Promising Database for Palm Vein classification

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***Abstract*—Palm vein authentication is one of the modern biometric techniques, which employs the vein pattern in the human palm to verify the person. The merits of palm vein on classical biometric (e.g. fingerprint, iris, face) are a low risk of falsification, difficulty of duplicated and stability.**

With the expanding application of palm–vein pattern recognition, the corresponding databases available for public use are rare and their growth has resulted in a long response time where the algorithms used for identification are complicated.

To simplify the identification process and add more public databases, this paper proposes a new algorithm for palm–vein identification using Gabor filter. Firstly, images are exchanged using Gaussian filter and histogram equalization and then the features are extracted by using bank of Gabor filters. Then, we apply L2-max norm of superposition to the output of Gabor filter to reduce the dimension of the features vectors. Finally, Nearest Neighbors and support vector machine classifiers are used for palm vein verification.

Our proposed method is evaluated by using a public dataset, namely VP base and our database where images are captured from a Christie flex and vision camera.

The efficiency of the identification process by the proposed methods is high compared to traditional methods, where simplified extraction features methods is used. The experimental results confirm that the proposed approach is efficient compared to the traditional methods.

***Keywords*—Gabor Filter, L2 max superposition, nearest neighbors' method, support vector machine.**

I. Introduction

THE problem of truly identifying individuals in our society has become bigger in recent years, due to our complex, mobile and vastly interconnected information society [1]. Nowadays, determining the identity of a person is becoming very important. The most secure way of identifying people is said to be the verification of a concrete entity, inherently belonging to this person. This is what biometrics is: the automated use of physiological or behavioural characteristics to determine or verify identity [2]. The security of biometric identification has however been questioned, especially for established techniques like fingerprint verification [3]. A relatively new biometric feature is the hand vein pattern.

The vein information is hard to duplicate since veins are internal to the human body. The palm vein authentication technology offers a high level of accuracy. Palm vein authentication uses the vascular patterns of an individual's palm as personal identification data. Compared with a finger or the back of a hand, a palm has a broader and more complicated vascular pattern and thus contains a wealth of differentiating features for personal identification [4]. The importance of biometrics in the current field of Security has been depicted in this work.

II. Problem Statement

There are two fundamentally distinct types of identification problems; the first is verification and the second is recognition. Both problems are very challenging and have different complexities. A practical approach is to reduce the problem of verification of a person's identity is to the problem of verification of a concrete entity related to the person. These entities can be categorized into:

- Something that you have in your possession, such as an ID or member card. Or in a more general way: everybody allowed in a building has a key that identifies this group.
- Something that you know, such as a password and login for a computer. Some systems combine the first and second entities, e.g. the ATM card and PIN code combination.
- Something that you are or that you do, which is the measurement of the physical or behavioural characteristics of a person. This is essentially what biometrics is. Examples of biometric features are the fingerprint, iris, ear, gait, keystroke dynamics, voice, signature, DNA, hand geometry, hand vein pattern, etc.

These three levels also incorporate an increasing level of security where the first category is the least secure, and the last one is said to reach the highest level of security. Therefore, it is logical that the use of biometrics is seen as an exciting solution to many security and identification problems.

A lot of drawbacks are still attached to this promising technology, and a lot of countermeasures have to be taken for the biometric identification systems to live up to their big promises. The many different biometric features that are optional for identification all have their individual pros and cons. Especially for the more established biometrics features, such as the fingerprint, the disadvantages are well-known.

Many disadvantages are related to the reliability of the method, particularly in the light of impostor attacks at security systems. In fingerprint technology the main threat is the ease with which you can obtain somebody's fingerprint. People leave their fingerprints everywhere; on everything they touch. In addition, many techniques to make artificial fingerprints with gelatine or silicon are available.

Partially to overcome these problems of leaving your biometric feature behind for anybody to copy, hand vein pattern recognition techniques are developed. The characteristics of the vascular structure in the hand or finger are captured and used for identification. This relatively new biometric identification technique is thought to be a promise for the future.

Palm vein authentication uses an infrared beam to penetrate the users hand as it is held over the sensor. Palm vein authentication has a high level of authentication accuracy due to the uniqueness and complexity of vein patterns of the palm. Because the palm vein patterns are internal to the body, this is a difficult method to forge. Also, the system is contactless and hygienic for use in public areas.

The cost of implementing palm vein biometric technology is significantly higher when compared to fingerprint recognition technology. This a compromise between cost and accuracy. As the quality of the sensor increases, the resolution of images increases and the expected accuracy of the recognition system increases where the cost of the sensor device increases. Here comes the role of the implemented algorithm in using features extracted from low resolution images of palm hand veins and giving high performance of recognition.

With the expanding application of palm–vein pattern recognition, the corresponding databases available for public use are rare and their growth has resulted in a long response time where the algorithms used for identification are complicated. This makes simplifying the identification process and adding more public databases, a new challenge in using this identification modality.

