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An Efficient Dorsal Hand Vein Recognition Based on Firefly Algorithm

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ABSTRACT

Biometric technology is an efficient personal authentication and identification technique. As one of the main-stream branches, dorsal hand vein recognition has been recently attracted the attention of researchers. It is more preferable than the other types of biometrics becuse it’s impossible to steal or counterfeit the patterns and the pattern of the vessels of back of the hand is fixed and unique with repeatable biometric features. Also, the recent researches have been obtained no certain recognition rate yet becuse of the noises in the imaging patterns, and impossibility of Dimension reducing because of the non-complexity of the models, and proof of correctness of identification is required. Therefore, in this paper, first, the images of blood vessels on back of the hands of people is analysed, and after pre-processing of images and feature extraction (in the intersection between the vessels) we began to identify people using firefly clustering algorithms. This identification is done based on the distance patterns between crossing vessels and their matching place. The identification will be done based on the classification of each part of NCUT data set and it consisting of 2040 dorsal hand vein images. High speed in patterns recognition and less computation are the advantages of this method. The recognition rate of this method is more accurate and the error is less than one percent. At the end the correctness percentage of this method (CLU-D-F-A) for identification is compared with other various algorithms, and the superiority of the proposed method is proved.

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1. INTRODUCTION

Veins structure is unique to every individual. There are different imaging methods that near infrared lighting sensors are more common in capturing dorsal hand vein, palm vein and fingers vein patterns. Normally, black and white CCD cameras are also sensitive in the near infrared region, so a filter blocking the visible light is all that is needed on the camera.Since, shape and state of skin have no effect on the system's result, dorsal hand vein patterns are more secure than finger print and hand geometry[16]. These are one of the highest popular systems among security and biometric systems because of their uniqueness and stability. Most of patterns of dorsal hand veins are in form of direct lines with one or more branches toward fingers or wrist. Thus, these patterns may lose some of their important information because of being uncomplicated.

Recently, humans’ identification has broadly been evaluated through images and patterns of dorsal hand veins with high recognition rate methods. In addition, among biometric features, patterns of dorsal hand veins are frequently applied in both researches and industry. For these patterns several techniques are presented. For instance, Sanchit et al [1] introduced a system of dorsal hand and palm vein biometric information in a primitive level. They used veins patterns as a tissue sample in order to automatically extract features of images through binarized Gabor filter. Additionally for extracting tissue features in matching stage, a comparison between new biometric samples, saved samples in system data base and HammingDistance measurement criterion has been performed. In this new multi- model system less empirical results exist for EER[1] in comparison with available single- model systems. Khan and Khan [2] replaced each pixel quantity with dorsal hand veins pattern in a study, though their processing and matching was time consuming. Therefore, to solve the problem they applied dimension reduction technique and ICA[2] . Comparing this method with images obtained from patterns of one hundred peoples' dorsal hand veins besides measurement of rejected or false acceptance rate they increased system efficiency. In other study, Zokaee an Aghakabi [3] presented a noble approach in identification via patterns of dorsal hand veins and biometric ECG to achieve a compound biometric system.MFCC [3]method also used to extract ECG features of biometric module and LsHD[4] for matching vein structure. Euclidean distance was applied in measurement of extracted features of biometric ECG and finally KNN classifier used to identify patterns. Two databases a) with 294 people at ages 18 -54 and different sexes in addition to two images per every individual taken from different distances of their left-hand and b) standard data base PTB of ECG [5] consists of 549 cases collected from 294 peoples. At the end, the method showed a 94.7% detection rate. Heenaye-Mamode Khan et al [6] reduced matching time of dorsal hand pattern in the identification process in order to utilize PCA[5] .

They applied Cholesky analysis and simplification of features matrix to show limited dimensions of the veins structure. In this method, without losing related information to eigenveins matching the consuming processing time would be 6 seconds. It has successfully been verified on data base including 200 images with 0.9 threshold level. Zhicheng Liu, Xiangbin Liu and Xi Li [7] method tried to identify and train patterns of dorsal hand veins which as a result achieved a maximum detection rate of 95.5% through SVM. Liukui Chen et al [8] initiated a new method for classification of dorsal hand veins based on local thresholds and black and white morphology. The images are taken by CMOS infrared camera in low light and high noise state.

