patterns from an image are analogous to ridges and also have bifurcations and terminations. The x and y coordinates of these minutiae can be used as features. However, such features are not invariant to rotations or translations. This problem can be solved by forming a topology of the bifurcation points instead of using the absolute positions of the bifurcations as features and using the relative distance and angles between each point. The disadvantage of this approach is its computational cost.

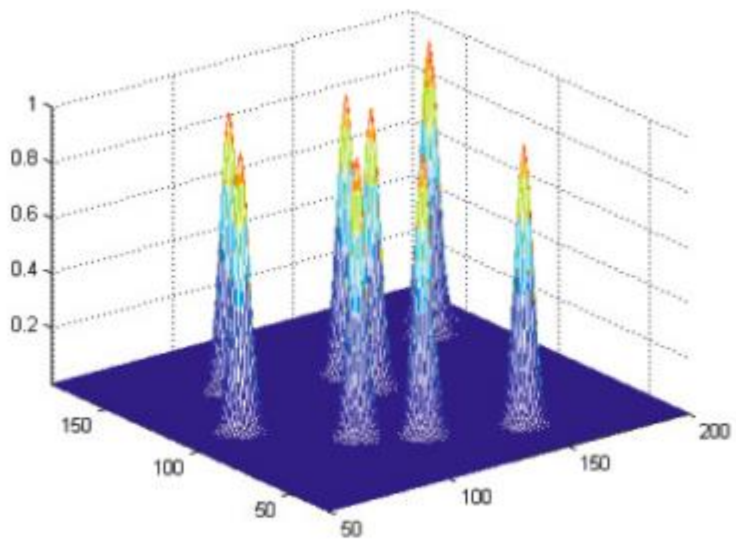

Fig 3.3 Palm vein minutiae as two dimensional Gaussian functions

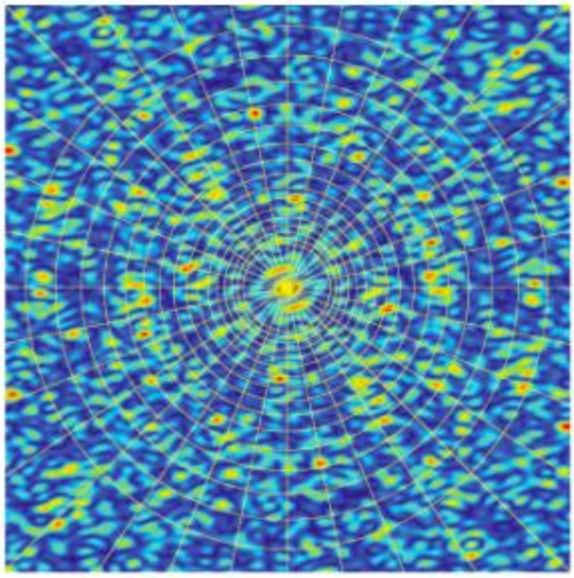

Fig 3.4 Fourier spectrum in Cartesian coordinate

3.6.3) Local Binary Pattern (LBP)

Local Binary Patterns (LBP) were originally introduced by Ojala et al. [15] as a feature descriptor for fine scale textures. An LBP description of a pixel in its canonical form is simple and created by comparing the pixel’s intensity value to all eight of its neighbours. These values are then thresholded according to the value of the centre pixel, and the result is interpreted as a binary number.

Another important extension is the definition of “uniform patterns” [39]. An LBP is defined as uniform if it contains at most two 0-1 or 1-0 transitions when viewed as a circular bit string. For example, the pattern 01100000 is uniform whilst 10100000 is not. Ojala observed that uniform patterns accounted for nearly 90% of all patterns in his test images when using eight sampling points [15]. Hence, little information was lost by assigning all non-uniform patterns a particular code word. Since only 58 of the 256 possible 8-bit strings are uniform, we can thus encode all 256 8-bit Local Binary Patterns using 59 uniform code words. To indicate that uniform patterns are being used, the superscript, u2 is added to the LBP operator.

Ahonen [41] developed this idea further by using histograms of uniform LBP features for face detection. He first computed LBP descriptors for the entire image before partitioning the image into non-overlapping grids. Histograms were then computed for each region and the resulting histograms were then concatenated together to form one feature vector. Spatial information was implicitly encoded into this feature vector from the order in which the histograms were concatenated. Ahonen [41] also showed that rotation invariant features could be obtained by computing the Fourier transform of the number of elements in each bin of the histogram.