The main objective of this paper is to develop an accurate and efficient personal identity verification system based on hand palm vein patterns using easier and simplified acquisition of data with good performance comparable to established biometric verification methods.

III. STATE OF THE ART

Palm vein recognition is developing a new direction in biometric identification technology. It has been the interest of researchers from many years because of vein's uniqueness, stability, and not easily spoofed and damaged characteristics.

From more than eight years, researchers studied how to enhance the accuracy of palm vein identification. Zhang et al. [5] developed a palm vein recognition system that uses blood vessel patterns as a personal identification factor. In this paper, the features are extracted from multi-spectral palmprint images using Gabor filters and employed score level fusion to obtain matching score. They used the PolyU database of 250 users and resulted in performance of EER 0.012%. Hao [6], discusses about OLOF features from fusing palm images which have been considered for recognition using hamming distance. It uses 165 users and the performance rate gives EER of 0.5%. Deepamalar and Madheswaran [7], discusses the shape and texture features; which have been considered for recognition of authenticated users and it was validated using neural network classifier. It is found that the recognition accuracy was 99.61% when the multimodal features fused at matching score level. This proposed multimodal system was expected to provide reliable security.

Harmer and Howells [8], did an investigation into the feasibility of applying the palm-vein biometric modality within a template-free key generation framework were conducted. The experiments resulted in both the key reproducibility and key uniqueness rates achieving 100% with considerable effective key length. Hartung Olsen, Xu, and Busch [9], shows an approach to extract vein minutiae and to transform them into a fixed-length, translation and scale invariant representation where rotations could be easily compensated. The proposed solution based on spectral minutiae was evaluated against other comparison strategies on three different datasets of wrist and palm vein samples.

Xuekui Yan , Wenxiong Kang , Feiqi Deng , Qiuxia Wu [10] have proposed a method for Palm vein recognition based on multi-sampling and feature-level fusion to ensure that richer feature information can be extracted for better recognition performance. He used a bi-directional matching algorithm instead of uni-directional matching algorithm for efficient mis-matching removal. Gitanjali Sikka , Er. Vikas Wasson [11] have proposed a method for Palm Vein Recognition with Fuzzy-Neuro Technique to enhance the response time and accuracy of system.

Noh et al., [12] represented some overview and challenges of palm vein biometric system. Akbar et al., [13] made a palm vein biometric identification system using local derivative pattern.Lu et al., [14] palm vein recognition using directional features derived from local binary patterns.Lan et al., [15] made a design based on FPGA-based palm vein acquisition system. Dere et al., [16] designed a human identification model using palm vein images.

Recent studies use new direction to reach same goals of enhancement and accuracy of results. Suganya [17], gives a new direction. The field of biometric Cryptosystems analyzed with the palm vein image template.

Pengzhuang Wang [18], proposed a new algorithm of palm vein recognition and used local binary pattern (LBP) matching strategy to conduct experiments. First, discussed two methods to obtain ROI of palm vein. Then the maximal principal curvature (MPC) algorithm and k-means method are utilized to extract the features of palm vein. Finally, template matching and LBP are used to recognize the feature. A series of experiments on CASIA multispectral palm image database were conducted. The lowest equal error rate (EER) is 0.01965.

Dini Fronitasari, Dadang Gunawan, [19], proposed a vein extraction method modified of the Local Binary Pattern (LBP) combining with Probabilistic Neural Network (PNN) for matching. The aim of the proposed system is to improve the accuracy of palm vein recognition. Simulation result show that the proposed method has a higher recognition rate for palm vein recognition comparing to the other basic Local Binary Pattern.

In our work, we proposed using feature extraction technique based on Gabor filter bank only but enhancing the image quality to a large extent will enhance the accuracy of palm vein identification of captured images where Nearest Neighbours method and multi support vector machine are used for identification and verification.

IV. FRAMEWORK

As show in fig. 1, the proposed method is consisted of five parts as follows:

(i) Image Acquisition
(ii) Image pre-processing
(iii) Region of interest extraction
(iv) Feature extraction
(v) Classification

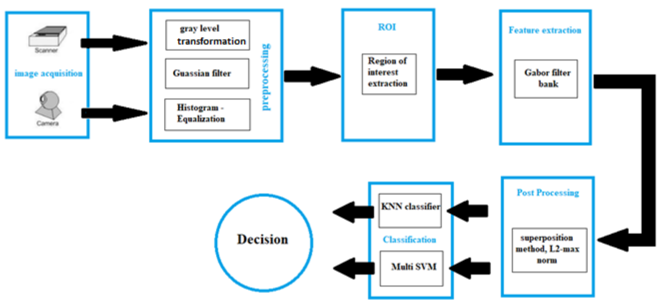

Fig. 1 Block diagram of the proposed framework.