Before processing, the images were normalized and to compute local threshold and segmentation, binary images obtained by dilation and erosion operation. The results consist of efficient experiments on forty images. Wenjing Lu [9] presented a multimodal system of biometrics based on dorsal hand vein and hand shape. Cordingly, Gaussian matching filter extracts veins pattern of regions of interest (ROI) from original images. This also is useful for extraction of hand shape features such as width and height as well as triangular features of dorsal hand images border. Similarly, for matching basic information, the linear discriminate analysis (LDA) used to adapt binarizedvectors and 1D vector space. The dorsal hand vein images were taken by an infrared camera as well. Empirical results show that matching process could significantly increase system accuracy, however, results obtained from using either state individually is insignificant. Kumar also has introduced a novel method for individuals' identification using division of separate regions as adjucent triangles for area of dorsal hand veins images and extraction of knuckle form information simultaneously [10].

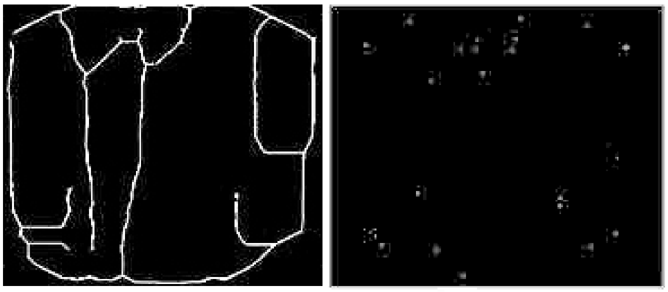
This is a pretty automatic method which might be applied on images of dorsal hand veins obtained by inexpensive methods and infrared light. The matching process happens in two parallel phases: (a) hierarchical matching score from four topological levels in order to divide regions into adjucent triangles, in binarized veins structure and (b)geometrical features composed ofknuckle point distances in images. The combined level weight of these two matchings is used for identification. Empirical results obtained from suggested system showed users' identification error rate of 1.14% . in biometric system to achieve higher security and accuracy, more than one biometric form is necessary. Thus, to mix different biometric methods, Shahin has designed and developed all biometric systems that demonstrate an example of hand. Indicators like right and left hand with Near Infrared (NIR), finger print (FP), patterns of dorsal hand veins (HV), and hand geometry were used as well [11].

Achieving the identification goal, he used a large data base included all of examples mentioned above. These samples were collected from 500 to 1000 individuals. Kai Chen also studied images of multispectral system through line features extraction method without concerning different types of tissues to measure relationship between recognition performance of dorsal hand vein with visible light and infrared light [12]. The effects are clearly observable on spectrum with 520- 1040 nm wave length (the most optimum band for identification of effective features). The EER shows the best performance in verifying identity using the suggested method in range of 880nm.

[1]equal error rate
[2]independent component analysis
[3]Frequency Coefficient Cepstrum
[4]Line Segment Hausdorff Distance
[5]principle component analysis

In order to improve the rate of identification, extraction of vein skeleton with little distortion of vein images are important. Lin Yang has in addition presented an algorithm for segmentation of images of dorsal hand veins and extraction of total skeleton of veins [13]. Such that in the first stage, normalization of size and gray color surface of images and Gaussianlow-pass filter and median filter applied to remove the particle and horizontal strip scanning noises. After, Niblack improvement algorithm of vein patterns and region threshold algorithm for removing noise blocks of vein patterns used. Third, to make vein limit smooth, the opening, closing and median filter as well as thinning vein pattern via Kejun Wang method occurred.