3.7) Machine Learning

In computer science there exist a field called artificial intelligence in which one of the subset is called machine learning which makes computer learn (i.e. iteratively doing a task and improving performance on it) by using statistical techniques and not by being explicitly programmed.
Among many sections in artificial intelligence one section is pattern recognition and computer learning. Machine learning has evolved from this section. Machine learning is oriented towards building and study of algorithms and models that can learn by making predictions on given data. It learns from this given data itself. The machine learning algorithms overcome the problems of static programming by making predictions based on data or decisions based on data by constructing a model from provided data. It is deployed in a variety of computing tasks where designing, creating and programming explicit and static algorithms with good output is tough or is not feasible; example of its deployment include spam detection, detection of intruders on network or data breach by malicious inside elements, optical character recognition, computer vision and rank giving learning.
Computational statistics is a field closely tied to the field of machine learning. In both the fields the focus is to make predictions with the help of computers. It has connections to mathematical optimization, in which methods, application and theory are delivered to the field. Machine learning is on occasion combined with data mining, where the data mining is more oriented towards exploratory data analytics and is called as unsupervised learning. Machine learning can be supervised and unsupervised and can be implemented to establish and learn behavioural baseline profiles for different entities and after that can be used to find anomalies which are meaningful.
Predictive analytics is a subset in the field of data analytics in which machine learning is used to create complex algorithms and models that helps in prediction. These analytical models allow data scientists, engineers, researchers and analysts to "produce repeatable,

reliable results and decisions" and discover "new insights" through gaining knowledge from trends and historical relationship in the data.

Classification is the final stage in the biometric pipeline and relies heavily on Machine Learning theory. In this phase, the features obtained from the previous stage are used to identify the query image. The classifier must "learn" the pattern of the training data so that when it is presented with an unseen query image, it can correctly identify it. We consider two pattern classifiers – the Nearest Neighbour algorithm and the Support Vector Machine (SVM). Furthermore, we discuss distance metrics used by these classifiers as well as parameter selection methods for the SVM. Finally, we also discuss the k-means clustering algorithm.

3.7.1) Nearest Neighbour

The Nearest Neighbour (NN) algorithm is one of the oldest and simplest pattern classification algorithms, which nevertheless, is often found to achieve performance comparable to that of more sophisticated approaches [23].

Given a set of n labelled training example denoted by Dn = {X1, ... , Xn} where X ∈ R and class labels Yi ∈ {ω1, ... , ωn} [23], the nearest neighbour rule assigns a query point the same class label as the training point "closest" to it [24]. In order to identify the nearest neighbour of a query pattern, a distance function has to be defined to measure the similarity. The most common distance metric is Euclidean Distance.

A problem with the NN classifier is that it is susceptible to noise and outliers. Query patterns can be classified incorrectly because their nearest neighbour happens to be an outlier in the training data. This can lead to the NN classifier "overfitting" the data – it could have high predictive accuracy when tested with the training data, but could end up generalising very poorly to new test data [24].

However, the NN classifier does not cope with the fact that the classes overlap in the input space [23]. As a result, a highly irregular decision boundary is produced which does not capture the overall trend of the data.

This difficulty can be remedied by using the k-Nearest Neighbour (kNN) classifier.

(a) Decision boundary obtained from NN classifier

(b) Decision boundary obtained from kNN classifier where k = 11

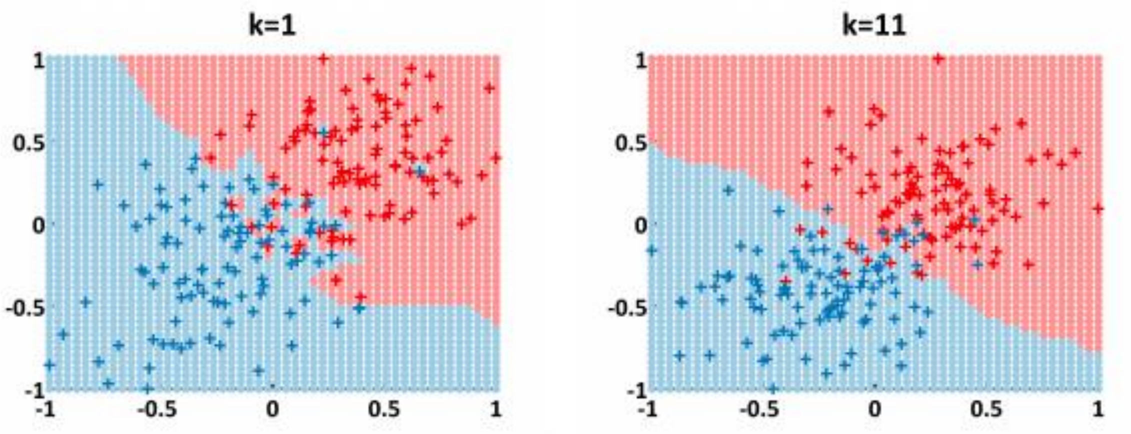

Fig 3.5 Comparison of NN and kNN where input is linearly separable

3.7.2) Separability Index

Thornton's Separability Index [26] is defined as the fraction of training data points whose classification labels are the same as those of their nearest neighbours. It thus follows that the separability index can be obtained by performing Leave-One-Out (LOO) testing using the classifier's training data [26]. However, this result is critical as the separability index is identical to the asymptotic result that would be obtained from many train-and-test cycles using random partitions of the overall data each time [24].

Hence, a NN or kNN classifier can be tested sufficiently by calculating just the separability index (which amounts to performing LOO testing). In LOO, we test our NN classifier with every training sample besides the one being tested.

3.7.3) Remarks

An attractive feature of Nearest Neighbour methods is that they are quick and simple to implement. Hence, they can be used to quickly identify whether the features obtained from an image are adequate for identification. A number of researchers have used this classifier to test their methods.