A. Image acquisition

Vein patterns invisible to the naked eyes, can be viewed through infrared light that passes through tissues of the human body and blocked by pigments such as haemoglobin or melanin. As haemoglobin exists densely in blood vessels, infrared light shining through causes veins to appear.

Image Acquisition is the process of getting the images that are required for the authentication process.

In literature, there is different databases used for palm as follows [20]:

Data base name	Database size and features
Fujitsu database	140,000 images (70,000 individuals from 5 to 85 years old)
PolyU database	3000 images (250 individuals)
VPbase database	600 images (50 individuals)

Table I. Databases used in palm vein authentication research

In our project, we used two databases as follows:

1. VPbase database:

Description: It consists of 2400 images presenting human vein patterns. Half of images contains a palmar vein pattern (1200 images) and another half contains a wrist vein pattern (another 1200 images). Data was acquired from both hands of 50 students; which means it has 100 different patterns for palm and wrist region. Pictures were taken in three series, four pictures each, with at least one-week interval between each series. In case of palm region volunteers were asked to put his/her hand on the device to cover acquisition window, in way that line below their fingers coincident with its edge. No additional positioning systems are used. Images in database have 1280x960 resolution and are saved as 24-bit bitmap.

Images used: images of left hand, where four images of left hand of each person are taken based on series one conditions (total of 80 images).

2. Our own database:

Researchers working on palm vein recognition built their own acquisition devices to acquire vein pattern images. This resulted in many different proposals for the choice of region of interest (ROI), different positioning equipment, various image parameters such as resolution, and different image collection processes. For those reasons, all these works present different protocols and performance results, which in such different conditions are thus difficult to compare. To the best of our knowledge, there are no works in the literature providing any kind of experimental framework, which allows the fair comparison of the performance results similar to the new one that we present here.

Images are taken using infra-red camera, Christie flex and vision [21] used in medical field for helping nurses in finding the superficial veins for patients for saline injections.

a. Image capturing process for our work:

Methods and techniques proposed in various scientific papers cannot be replicated due to the lack of the access of the original image set. For this reason, we create our own process.

Images are captured under these conditions where the resulting images are noiseless as possible and providing a good contrast between the veins and the surrounding tissues:

a- 890nm is the wavelength of the camera.
b- The camera is 30 centimetres far from the hand as shown in fig. 2.
c- Since position invariance is a difficult task, we use one approach of positioning of hands.
d- Left hands are used for all persons.
e- Sixteen persons' hands are imaged where ages of patients ranged from 19 years old to 60 years old – the number is based on number used in database.
f- ID number is used other than names for privacy using their left hands.
g- Four images of each hand are taken (total of 64images).
h- Universal mode as imaging suite is used on all persons.
i- Medium window size is used during scanning.

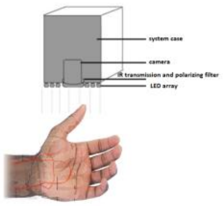

Fig. 2 Palm vein-scanning technique.

B. Pre-processing

Many techniques can be used for image enhancement in the purpose of clarifying the veins and texture patterns of the hand palm.

In our project, many techniques are used to develop the quality of captured images as follows:

i. Grey-level transformation

Captured images are transformed to grey for the purpose of consistency of the dynamic range of the captured image.

The normalisation of a grey-scale digital image is performed according to the formula [22]:

$$g = 255x\frac{f - f_{min}}{f_{max} - f_{min}} \quad (1)$$

Where g is the normalized pixel, f is the intensity of the original pixel, fmin and fmax are the minimum and maximum pixel intensity in the image to be "normalized".

ii. Gaussian filter is used for noise reduction

It is used for the purpose of neglecting useless data from the image.

In signal processing, a Gaussian filter is a filter whose impulse response is a Gaussian function (or an approximation to it). Gaussian filters have the properties of having no overshoot to a step function input while minimizing the rise and fall time. A Gaussian filter is similar to the mean filter, but it uses a different kernel shape, like a Gaussian hump. In palm vein recognition, the Gaussian filter is a 2-D convolution operator used to remove detail and noise in an image. The Gaussian function can be expressed as [23]:

$$g(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (2)$$

Where σ is the standard deviation of the Gaussian distribution. A Gaussian mask template is given by the formula (3) and (4) [Haddad and Akansu, 1991] [22]. Different Gaussian kernel functions can decided by choosing different standard deviations and template sizes M×M;

$$h(i,j) = \frac{h_g(i,j)}{\sum_i \sum_j h_g(i,j)} \quad (3)$$

$$h_g(i,j) = e^{-\frac{i^2+j^2}{2\sigma^2}} \quad (4)$$

iii. Histogram Equalization

It is also used as a processing technique to decrease the effect of dark background of the images increasing global contrast.