Dimension reduction could be happened in patterns with extreme complexity such as face, and retina etc through LDA and PCA methods. However, because of simplicity of dorsal hand veins the dimension reduction causes destruction in proper patterns and false identification resulted. By dorsal hand pattern we mean direct lines with one or more branches going towards fingers or wrist. If no appropriate method for dimension reduction and feature extraction exist low speed and large computations will be produced which is costly and weakly recognized. After pre-processing stage in each image, the above problem may be solved using extraction of dorsal hand veins and thinning of veins as Figure 1(a).as dorsal hand veins extracted according to Fig1(b) we get involved in fetching and extraction of veins intersections.



(a) (b)

Figure 1.(a) The image after improvement process and extraction of dorsal hand vein, (b) Extracted intersection from dorsal hand

As it can be seen above, feature extraction and image patterning perform with no loss of dorsal hand features which also have lower data space rather than PCA and LDA methods. Additionally, regularity of intersection pattern of dorsal hand veins leads to increased speed and accuracy in computations. Even though, in methods of PCA and LDA features extraction causes loss of data order and decrease of accuracy. General scheme of recommended method, as Figure 2.

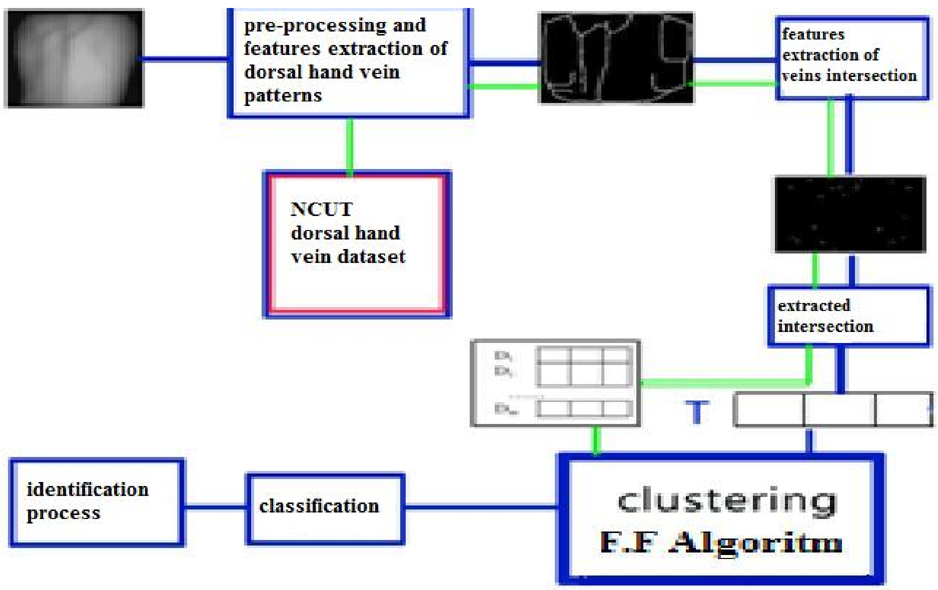


Figure 2. Recommended flowchart

In sections 2 and 3 we are going to study methods of producing images of dorsal hand veins, their pre-processing and features extraction of veins intersection. Then in section 4 clustering methods and new approach in clustering through firefly algorithm is proposed for solving false identification in presence of noise in imaging dorsal hand veins pattern.

2. Preparing images

In recent paper we used a data base created by a number of Tenancy University research members (Knoxville) such as professor Ahmad Badavi which consists of one hundred dorsal hand pattern[14]. These images were taken by a monochrome camera (CCD) that shows the image of a fist in which thumb and other fingers are hidden. In order to equally distribute light an IR source applied in the hand area. The prepared images created only for computer processing.

Two far infrared (FIR) and near infrared (NIR) methods were used to record dorsal hand veins images. In FIR the thermal radiation of veins in range of infrared waves are useful [15]. In NIR small lamps called Light emitting diodes (LED) are utilized which their wave length close to infrared wave. Since existing hemoglobin are sensitive to this wavelength and absorbs it from environment, therefore, it looks much darker than environment around. The Conventional charged –couple device (CCD) camera equipped with LED lamps used to record veins images [14, 16].