On the other hand, a disadvantage of Nearest Neighbour approaches is the long classification time. This occurs because NN classifiers are "lazy" learners. Training a NN classifier is essentially creating a database of training vectors. However, when a prediction is made, the query example must be compared to each training example. For N training examples, each of dimension M and using Euclidean distance function, the time complexity for each prediction is O (MN). Furthermore, the classifier is not scalable as classification time increases as the training database grows.

3.7.3) Distance Functions

As mentioned in the previous section, Nearest Neighbour methods use a distance function to compare the similarity of a query sample to existing training samples. In this section, we discuss some common distance functions and their applications to vein recognition.

3.7.4) Euclidean Distance

Euclidean distance is a simple distance metric defined as

$$D(X,Y) = \sqrt{\sum_{i=1}^{N} (x_i - y_i)^2}$$

Despite its simplicity, Euclidean Distance was used by both Kang [23] and Yousefi [19] to compare Fourier descriptors of the shape of the finger whilst Wang [2] used it to compare the coordinates of bifurcations obtained from the segmented vein. It should however be noted that Euclidean Distance can only be computed when the two feature vectors being compared are of the same dimensionality, N.

3.7.5) Hamming Distance

The Hamming Distance between two strings of the same length counts the number of positions where corresponding symbols are different. It is commonly applied to binary strings, in which case it is calculated as

$$HD(X, Y) = \|CodeX \otimes CodeY\| / Code\ Length \qquad (3.1)$$

where X and Y are equal-length binary strings, $\otimes$ is the bitwise XOR operator and x counts the number of "ones" in the binary code x [49]. Here, the distance is normalised by the length of the binary code, although it is not necessary if we are always comparing binary strings of the same length.

The Hamming Distance has been used by Rosdi [7], Park [22] and Lee [23] when comparing features extracted using Local Binary Patterns.

3.7.6) Hausdorff Distance

The Hausdorff distance between two sets of numbers X = {a1, a2, ..., an} and Y = {b1, b2, ..., bm} is defined by [50] as

$$D(X,Y) = \max\{\max_{x\in X}\min_{y\in Y}|y-x|,\ \max_{y\in Y}\min_{x\in X}|x-y|\} \tag{3.2}$$

In other words, the distance, D, between sets X and Y (which can contain different numbers of elements), is the smallest value of D such that every point of Y has a point of X within distance D of it. Similarly, every point in X has a point in Y within a distance D. The distance metric used to compare points of X and Y is the Euclidean distance.

However, this metric is vulnerable to outliers since just a single exception in either set, X or Y, can modify the overall distance significantly. As a result, Leedham et al. [17] modified the function to

$$MHD(X,Y) = \frac{1}{N}\sum_{x_i\in X}\min_{y_j\in Y}\|x_i - y_j\|_2 \tag{3.3}$$

Intuitively, this is the cumulative distance between the two closest points in sets X and Y where N is the smallest number of points in either set X or Y. This metric has been used by Leedham et al. [17] as well as Kang [23] for comparing bifurcations from veins.

3.7.7) Chi-Square Distance

The Chi-Square Distance compares two normalised histograms. Each histograms must have n bins and the sum of all their entries must be 1. It effectively compares two histograms, X and Y, according to the number of elements in each bin which are different and can be computed by

$$\chi^2(X,Y) = \frac{1}{2}\sum_{i=1}^{n}\frac{(x_i - y_i)^2}{(x_i + y_i)} \tag{3.4}$$

Note that this metric emphasises differences between bins with low amounts of entries. For example, the distance between two bins with 1 and 2 elements respectively is more than two bins with 99 and 100 elements respectively. The Chi-Square Distance was used by both Ahonen [21] and Maturana [29] to compare distances between histograms of Local Binary Pattern features.

3.8) Support Vector Machine (SVM)

The Support Vector Machine (SVM) is a more advanced proximity classifier in comparison to Nearest Neighbour method. Given a set of labelled training examples, the SVM creates a model which classifies new queries into one category or the other [21]. Whilst the SVM is essentially a binary classifier, it can be extended to multiple classes using the one-vs.-all rule: If there are k classes, we train k different SVM's which each separate one class from the (k − 1) others. When classifying, we assign the output label of the classifier with the highest confidence [22].

The SVM creates an optimal hyperplane which acts as a decision boundary for linearly separable data [21]. This hyperplane can be visualised for two-dimensional data (where it is simply a straight line). There are multiple hyperplanes which separate the data and the SVM creates the hyperplane which maximises the distance between itself and the nearest data point of the other class. Hence, the SVM is effectively trained using a number of "difficult" points in the dataset, instead of all of them. These points are known as "support vectors" as they would change the position of the hyperplane if they were removed [21]. Hence, the SVM is also known as a "large margin" classifier as it maximises the margin, or separation, between two classes [21].