Histogram equalization is a histogram correction method based on a transformation of the cumulative distribution function, which is generally adopted to increase global contrast, in particular where the distribution of grey levels in the image is excessively concentrated to a narrow interval [24].

The method is useful in images with backgrounds and foregrounds that are both bright or both dark. In particular, the method can lead to better views of bone structure in x-ray images, and to better detail in photographs that are over or under-exposed. A key advantage of the method is that it is a fairly straightforward technique and an invertible operator. So in theory, if the histogram equalization function is known, then the original histogram can be recovered. The calculation is not computationally intensive. A disadvantage of the method is that it is indiscriminate. It may increase the contrast of background noise, while decreasing the usable signal.

This method is used for enhancing image contrast by adjusting image intensities.

If *f* be a given image represented as a mr by mc matrix of integer pixel intensities ranging from 0 to L – 1 where L is the number of possible intensity values, often 256 and *p* denote the normalized histogram of *f* with a bin for each possible intensity. So that [25]

$$p_n = \frac{\text{number of pixels with intensity } n}{\text{total number of pixels}}$$

n = 0, 1, ..., L − 1.

The histogram equalized image g will be defined by

$$g_{i,j} = floor((L-1)\sum_{n=0}^{f_{i,j}} p_n) \quad (5)$$

Where floor () rounds down to the nearest integer. This is equivalent to transforming the pixel intensities, *k*, of *f* by the function

$$T(k) = floor((L-1)\sum_{n=0}^{k} p_n)$$

The motivation for this transformation comes from thinking of the intensities of *f* and *g* as continuous random variables X, Y on [0, L − 1] with Y defined by

$$Y = T(X) = (L-1)\int_0^x p_x(x)\,dx \quad (6)$$

Where P_x is the probability density function of *P*. T is the cumulative distributive function of X multiplied by (L − 1). Assume for simplicity that T is differentiable and invertible. It can then be shown that Y defined by T(X) is uniformly distributed on [0, L − 1], namely that Py (y) = 1/ L−1.

$$\int_0^y p_Y(z)dz = probability\ that\ 0 \le Y \le y$$
$$= probability\ that\ 0 \le X \le T^{-1}(y)$$
$$= \int_0^{T-1(y)} p_X(w)dw$$
$$\frac{d}{dy}(\int_0^y p_Y(z)dz) = p_Y(y) = p_X(T^{-1}(y))\frac{d}{dy}(T^{-1(y))}$$

C. Region of interest (ROI) extraction

In our proposed method, we used Palm Vein ROI Extraction based on square Method of size 376x376.

The following steps are implemented using square method [26]:

1- Determine the joints by scanning the image vertically row-by-row (green points) as shown in “Fig. 3 “
2- Determine the location of the thumb end then start from the opposite direction and determine the first joint horizontally as the first point (p1) that is shown in figure (2.3). The two reference points which will be used to draw the ROI are First point between the little finger and ring finger as (p1), second point is the point between middle finger and index finger as (p3). These points are considered as connecting points.
3- Determine the second point through the third joint and draw straight line between the two points (p1, p3).
4- Rotate image to draw the line of ROI correctly.
5- From these connected points, draw the rectangle (ROI).

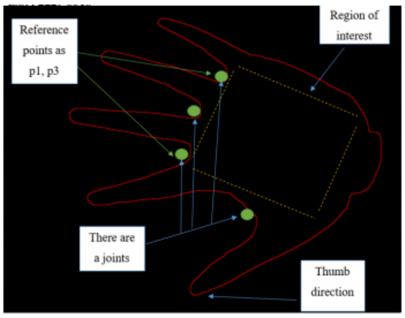

Fig. 3 Important points to define the palm [27].

D. Feature extraction

There are four common approaches to extract vein pattern features: line-based, appearance-based, code-based and texture based methods.

In our work feature extraction technique based on Gabor filter which is a type of texture based feature extraction techniques. Gabor filter is a band pass filter which have orientation selective or frequency selective features and optimal joint resolution in both spatial and frequency domain [28, 29].

In this approach, we apply Gabor filter bank taking into consideration the aspect of orientation of palm veins of the captured images, and used out as a final feature.

D.1 Gabor filter

It is a band pass filter which have orientation selective and frequency-selective features and optimal joint resolution in both spatial and frequency domain [30, 31].

A two dimensional Gabor filter is a combine function with two components: a complex plane wave and a Gaussian shaped function. It is defined as following:

$$G(x,y) = kexp\left\{-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)+j2\pi f.x.\right\} \quad (7)$$
$$x. = x\cos\emptyset + y\sin\emptyset$$
$$y. = -x\sin\emptyset + y\cos\emptyset$$
$$k = {}^{1}\big/_{(2\pi\sigma_x\sigma_{y)}}, j = \sqrt{-1}, \theta$$

Where $\emptyset$ is the orientation of Gabor filter, f0 represent the filter center frequency, σx and σy are the scale of the Gaussian shape, x0 and y0 are the two vertical Gaussian axes. The most important parameters, x f0, σx and σ y in Gabor function that make the filter appropriate for some specific application. The Gabor filter can be split to imaginary part and real part. The imaginary part (odd symmetric) Gabor filter is used for edge detection. The real part (even symmetric) Gabor filter is used for detecting the ridge in the image [32, 33].