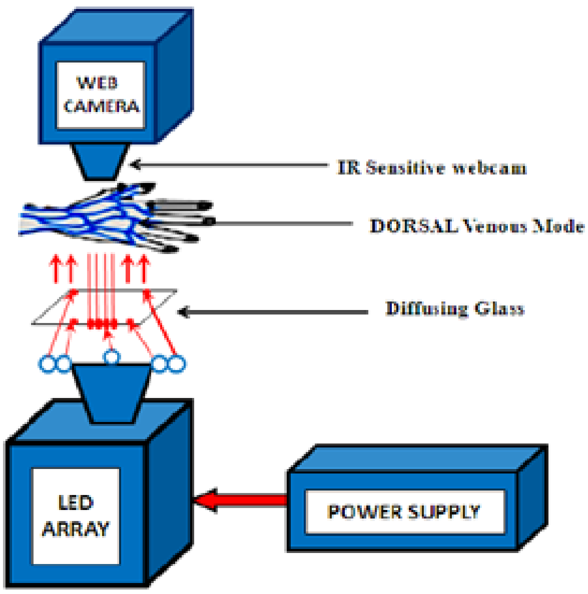


Figure 3. Method of imaging dorsal hand veins pattern and passing through IR filter

Every image is taken by video-digital camera with 8 pixel resolution in gray scale [11, 14, 17]. Images are in 320 *240 pixels, width and height respectively. The following image shows one of obtained dorsal hand vein patterns.

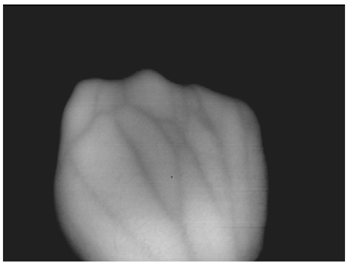


Figure 4.A sample of dorsal hand vein patterns

3. pre-processing and features extraction stages

3.1. pre-prcocessing stages

Pre-processing stage of images is known to be the most primary and principle stage in identification methods. The primary images of dorsal hand veins must be prepared for extraction of features during several pre-processing stages. In this part each module of image pre-processing will be discussed in detail.

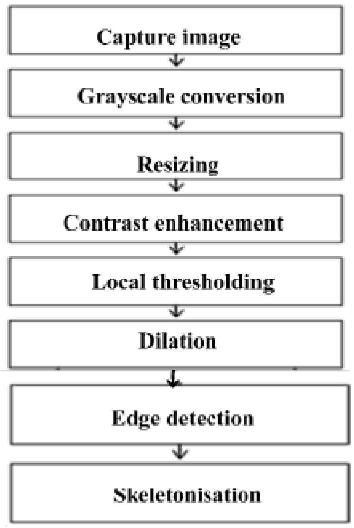


Figure 5. Pre-processing stages

3.1.1. conversion of images format from JPEG to BMP

With conversion of color image to gray scale image, the image size could be decreased from 24 bits in each pixel (color image) to 8 bits in each black and white pixel. This conversion sounds to be practical due to ability to be manipulated more easily.

3.1.2. contrast enhancement

The resulted images of dorsal hand veins possess low contrast. In a way that spots on vein pattern are indistinguishable. So, equal transfer functions (equalization) of histogram are helpful in improvement of veins pattern contrast. In equalization of histogram, a group of adjucentd peaks are changed into a flat histogram. This causes dark pixels seem darker and light pixels seem brighter.

3.1.3. local thresholding

Local thresholding is a way for conversion of black and white picture to a binarized show. The white pixel is 255 and black pixel is 0. This method in current paper is used on dorsal hand images to extract veins pattern. Easy and efficient usage of this method with dynamic local threshold has been approved.

3.1.4. morphological processing

Morphological processing holds such a capability through which small or extra particles on an image could be taken out in a way that no damage threats larger particles or the pictured shape. Generally, morphology will be changes in binary geometrical structure with evaluation of structural elements. Thus, selection of size and structural element regarded to be a significant stage in morphological operation. The major operation includes abrasion and enlargement that add or reduce few pixels from binary images according to rules of neighborhood pixels in the pattern. Abrasion operation shrinks size of image; however changing volume operation enlarges its geometrical size [8].