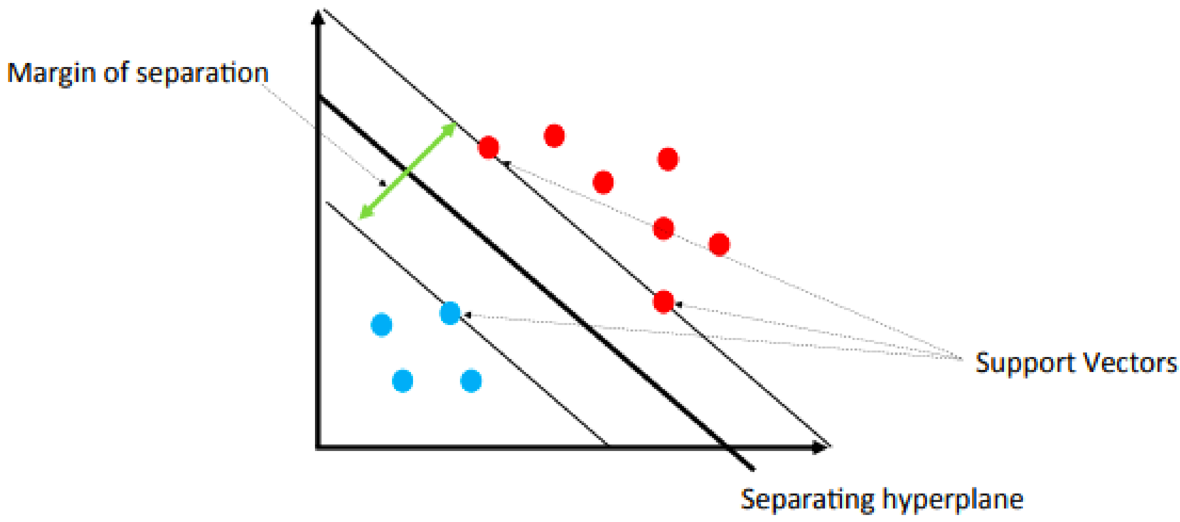

Fig 3.6 Visualization of hyperplane when using linear kernel

The SVM can be adapted to produce non-linear decision boundaries by first mapping the input data to a different coordinate system. For example, data which require a circular boundary can be linearly separated if we first map the input into a polar coordinate system. However, a more robust approach is to map the input data to a higher dimension using a nonlinear function φ.

This improvement is a consequence of Cover's theorem which states a classification problem is more likely to be separable when cast into a higher dimensional space using an over-complete non-linear mapping [54]. In fact, translating the input data to a higher dimension is used by other machine learning techniques such as Neural Networks (where the dimensionality increase is determined by the number of hidden units) and Kernel Ridge Regression.

3.8.1) Kernel functions and parameter selection

The kernel function is defined as $K(xi,xj) \equiv \varphi(xi)^T\varphi(xj)$ and controls the shape of the decision boundary [35]. There are two common kernels [35]:

linear: $K(xi,xj) = x^Ti\ xj$

radial basis function (RBF): $K(xi,xj) = e^{-\gamma\|xi-xj\|^2}, \gamma > 0$

However, using the radial basis functions creates complex non-linear boundaries. When training an SVM with the RBF kernel, the parameter γ, which determines the spread of the radial function, must be determined. Irrespective of the kernel, we must also tune the C parameter which determines the penalty of misclassifying a training point. From the cost function, it follows that if we set C too high, the SVM will create a hyperplane which fits the training data exactly. This is because the cost function we are minimising will become large if a point is misclassified. This will lead to “overfitting” and the learnt decision boundary will not generalise well to new testing data. Hence, C is essentially a regularisation parameter [36] which can be tuned to control overfitting.

We can tune these parameters by performing a “grid-search” [35]. This process involves training an SVM multiple times using different values of C (and γ for the RBF kernel) and recording the test error. The optimal parameters are those that minimise the test error.

Note that in order to prevent overfitting, we must not test with the data we used to train the SVM and must hence partition our input data accordingly into training and testing sets as described by [35]. However, a grid-search can be time-consuming to perform since training an SVM is a lengthy process. In order to speed up this process, we can initially search a coarse grid before identifying a “better” region of the grid in which we can conduct a finer search [35]. One method of doing this is to initially search on a logarithmic scale (for example, we set C = 2−5,2−4...,25). Thereafter, we do a finer search between the values which gave the best results.

Another option would be to use a stochastic searching algorithm such as evolutionary algorithms [38]. These algorithms initially populate the search space randomly before iteratively refining their search upon areas which yield the best solutions. Whilst stochastic optimisers may be faster than performing an exhaustive grid-search (since they do not consider the whole search space), they do not offer any guarantees on finding the optimal solution. As a result, they should only be considered when grid-search cannot be completed within a practical time frame.

3.8.2) Additional applications of the SVM

In addition to conventional use as a classifier, The SVM has been used by a number of researchers for Score Level Fusion [22, 23, 33, 39]. In this approach, multiple classifiers are trained with different features and the matching scores produced by each method are concatenated together to form a score vector. For example, Kang [23] combined matching scores from comparing bifurcations using the Hausdorff Distance and Fourier descriptors of the finger using Euclidean Distance.

An SVM is then used to determine whether a combination of scores from different classifiers constitute a valid match or not (it essentially performs binary classification). The SVM is thus trained with a set of genuine matching score combinations and imposter score combinations. An SVM is not the only way of implementing Score Level Fusion, for other approaches refer to Arun et al. [39]. However, it has proved to be an effective method for combining multiple classification methods which output scores on different scales and have varying accuracy levels.