To analysis the Gabor filter in terms of real part and imaginary part, can be represented as following:

$$G_{mk}^{c}(x,y) = kexp\left\{-\frac{1}{2}\left(\frac{x.^2}{\sigma_x^2}+\frac{y.^2}{\sigma_y^2}\right)+\cos(2\pi f_{mk}x._k)\right\} \quad (8)$$

where m is the scale index, k is the channel index and mkf represents the center frequency of the real part and imaginary part of Gabor filter at the kth channel. After create a bank of Gabor filter, the enhanced palm image is convolved with the Gabor filter ($f., \sigma_x, \sigma_y$ and $\emptyset$) bank. The best output to the Gabor filter is depend on its parameters in palm vein recognition where we have various orientations in vein network Gabor filter banks are used.

D.2 Gabor filter banks

Gabor expansion was introduced by a Hungarian-born British physicist, Dennis Gabor in 1946, particularly suitable for analysis of signals with sharp changes but which stay for a small duration of time. It suggests expanding a signal into a set of functions that are concentrated in both time and frequency [34]. This set of functions, also called the Gabor coefficients, plays the main role in analysis of signal's local properties. Gabor expansion can be written mathematically as follows [35]:

$$s(t) = \sum_{m=-\infty}^{\infty}\sum_{n=-\infty}^{\infty} G_{m,n}h_{m,n}(t), with\ h_{m,n}(t) = h(t - mT)e^{jn\omega t} \quad (9)$$

Where, Gm, are called the Gabor coefficients. The set of elementary functions $h\,m,n(t)$ consists of a timefrequency shifted function $h\,(t)$. In practice, to describe the texture of an image $(x,\ y)$, a filter structure is employed where image is filtered using the band pass filters, also called Gabor elementary functions (GEF) $h\,(x,\ y)$ to extract a specific frequency band from an image. Usually a convolution operation $(*)$ of GEF's,$h\,(x,\ y)$, with the original image, $i(x,\ y)$, is employed to obtain a Gabor filtered image, m$(x,\ y)$, as follows:

$$m(x,\ y) = |i(x,\ y) * h\,(x,\ y)|. \quad (10)$$

Description of the Gabor elementary functions Gabor coefficients or GEF's are not unique and can be described in many different ways. GEF's are sometimes also referred as Gabor wavelets, which are nothing but the Gaussian modulated by a complex sinusoid as follows (Super & Bovik, 1991) [36].

$$h\,(x, y) = g(x'\,,\, y'\,)ej2\pi(Ux{+}Vy)\,. \quad (11)$$

Here, $(x'\,,\, y'\,) = (x \cos \emptyset + j \sin \emptyset\,,\, -x \sin \emptyset + j \cos \emptyset)$ are the rotated rectilinear coordinates in spatial domain, and $(U,\ V)$ are the particular 2-D frequencies in the complex-sinusoid. The 2-D Gaussian function $(x,\ y)$ with its corresponding Fourier transform $(u,\ v)$ is given as [37]:

$$g(x,y) = \frac{1}{2\pi\,\sigma_x\sigma_y}\,exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_u^2}+\frac{y^2}{\sigma_v^2}\right)\right], \quad (12)$$

$$G(u,v) = exp\{-2\pi[(\sigma_x[u-U]')^2 + ((\sigma_y[v-V]')^2]\}$$

Here, $([u - U]'\,,[v - V]'\,) = [(u - U) \cos \theta + (v - V) \sin \theta\,,\, -(u - U) \sin \theta + (v - V) \cos \theta]$, are the shifted and rotated rectilinear coordinates in the frequency-domain, with $\sigma u = 1/2\pi\sigma x$, $\sigma v = 1/2\pi\sigma y$ characterizing the spatial extent and bandwidth of $h\,(x,\ y)$. Filter parameters (σu and σv) can be computed in several ways. The Gabor wavelets are non-orthogonal in nature unless they are poorly concentrated in time or in frequency domain. While keeping a good time and frequency domain concentration, nonorthogonality is

allowed at the cost of redundant information in the filtered image. In order to reduce this redundancy, following formulation to compute σu and σv has been proposed in (Manjunath & Ma, 1996) [38]:

$$\sigma_u = \frac{((U_h/U_1)^{\frac{1}{S-1}} - 1)U_h}{((U_h/U_1)^{\frac{1}{S-1}} + 1)\sqrt{2log2}}$$

$$\sigma_v = \tan(\tfrac{\pi}{20})\left[U_h - 2log\left(\frac{2\sigma_u^2}{U_h}\right)\right]\left[2log2 - \frac{(2log2)^2\sigma_u^2}{U_h^2}\right]^{-\frac{1}{2}} \quad (13)$$