3.1.5. edge detection

Edge detection is a principally important instrument in processing of an image which aims to identify spots on a digital image in a way that light changes may be sharp or discontinuous. Using an edge detector in an image contributes to establishment of a set of connected curves for specifying the object's boundaries. In our algorithm, by use if Sobel edge detector and approximate calculation of image gradient the image edges will be discrete.

3.1.6. thining

An image thining associates to a connected region. Though, reaching a pixel width is often difficult. end–point , intersection point and image length are disadvantages of this method. Determination of intersection point of thin lines with large pixel width counts to be challenging.

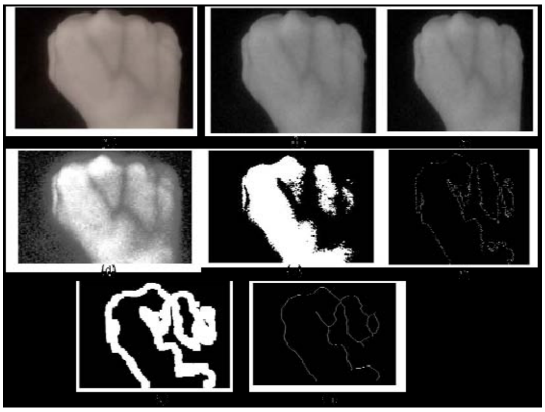


Figure 6. A) main picture B) black and white picture C) sized picture D) enhancement of image contrast E) local threshold F) Sobel edge detector G) morphological processing H) thininig

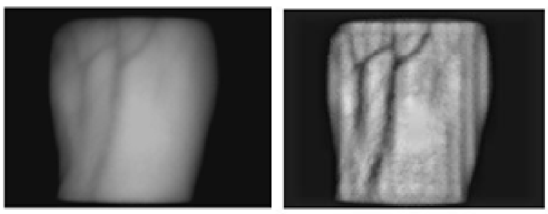
p_1	p_2	p_3
p_8	p_0	p_4
p_7	p_6	p_5

Figure 7. Procedure of finiding veins intersection in images

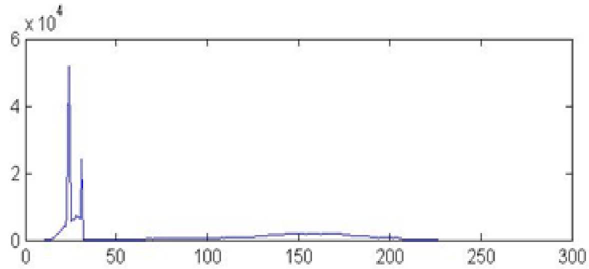
By following formula the intersection will be found:

$$N_{trans} = \sum_{i=1}^{8} |p_{i+1} - p_i| \text{, where } \quad p_9 = p_1 \tag{1}$$

Order of arranging and extraction of images features are as Figure 8.



a. input image, b. enhancement of contrast



c. Diagram of contrast enhancement

Figure 8. Order of arranging and extraction of images features

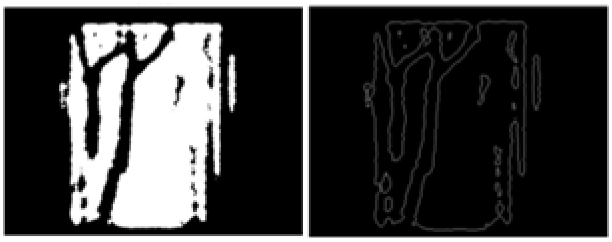


Figure 9. (a) local threshold (b) morphological processing

3.2. Stage of feature extraction in veins intersection

Features extraction from images of dorsal hand veins takes place after primary pre-processing stage. So, four images per each person are given to the system as input then pre-processing stages performed on every single image. In next step, a unique and common feature allocated to all four images and a couple of random points will be selected for every individual separately. After the primary pre-processing stage, per total number of input images of dorsal hand veins for each individual, value *i*is counted as a random value.