3.9 K-means clustering

K-means clustering divides a dataset into k partitions where k is a natural number [31]. This method is not a supervised learning algorithm and hence cannot be used for classification. Nevertheless, it has other applications as mentioned in the next section. The algorithm operates on a set of d-dimensional vectors and is initialised by picking k initial centroid points. Thereafter, two steps are repeated until convergence:

1. Data Assignment: Each data point is assigned to the closest centroid. The distance metric used to determine "closeness" is generally Euclidean Distance [31].

2. Relocation of "means": The centroid representing each cluster is relocated to the centre, or mean, of the data points assigned to it [31].

The algorithm converges after the centroid positions stop changing, although it may also be halted after a fixed number of iterations. The initial points have an effect on the final result of the algorithm [51]. This is because the k-means algorithm is really attempting to find an iterative, greedy solution to the following optimisation problem [31]:

$$\arg\min_{S} \sum_{i=1}^{k} \sum_{x_j \in S_i} \|x_j - \mu_i\|^2 \tag{3.5}$$

where μi is the centroid of the points in the cluster Si. There are k such clusters where the user defines k. The k-means algorithm attempts to provide the optimal solution to this problem by finding the optimal centroids and hence S and μ. However, it can also discover local optima. A method of combating this problem is to run the algorithm multiple times and then choose the best solution [31].

Researcher	Features	Classifier	Distance metric	EER (%)
Yousefi [19]	Fourier descriptors	NN	Euclidean	20
Kang [23]	Fourier descriptors	NN	Euclidean	1.70
	Bifurcations	NN	Modified Hausdorff	1.16
	FD and Bifurcations	SVM	-	0.075
Wang [2]	Bifurcations	NN	Number of points within threshold	13.5
Leedham [17]	Bifurcations	NN	Modified Hausdorff	0
Park [22]	Local Binary Patterns	NN	Hamming	0.071
	Wavelets	NN	Euclidean	0.065
	LBP and Wavelets	SVM	-	0.011
Rosdi [7]	Local Binary Patterns	NN	Hamming	7.27
	LBP extension	NN	Hamming	3.28
Lee [42]	Local Binary Patterns	NN	Hamming	1.53
Wang [61]	Gabor filter response	NN	Hamming	3.70

Table 3.1 Comparison of features and classifiers against EER

3.10 Decision Tree

Decision tree is a type of predictive model to reach to conclusions (represented through leaves) when observations(represented as branches) are given about an item. The process is called decision tree learning. It is one of the predictive modelling approaches used in machine learning, statistics and data mining. Classification trees are the tree models where discrete set of values can be taken by the target variable. In this particular type of tree structures, class labels are represented by leaves and conjunction of features are represented by branches that lead to the labels of that class. Regression trees are that type of decision trees where continuous values (usually real numbers) are taken by the the target variable.

A decision tree in decision analysis, can be used to explicitly and visually show decision and decision making. A decision tree can be described as data also(like in data mining), but the resulting classification tree will be used as an input for making decisions.

Learning with the help of decision trees is a commonly deployed method in data mining. The objective is to create a model that takes various input variables and predicts the target variable value. The tree structure is divided into nodes and these node represent one of the inputs; edges are there for each node representing of the values for that input variable. The value of target variable is represented through a leaf given with input variable and the path traced to that leaf.

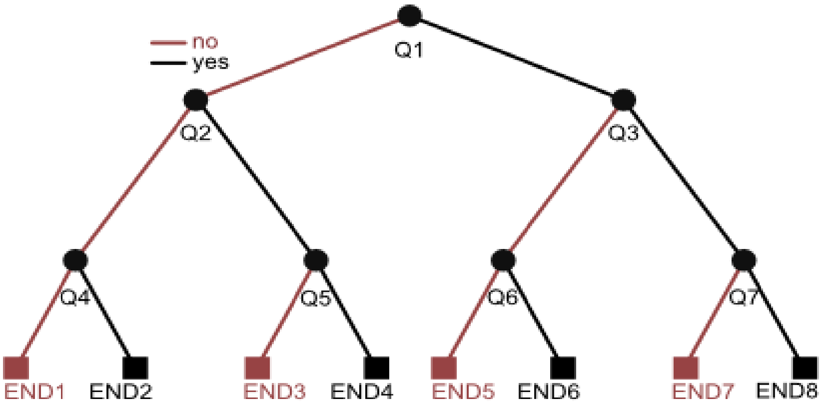

Fig 3.7 Decision Tree

Decision trees are classifying algorithms. They are networked like a tree with each node acting as a decision node. The end nodes of a tree are classes in which classification is to be done. The input nodes that is the non-leaf structures are labelled with input feature.

The connections coming from nodes represent the possible values of the decisions. In ensemble methods the number of trees constructed are not limited to one. These methods can be briefly described as
Boosted trees: Progressively building an ensemble of trees with new instance being used to emphasize the previously mis-modeled training instances. Adaboost is one of the example. These methods can be used for classification-type and regression-type problems.