Here, Uh and Ul are the upper and lower center frequencies of interest in the Gabor kernel, S is the number of stages and O is the number of orientations used in the multi-scale/ multi-resolution Gabor decomposition. The choice of Gabor coefficients is not restrictive but the foundations for wide usage of Gabor filter banks for texture description were mainly laid in (Manjunath & Ma, 1996) [167] with the proposal of a homogeneous texture (HT) descriptor, and later advocated in diverse fields studies (Kandaswamy, et al., 2005) [35], (Riaz, et al., 2012) [39].

In literature, most of the proposed algorithms used Gabor filter technique as a step of feature extraction process taking benefit from the textured features of veins in vein pattern recognition and using orientation properties of palm hand veins. However, it was popular to add another technique besides Gabor filtrations to extract final feature to be used for matching.

In our work, we used only Gabor filtration technique and specifically Gabor bank filtration to insure that we can simplify the feature extraction process when using good pre-processing steps reaching good results with simplified algorithms.

Listing below in fig. 4 an example of Gabor bank filtration of captured images.

In our work, Gabor filter consists of two parts (a) Gabor filter bank part and (b) Gabor features extraction part. Gabor filter banks parts generate a custom Gabor filter bank. It creates a u by v cell array, whose elements are m by n matrices; each matrix being a 2D Gabor filter, whereas Gabor features extraction parts extract the Gabor features of an input image. It creates a column vector, consisting of the Gabor features of the input image.

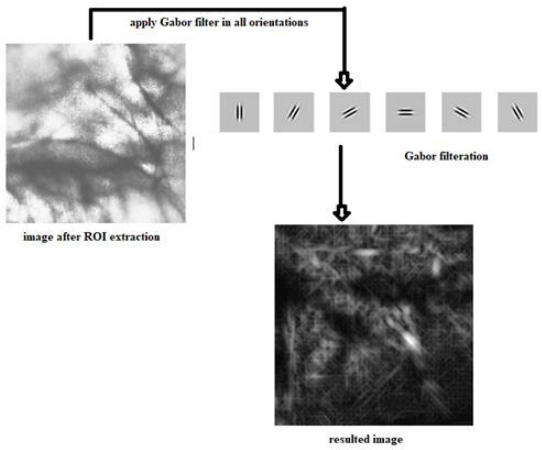

Fig.4 Gabor filter bank application on palm veins image.

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E. Feature Reduction

As the number of features extracted by the Gabor filter is very large, we apply a superposition method L2 max-norm type (Euclidean norm) in order to reduce the feature vectors so that the final value is the maximum value found by any of the filters.

Euclidean distance is employed for inter-distance computation of cross through intersections. Cross through intersection were used to reduce time taken for inter distance computation. The intersections are gotten by the following method:

1	0	1	0	1	0
0	1	0	1	1	1
1	0	1	0	1	0

For any nine pixels arranged in any of the two forms above, the coordinate of the central pixel is taken as the intersection points. The intersections are used in the computation of the inter-distance using the Euclidean distance formula.

$$D = \sqrt{(x_{1-} x_{0)}{}^2 + (y_{1-} y_{0)}{}^2} \qquad (14)$$

Where x0, y0 are coordinates of the first intersection x1, y1 are coordinates of the second intersection The computed inter-distances are stored in the created database. When a test sample is brought to the system, all the previously analysed process performed for the training set is as well performed on the test image, after which the stored inter-distances is matched with the trained one retrieved from the database to verify if it is the same palm sample.

F. Classification

It is the most important step that shows the impact of all before mentioned steps from capturing tell feature extraction. It gives an idea about the success of the framework used in any recognition work.

The classification process must include an important step, which is the determination of training and testing datasets taking into consideration that as training increase, the accuracy of the classifier increase so that to generalize a classifier result on datasets a compromise between training and testing must be done.

For vein pattern verification, our method uses:

F.1 Nearest Neighbours method

K-nearest neighbours classification algorithm can be expressed, [40]

K ← number of nearest neighbours
For each object *X*in the test set do calculate the distance D(*X*,*Y*) between *X* and every object *Y* in the training set neighborhood ← the *k* neighbors in the training set closest to *X*
X.class ← SelectClass (neighborhood)

As seen above an input sample is classified by calculating the distance to the training cases, and the minimum of the results then determines the classification of the sample.

Assuming there are *c* pattern classes denoted by *wi* ,*i* ={1, 2, …*c*} , and each pattern class contains *N i* training samples denoted by *k* , where *v i* ,*i* ={1,2, ..*c*} , *k* ={1,2,..*Ni*}, the discriminant function is:

$$g_i(v) = min_k \left\| v - v_i^k \right\| \qquad (14)$$

The decision rule is:

$$g_i(v) = min_k\{g_i(v)\} \Rightarrow v \in \omega_j \qquad (15)$$

It means that the input sample is classified to the pattern class based on the nearest distance to one of its member patterns.