4. Identification using clustering method

Soon after pre-processing of the image, extraction of dorsal hand veins and making veins intersections, it's time to classify and extract dorsal hand veins. In previous methods through distances between veins intersections or their location the identification process performed. However, due to probable errors like noises or loss of a part of dorsal hand image during imaging time the existing data among spaces between veins or intersections disappeared and no identification happens. Also, it was likelihood that identification goes wrong and some evidences needed to confirm identification.

In order to solve this problem, firstly, the clustering method based on data features in each pixel of veins intersection points used. Secondly, classes are compared and the common class will be selected as true recognition.

The privileged of using clustering method is that in case of losing a part of picture the identification process keeps going by help of other part of image. According to amount of similarity of features the identification happens. Hypothetically, by tough comparison of all data we will reach a right recognition rate and with concerning only one similarity the entire similarity will be found. After individual's identification and confirmation it's time to remove noises or improve missing parts and save the resulted image in your own database.

4.1.Clustring through Firefly algorithm

4.1.1. Clustering

Clustering is an unsupervised important classification technique in which a range of patterns (mostly vectors in a multi dimensional space) in clusters are clustered based on criteria of similarity measurement such as Euclidean distance, Mahalanobis distance,Chernoffdistance, etc. clustering technique more often is useful for different applications of statistical data analysis, image analysis, data mining and other engineering and scientific issues.

Clustering algorithms may be divided into two categories: hierarchical clustering and partitioning clustering. Hierarchical clustering holds a hierarchical structure of clusters obtained by division of a large cluster into smaller ones and then integrating smaller clusters based on the closest centroid. Two major methods for hierarchical clustering has been defined.

A) Top-down or divisive method

Here, every large cluster will be divided into smaller or more clusters.

B) Bottom-up or agglomerative method

In this method every single large cluster will be formed from agglomeration of two or more smaller clusters. On the other hand, partitioning clustering method attempts to divide data set into a set of non-hierarchical discrete clusters. In most of usedpartitioningclustering algorithms, the clustering algorithms based on primary samples in which every cluster revealed by its center are applied. Target function (square error function) is sum of patterns distances from the center. In the present study we are mostly interested in the partitioning clustering for production of cluster center and classification of data set through this cluster.

4.1.2. Firefly algorithm

In nature fireflies are insects floodlight at nights. To describe firefly algorithm more easily following three rules should be learned:

- All fireflies are homogenous that a firefly can attract other fireflies regardless of its sex.
- An interesting and noteworthy behavior of fireflies observed in attraction of bait by brighter shine firefly and sharing it with the rest.
- The criterion to classify a firefly is its lighting. Thus, a firefly always moves toward its neighbor which is brighter and shines more.

FA is a population-based algorithm that seeks to find overall optimum of target functions based on swarm intelligence to evaluate exploratory behavior of fireflies. In FA physical subjects (agents or fireflies) are randomly distributed into the problem area. Agents are known as fireflies. Quality of light called light intensity which every one of fireflies has the chance to be absorbed by its brighter neighbors. More distance increases more attraction decreases as well. If no brighter firefly exists then they move at random.

At time of applying FA clustering, the decision variables are cluster center. Target function consists of sum of Eucilideous distance for all training data samples in N- dimension space. Regarding this target function all agents (fireflies) are randomly distributed in search space and initialized.

Two FA phases could come as follows:

A) Change in light intensity

Light intensity refers to target values. In maximizing issues a firefly naturally attracts other firefly based on high light intensity. Suppose we have a set of n agents (firefly) and $x_i$is a solution for i firefly that f(x_i) shows fit value. Here, I_i is light intensity for a selected firefly for radiation of current position of x and fit value of f(x).