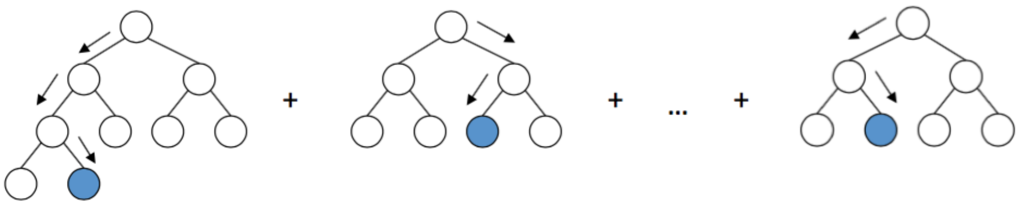

Fig 3.8 Tree Gradient Boosting

Bootstrap aggregated (or bagged) decision trees, an early ensemble method, builds multiple decision trees by repeatedly resampling training data with replacement, and voting the trees for a consensus prediction.
A random forest classifier is a specific type of bootstrap aggregating Rotation forest – in which every decision tree is trained by first applying principal component analysis (PCA) on a random subset of the input features.

The algorithm for Boosting Trees evolved from the application of boosting methods to regression trees. The general idea is to compute a sequence of (very) simple trees, where each successive tree is built for the prediction residuals of the preceding tree.

As described in the General Classification and Regression Trees Introductory Overview, this method will build binary trees, i.e., partition the data into two samples at each split node. Now suppose that you were to limit the complexities of trees to three nodes only: a root node and two child nodes, i.e., a single split.

Thus, at each step of the boosting (boosting trees algorithm), a simple (best) partitioning of the data is determined, and the deviations of the observed values from the respective means (residuals for each partition) are computed. The next 3-node tree will then be fitted to those residuals, to find another partition that will further reduce the residual (error) variance for the data, given the preceding sequence of trees.

It can be shown that such "additive weighted expansions" of trees can eventually produce an excellent fit of the predicted values to the observed values, even if the specific nature of the relationships between the predictor variables and the dependent variable of interest is very complex (nonlinear in nature). Hence, the method of gradient boosting - fitting a weighted additive expansion of simple trees - represents a very general and powerful machine learning algorithm.

One of the significant issues of all machine learning calculations is to "know that when to stop," i.e., how to keep the learning calculation to fit elusive parts of the preparation information that are not prone to enhance the prescient legitimacy of the separate model. This issue is otherwise called the issue of overfitting.

To repeat, this is a general issue material to most machine learning calculations utilized as a part of prescient information mining. A general answer for this issue is to assess the nature of the fitted model by anticipating perceptions in a test-test of information that have not been utilized before to evaluate the particular model(s). In this way, one wants to gage the prescient precision of the arrangement, and to identify while overfitting has happened (or is beginning to happen).

A comparable approach is for each back to back basic tree to be worked for just a haphazardly chose subsample of the full informational index. As it were, each back to back tree is worked for the forecast residuals (from every first tree) of an autonomously drawn irregular example.

The presentation of a specific level of irregularity into the investigation in this way can fill in as a ground-breaking shield against overfitting (since each sequential tree is worked for an alternate example of perceptions), and yield models (added substance weighted developments of basic trees) that sum up well to new perceptions, i.e., show great prescient legitimacy. This method, i.e., performing back to back boosting calculations on autonomously drawn examples of perceptions, is known as stochastic angle boosting.

Boosting trees method can without much of a stretch be extended to deal with classification issues too.

To start with, various boosting trees are worked for (fitted to) every category or class of the dependent variable, in the wake of making a coded variable (vector) of values for each class with the values 1 or 0 to demonstrate regardless of whether an observation does or does not belong with the individual class.

In progressive boosting steps, the algorithm will apply the logistic change to process the residuals for ensuing boosting steps. To process the last classification probabilities, the calculated change is again attached to the predictions for each 0/1 coded vector (class).

Note that the method for applying this technique to classification problems demands that separate chains of (boosted) trees have to be made for each category or class. Because of this, the effort required to solve a simple prediction problem becomes larger by multiple times (for a single continuous dependent variable).

Therefore, it is not practical to analyse categorical dependent variables (class variables) with more than, approximately, 100 or so classes; beyond that point, the computations executed may also require an unreasonable quantity of effort and time. (For instance, if 200 boosting steps and 100 classes for the dependent variable would yield 200 * 100 = 20,000 individual trees.)

The image will be converted into row vector and fed into the classifier

Now since the no. of samples available for 1 person is 6 only, the classifier will not have enough data for proper learning. So data augmentation is used.

3.11) Data Augmentation

The images in the training set are transformed so as to increase the ability of the model to recognize different versions of an image. This increases the breadth of information the model has. It now becomes better suited to recognize target objects in images of varied contrast, size, from changed angles and so on.

While training this network, the learning rate is kept the same in order to see the difference in accuracy only due to augmentation. When we use augmentation to train the network, for every epoch a new transformation of every image is generated. Thus the model sees the same number of images in every epoch (as many as there are in the original training data), albeit a new version of those images each time.

To reduce overfitting on data models, data augmentation is helpful and the training data is reused with minor modifications so that the training data is increased with the already present information .This field of augmenting data is not new, and has been in use for various problems using different kinds of approaches.

Image zooming and image rotation are example of the few approaches. Data warping is the main field of which data augmentation is a subset and in this field the main aim is that model space be directly augmented with data.