F.2 Support vector machine.

In this study, SVM classifiers are used to classify datasets.

An SVM is a binary classifier that categorize the input feature vector by evaluating the classifier function f(x) as follows [41]:

f(x)= sgn(ω™ ϕ(x)_b) (16)

Where x is the feature vector, b and ω are bias and the vector of SVM coefficients respectively, defines kernel function and sgn denotes the sign function. Since SVM is inherently a binary classifier, one against all approach is used in this study to create a multi-class SVM classifier for palm vein classification.

G. Evaluation methods

There are many types of evaluation methods and evaluation indicators that can be used in palm vein identification to show the performance of the classifier used.

In our work, two types of these indicators are used:

a. Accuracy
b. Confusion matrix

V. EXPERIMENTAL RESULTS

The experiments were conducted using Matlab 2011a in an i3-3240 CPU at 3.4 GHz with 4 GB RAM.

We apply our proposed framework on 20 persons (80 images) of VP base database and16 persons (64 images) of our own database.

Two types of classifiers are used on the same datasets:

- KNN classifier
- Multi support vector machine with linear kernel function.

The recognition rate is deducted as follows:

- **For KNN classifier** by calculating the percentage of true results in the datasets.
- **For MSVM classifier** by using accuracy and confusion matrix.

Applying our framework on ten persons' images of VPBASE database, which sums up to 40 images, the results of the confusion matrix are as follows:

Persons recognized	Person one	Person two	Person three	Person four	Person five	Person six	Person seven	Person eight	Person nine	Person ten
Person one	1	0	0	0	0	0	0	0	0	0
Person two	0	1	0	0	0	0	0	0	0	0
Person three	0	0	1	0	0	0	0	0	0	0
Person four	0	0	0	1	0	0	0	0	0	0
Person five	0	0	0	0	1	0	0	0	0	0
Person six	0	0	0	0	0	1	0	0	0	0
Person seven	0	0	0	0	0	0	1	0	0	0
Person eight	0	0	0	0	0	0	0	1	0	0
Person nine	0	0	0	0	0	0	0	0	1	0
Person ten	0	0	0	0	0	0	0	0	0	1

Table II Recognition results based on confusion matrix of MSVM using ten persons' database images.

We Noted that 100 % of images are classified correctly.

The obtained results of both classifiers are summarized in table III.

Type of classifier		Persons #	Images #	Recognition rate %	Error rate %
KNN	K=1	10	40	100%	0%
	K=2	10	40	70%	30%
	K=3	10	40	50%	50%
Multi SVM		10	40	100%	100%

Table III Recognition results based on Gabor bank method.

The recognition rate is better with loer k value using KNN classification, giving maximum performance with k=1, without error.

On the other hand, recognition rate of MSVM classifier reflects the high performance of classification giving same results of KNN with k=1.

Where applying same algorithm on twenty persons' images of the same database which sums up to 80 images, the results of the confusion matrix are as follows:

Persons recognized	Person one	Person two	Person three	Person four	Person five	Person six	Person seven	Person eight	Person nine	Person ten	Person	Person	Person	Person	Person	Person	Person	Person	Person	Person
Person one	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Person two	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Person three	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Person four	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Person five	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Person six	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Person seven	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Person eight	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Person nine	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Person ten	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Person eleven	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Person twelve	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Person	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0

thirt een																				
Pers on fourt een	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Pers on fiftee n	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Pers on sixte en	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Pers on seve ntee n	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
Pers on eight een	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
Pers on ninet een	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Pers on twen ty	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Table IV Recognition results based on confusion matrix of MSVM using twenty persons' database images.

We Noted that 100 % of images are classified correctly.

The obtained results of both classifiers are summarized in table V.

Type of classifier		Persons #	Images #	Recognition rate %	Error rate %
KNN	K=1	20	80	100%	0%
	K=2	20	80	57.5%	42.5%
	K=3	20	80	42.5%	57.5%
Multi SVM		20	80	100%	0%

Table V Recognition results based on Gabor bank method of twenty persons' database images.

The recognition rate is better with lower k value using KNN classification, giving maximum performance with k=1, without error.

On the other hand, recognition rate of MSVM classifier reflects the high performance of classification giving same results of KNN with k=1.