(1) $I_i = f(x_i) \qquad 1 \leq i \leq n.$

B) Moving toward more attractive firefly

An attractive firefly emits a light intensity could be observed by other neighborhood fireflies. Each firefly possesses a defined β attractiveness which specifies how much powerful that firefly is in absorption of other members. The amount of fireflies attraction (β) links to r_{ij} which shows distance between two firefly i and firefly j and places on x_i and x_j respectively. The r_{ij} is defined as below:

$$r_{ij} = \|x_i - x_j\| \tag{2}$$

The function of firefly attraction β(r) is determined as below relation:

$$\beta(r) = \beta_0 e^{-\gamma r^2} \tag{3}$$

Where β0 is attraction level in r=0 and γ is coefficient of light absorption. The movement of firefly i in x_i which goes toward brighter firefly j in x_j is illustrated by relation (5).

$$x_i(t+1) = x_i(t) + \beta_0 e^{-\gamma r^2}(x_j - x_i) \tag{4}$$

4.1.3.Firefly clustering algorithm

Regardless of objects in group or classes, clustering methods have been developed based on unsupervised learning. In unsupervised technique, training data series are categorized according to numeral information (e.g. clusters' centers) at first and then matched by information classes analyst. Therefore, the main purpose is to find clusters enter through minimizing target function (overall distance of patterns from clusters centers). For N objects assumed in given problem the aim is to minimize squares sum of Euclidian distance between all patterns and allocation of every pattern to one of K clusters centers. Target function of clustering (sum of square errors) is computed through relation (6)

$$\mathrm{J(K)} = \sum_{k=1}^{k} \sum_{i \in c_k} (x_i - c_k) \tag{5}$$

In relation (6) , K is the number of clusters for *n* patterns (i=1,2,…,n) , x_i place of i pattern and c_k (c=1,2,…,K) the center of cluster k which is calculated with relation (7) :[9,10].

$$c_k = \sum_{i \in c_k} \frac{x_i}{n_k} \tag{6}$$

In relation (7) n_k is number of patterns in cluster k.

Analysis of clusters such as classification of patterns happens based on certain similarity measures in a cluster. To estimate the distance between patterns the use of similarity measures is usual. The centers of clusters categorized as decision variables which resulted through minimizing sum of Euclidian distance in all of training samples in n-dimensional space.

The target function for i pattern is calculated by equation (8):

$$f_i = \frac{1}{D_{Train}} \sum_{j=1}^{D_{Train}} d(x_j, p_i^{CL_{known(x_j)}}) \tag{7}$$

$D_{Train}$is the number of normal training data set between [0.0, 1.0] and $P_i^{CLknown(x_j)}$ ، In equ.(8) defined as the class to which samples of data base belong. It should be noticed that in FA algorithm the FA decision variables are clusters centers. The target function in FA algorithm is specified by equ. (8). For a dataset: n is the number of data points, d denotes to problem dimension, and c denotes number of classes. A data point belongs only to one of c classes.

Pseudo-code: A High-Level Description of firefly algorithm
Input:
Create an initial population of fireflies n within
d-dimensional search space x_{ik}, $i = 1, 2, \ldots, n$ and
$k = 1, 2, \ldots, d$
Evaluate the fitness of the population $f(x_{ik})$ which is directly
proportional to light intensity I_{ik}
Algorithm's parameter—β_0, γ
Output:
Obtained minimum location: $x_{i_{min}}$
begin
repeat
for $i = 1$ to n
for $j = 1$ to n
if $(I_j < I_i)$
Move firefly i toward j in
d-dimension using Eq. (4)
end if
Attractiveness varies with distance r via
$\exp[-r^2]$
Evaluate new solutions and update light
intensity using Eq. (1)
end for j
end for i
Rank the fireflies and find the current best
until stop condition true
end

Figure 10. Firefly diagram block

5.NCUT dataset

NCUT[17] is one of the biggest data sets obtained in the dorsal hand vein biometric field. Pattern of NIR images include 10 images of right hand veins and 10 images of left hand of 102 individuals.These 2040 dorsal hand vein images have been obtained by wang et al from industrial university in north of china. Generally, 10 images from both left and right hands of 102 individuals of age 18 to 29 are obtained. This is one of the biggest data sets obtained in the field of dorsal hand vein biometric. The best case for imaging is the time that individuals hands are fisted and illumination variations are very low. These are captured as row image NIR of hand veins.Our proposed method recognizes the discrimination of dorsal hand vein patterns to find out optimization spaces in final matching using euclidean distance. enerally, this data set is used for investigation and recognition of each biometric methods like one-to-many matching and one-to-one matching so that two dorsal hand vein patterns and 8 samples from 10 given samples in training data set are considered as test ones.