CHAPTER 4

RESULTS AND DISCUSSION

4.1) RESULTS

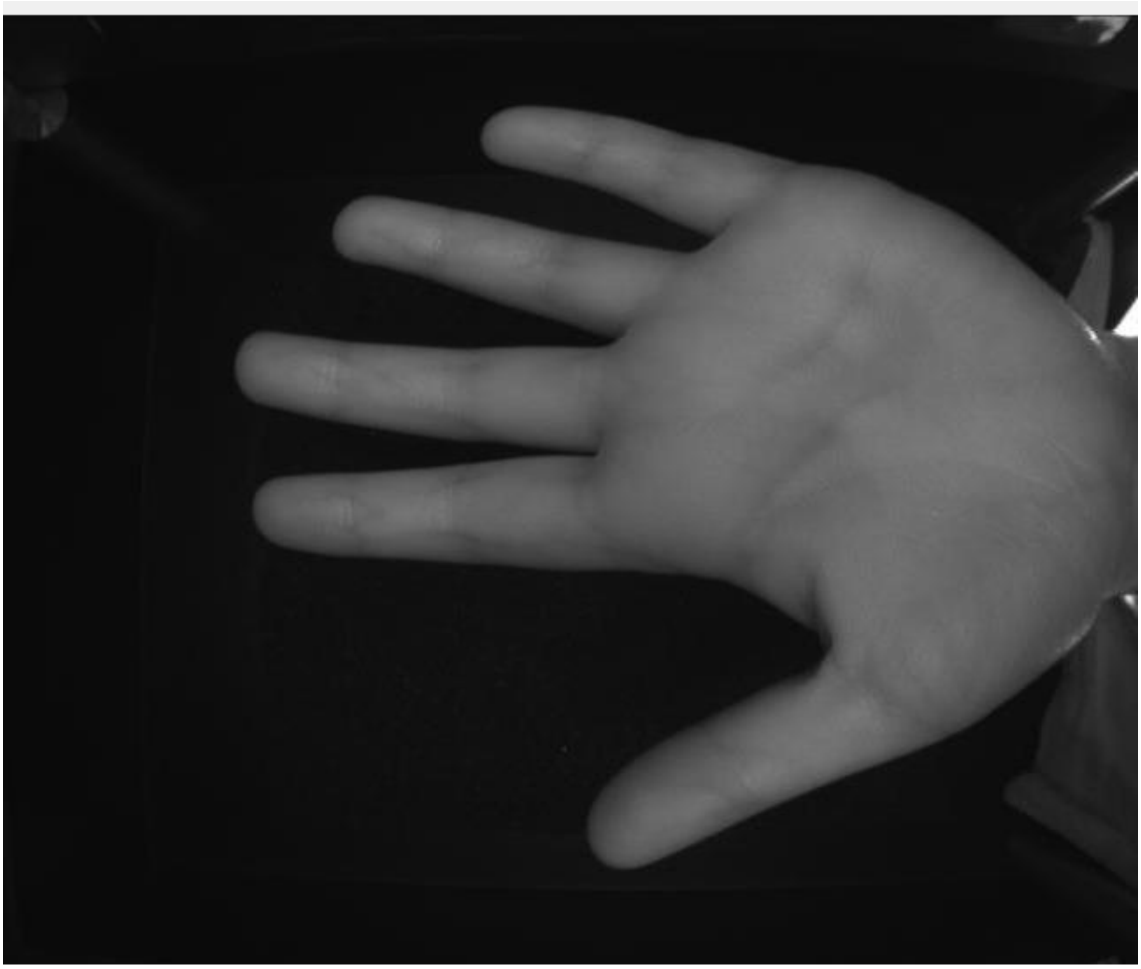

Fig 4.1 Infrared image of hand

The image will have hand veins in more identifiable form than a normal image.

Fig 4.2 CLAHE applied hand vein image

CLAHE applied image will highlight the veins for skeletisation.