Using our database created by vein viewer camera, we apply our proposed framework on ten persons' images sums up to 40 images; the results of the confusion matrix are as follows:

Persons recognized	Person one	Person two	Person three	Person four	Person five	Person six	Person seven	Person eight	Person nine	Person ten
Person one	1	0	0	0	0	0	0	0	0	0
Person two	0	1	0	0	0	0	0	0	0	0
Person three	0	0	1	0	0	0	0	0	0	0
Person four	0	0	0	1	0	0	0	0	0	0
Person five	1	0	0	0	0	0	0	0	0	0
Person six	0	0	0	0	0	1	0	0	0	0
Person seven	0	0	0	0	0	0	1	0	0	0
Person eight	0	0	0	0	0	0	0	1	0	0
Person nine	0	0	0.5	0	0	0	0.5	0	0	0
Person ten	0	0	0	0	0	0	0	0	0	1

Table VI Recognition results based on confusion matrix of MSVM using ten Persons' images of our database.

We Noted that 80 % of images are classified correctly. The percentage of error is 20%.

The obtained results of both classifiers are summarized in table VII.

Type of classifier		Persons #	Images #	Recognition rate %	Error rate %
KNN	K=1	10	40	75%	25%
	K=2	10	40	50%	50%
	K=3	10	40	50%	50%
Multi SVM		10	40	80%	20%

Table VII Recognition results based on Gabor bank method of ten persons' images of our database.

The recognition rate is better with lower k value using KNN classification, giving maximum performance with k=1, where recognition rate is 75% and error rate is 25%.

On the other hand, recognition rate of MSVM classifier reflects higher performance of classification than KNN classifier giving better results of recognition rate 80% and error rate 20%.

	Person one	Person two	Person three	Person four	Person five	Person six	Person seven	Person eight	Person nine	Person ten	Person eleven	Person twelve	Person thirteen	Person fourteen	Person fifteen	Person sixteen
Person one	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Person two	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Person three	0	0	0.5	0	0	0	0	0	0	0	0	0.5	0	0	0	0
Person four	0	0	0	0.5	0	0	0	0	0	0	0	0	0	0.5	0	0
Person five	0	0	0	0	0.5	0	0	0	0	0.5	0	0	0	0	0	0
Person six	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Person seven	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Person eight	0	0	0	0	0	0	0	0.5	0	0	0	0	0	0.5	0	0
Person nine	0	0	0	0	0	0	0	0	0.5	0	0	0	0	0.5	0	0
Person ten	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Person eleven	0	0.5	0	0	0	0	0	0	0	0	0.5	0	0	0	0	0
Person twelve	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Person thirteen	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
Person fourteen	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
Person fifteen	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Person sixteen	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Table VIII Recognition results based on confusion matrix of MSVM using 16 persons' images of our database.

We Noted that 82 % of images are classified correctly. The percentage of error is 18%.

The obtained results of both classifiers are summarized in table IX.

Type of classifier		Persons #	Images #	Recognition rate %	Error rate %
KNN	K=1	16	64	82%	18%
	K=2	16	64	50%	50%
	K=3	16	64	40.6%	59.4%
Multi SVM		16	64	82%	18%

Table IX Recognition results based on Gabor bank method of 16 persons' images of our database

The recognition rate is better with lower k value using KNN classification, giving maximum performance with k=1, where recognition rate is 82% and error rate is 25%.

On the other hand, recognition rate of MSVM classifier reflects same performance of classification of KNN classifier when k=1 giving same results of recognition.

Comparing the results of both databases, using both classifiers are summarized in table X.

The recognition rate is better with lower k value using KNN classification, giving maximum performance with k=1, without error.

On the other hand, recognition rate of MSVM classifier reflects the high performance of classification giving same results of KNN with k=1.

From the results of our database we can have a promising database for future work. Although results are lower than the other database but they can be considered good taking into account that images are taken directly without treatment depending only on the enhancement process.

Database		VP base		Our database	
Type of classifier		Recognition rate %	Error rate %	Recognition rate %	Error rate %
KNN	K=1	100%	0%	82%	18%
	K=2	57.5%	42.5%	50%	50%
	K=3	42.5%	57.5%	40.6%	59.4%
Multi SVM		100%	0%	82%	18%

Table X. Recognition results based on Gabor bank method

VI. Conclusion

In review of literature, more complicated algorithms are used for extraction of features in the purpose of getting higher performance. Gabor filter as a technique of feature extraction is used in combination with other techniques to assure the good quality of features used and attaining good results.

In the other hand the corresponding databases available for public use are rare and their growth of has resulted in a long response time

To solve the problem of a complicated feature extraction algorithms in palm–vein identification and availability of different choices of public free databases, more simplified technique for feature of extraction is used in this work, where we take benefit of the textured based features of the hand palm and in specific the orientation of the palm veins network using Gabor filter bank technique.

Compared with traditional complicated methods where different feature extraction techniques are fused, experiments by the proposed method showed the advantages on retrieval efficiency and identification using simplified algorithm based on enhancing the quality of image as a main step rather than feature extraction complicated methods, and introduce a base for a new method for developing a data base using a normal imaging technique rather than expensive imaging systems.

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