6.Experiments

In this experiment the pictures of dorsal hand veins will be tested under the noise and light conditions. The suggested method will be compared with previous methods:

A) In the first experiment the conditions of light were considered and identification proceeds

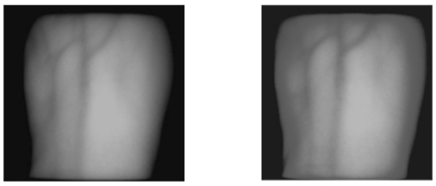


Figure 11. An individual's left-hand image with two different imaging

Table 1.Comparison of previous and recommended methods in evaluation of distances between patterns

Methods	Error rate	distances between patterns
CLU-D-F-A	0.005	1.651
Minutiae evaluation using MHD [18-19-20]	0.07	23.114
Hausdorff distance [21]	0.078	25.7556
Euclidean [22]	0.09	29.7118

The above results show the privilege of recommended method versus the previous ones. The obtained cluster centers for above intersections follows as:

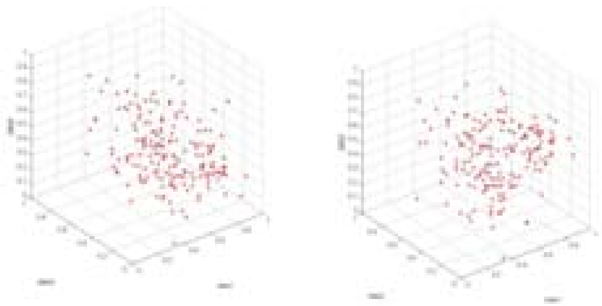


Figure 12.(a) cluster centers for main picture, (b) cluster centers for reduced light picture

As it can be seen the cluster centers are getting closer but they are in the same area yet.

B) The second experiment with 10 % Gaussian noise conditions

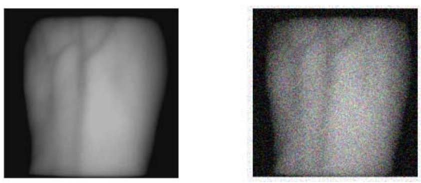


Figure 13. Picture of an individual's left-hand, the same picture with Gaussian 10% noise conditions

Table 2. Comparison of previous and recommended methods on evaluation of distances between patterns through noise filter

Methods	Error rate	distances between patterns
CLU-D-F-A	0.012	4.29
Minutiae evaluation using MHD	0.105	37.5375
Hausdorff distance	0.12	42.9
Euclidean	0.135	48.2625

Comparison of calculated time and level of error in one hundred dorsal hand vein patterns will be as follows

Table 3.Evaluation of previous and recommended methods on measurement of distances between patterns in one hundred pictures.

Methods	Error rate	Comparison of calculated time
CLU-D-F-A	98.02%	**M 10.35**
Minutiae evaluation using MHD	83.50%	**M 10.20**
Hausdorff distance	79.0%	**M 11.40**
Euclidean	76.50%	**M 10.25**

This implementation has been designed in version 2012a MATLAB and a 8G computer Ram, CPU core i5, Windows 7 version ultimate.

7. CONCLUSION

In previous methods, identification process on dorsal hand veins patterns occurred on distance between veins or place of vein individually that contained a high error coefficient and low recognition rate. The recommended method on the other hand consists of features extraction of dorsal hand intersections. The firefly clustering algorithm (FA) positions veins features in related classesof data numerically and proceeds identification via comparison of percentage membership ofsimilar data. Here, the class with the most similar features or data membership will be interpreted as identification result.

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