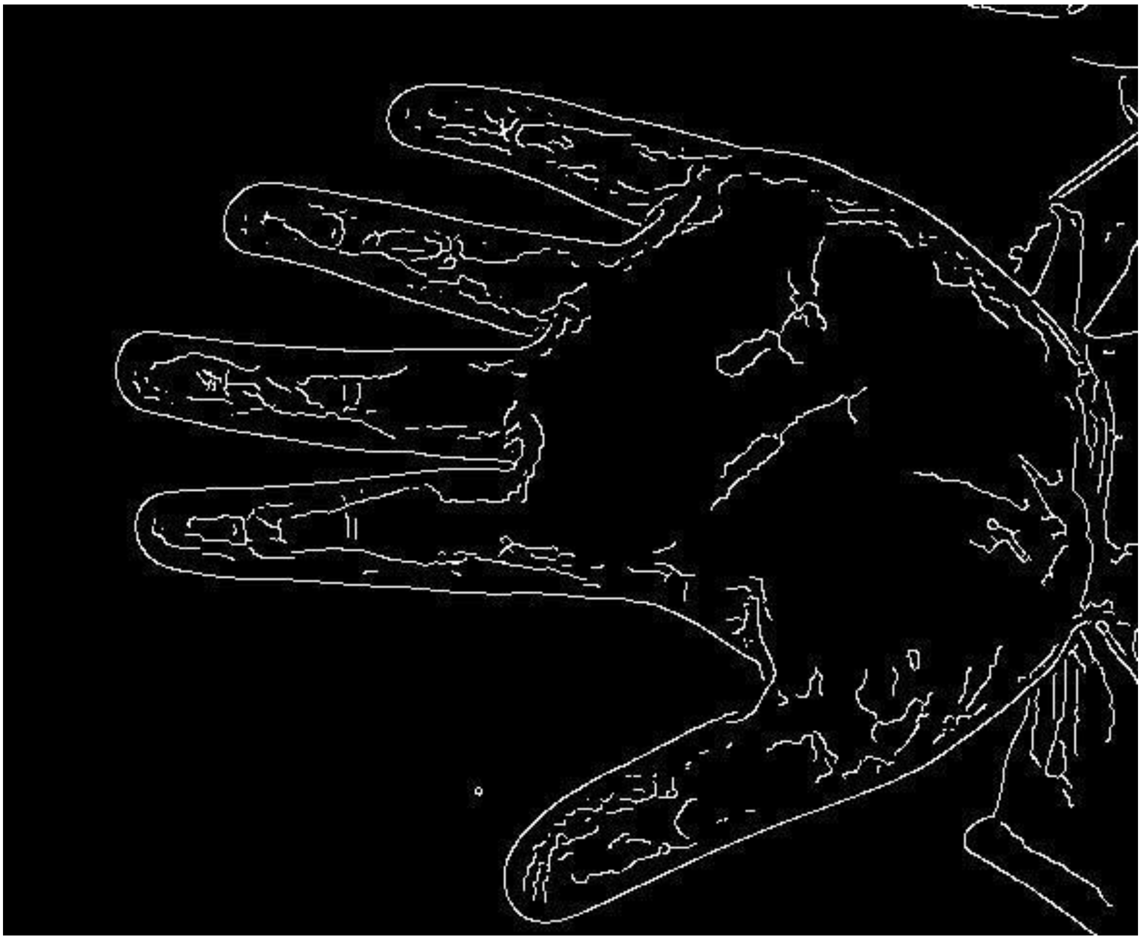

Fig4.3 Vein detected and skeletonized image

The veins are skeletonised and can be used as geometric template.

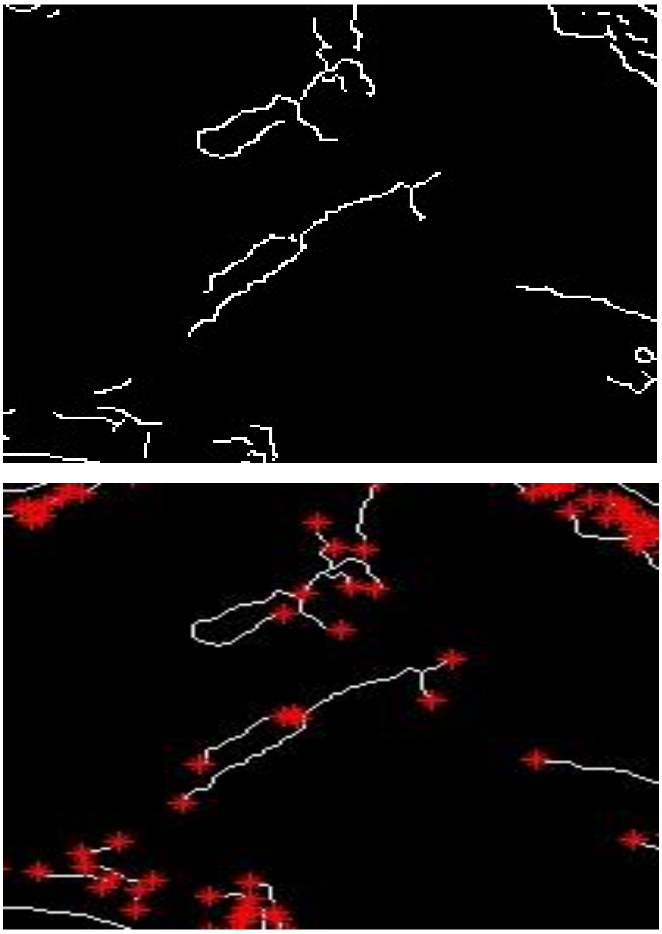

Fig 4.4 Minutiae Detected in ROI

The end points and bifurcations are marked and will be used as feature.

The boosted tree classifier achieves an EER of 1.7%.

4.2) CONCLUSION

Boosted tree is a good classifier for palm vein recognition because of its robustness. This also has the added advantage of fewer number of classes. Apart from this, it is better than random forest classifier because of gradient boosting due to which it gives more accurate results than the aforementioned classifier. Feature engineering required for this classifier is less than other classifiers and as the ability of classifier advances, the less and less feature engineering is required. Since in biometrics the number of training samples available is less, so data augmentation is required for this classifier to be used. Palm vein recognition is a secure method of biometric authentication and is easier to use than other biometric systems.

Chapter 5

FUTURE SCOPE

With the advances in the field of machine learning and emergence of new technologies and algorithms in deep learning the complexities of features can be reduced and authentication can be done by learning the image itself. The number of classes can be increased and more freedom in acquisition process can be obtained by the use of deep neural networks.

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