International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-7 Issue-5, January 2019

Feature Level Fusion of Iris and Finger Vein Biometrics for Multimodal Biometric Authentication System

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***Abstract*: With the intense need of security, a reliable authentication system can be attained using multimodal biometrics. Predominately vein patterns are attracting the researchers for developing authentication system. Multimodal biometric system not only aims at combining traits but also on fusion at various levels. Proposed approach fuses invariant iris features and finger vein shape features. The fusion at feature level framework is evaluated to perceive classification accuracy of biometric authentication system. Algorithm prioritizes on reducing high dimension features by considering iris Hu moments and finger vein shape features to accomplish a secured and convenient authentication system. SVM Classifier results prove that multimodal biometric outperforms compared to Uni-modal system.**

Index Terms: Biometrics, Feature Fusion, Hu moment, Multimodal, Shape Features

I. INTRODUCTION

A field of pattern recognition to identify an individual by a distinct and invariant physiological or behavioral characteristic is known as biometrics [1]. Security systems based on the concept of pins and passwords suffer from client attack, host attack, shoulder surfing, repudiation and Trojan horse attack. Biometrics stands as a perfect solution to handle these diversified attacks. The biometric based authentication system bids its demand in commercial, civilian and surveillance applications. The biometric traits used for authentication system are face, iris, ear, gait, palm print, finger print, finger knuckle print, finger vein, voice, teeth, DNA, ECG, and EEG etc.

Major limitations imposed by the unimodal biometric system are overcome in multimodal biometric system. Diversified methodologies are explored in literature to integrate physiological as well as behavioral modalities. Performance enhancement in authentication and recognition has been recorded by fusing the information present in the face along with fingerprint [2-10]. Face features are predominately fused with palm print [11-13], ear [14, 15], Iris [3], signature [15] and voice traits [16]. Experiments are conducted to fuse fingerprint and Iris [3, 8, 17, 18], fingerprint and palm print [19], fingerprint and finger vein [20], fingerprint and gait [6]. Fusion of visual and thermal image of face [24], shape and texture of face image [21] were investigated. The stable and diversified pattern of blood vessel structure located underneath the skin and hence insusceptible to forgery. Among various hand-based biometrics, vein pattern caters major role in security systems. Multimodal biometric system

using dorsal and palm vein have been demonstrated in [22]. Instead of fusing the traits biometric systems progress in performance is anticipated by fusing uncorrelated traits than correlated traits like voice and lip movement [23].

Fusions of biometric traits at various level are studied in the literature and can be listed as image level, feature level, score level or decision level fusion techniques. Experiments are conducted on image level fusion utilizing visual and thermal face images by Tao Wu et al [24]. Gabor and multi-scale wavelet decomposed features are concatenated and fuzzy c-means clustering algorithm (FCM) is used for performance estimation. Proposals on feature level fusion is recorded in [4, 5, 8, 12, 14, 16,17,18, 25, 26]. Niall et al. explored an audio–visual feature-level fusion of speech and facial modalities for person identification [16]. Morteza et al. [25] presented a feature level fusion of retina and iris using contourlet transform. Feature vector were normalized using Min-max normalization. Madeena et al. [26] worked retrieved content features from the biometric traits including color, texture, and shape features of face biometric and proposes feature fusion. Experiments were conducted to extract color features using Color histogram, texture information was extracted using Gabor filter and shape attribute of face shape features were utilized using pseudo Zernike moments. Gabor–Wigner transform (GWT) [12], Principal Component Analysis (PCA) [11, 14], Independent Component Analysis (ICA), latent semantic analysis [5], Linear Discriminant Analysis [9], FLDA a combination of PCA and LDA [27], Dimension of feature vector was reduced by Particle Swarm Optimization technique [12].

Evidences for Multimodal Score level fusion is recorded in [3, 9,10,11, 14, 19, 22, 28]. Combination of Multi-algorithm and Multimodal approaches for face and palm-print traits were experimented by M. Imran et al. [11].

Revised Manuscript Received on 30 January 2019.
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Classification performance was advanced by integrating One-class classification and the Real AdaBoost [3]. Serial concatenation and parallel fusion framework was investigated [14]. Dempster–Shafer (D–S) concept for fusing face and fingerprint at score level has been recorded.

Proposals on Decision level fusion found in [15, 20, 27]. Paul et al. [27] explored on the utilization of Social network analysis (SNA) technique to arrive at the decision level fusion. Behavioural biometric like keystroke dynamics which gives the timing information of key pressed, mouse movement pattern, stylometry- analysis of linguistic style and web browsing history were used to achieve authentication [15].

The experiments were conducted using the benchmark database SDUMLA-HMT involving face, fingerprint, gait and finger vein images [6, 29-35]. Author in [29] illustrates Semi-Supervised Learning (SSL) one with the fusion of face and fingerprint traits and another for gait and a fingerprint images from the benchmark database. Gaussian Energy Model based quality assessment of finger vein was done utilizing hierarchical vein feature [29]. Monogenic Local Binary Pattern (MLBP) [31], number of intersections in the vein pattern, and the pattern around the intersection point [28]. Contrast enhancement is based on Radon like Features in [34]. Yu Lu et al. investigated matching score-level fusion of finger vein [30] and proposed a weighted sum rule to fuse the matching score.Feature level fusion of iris and finger vein is advantageous as both the traits are difficult to forge, unique features are available and has stable structure. Extracted prominent features of any biometric traits are fused at feature level than at the match score or at the final decision to witness the good authentication result. It has been investigated that fusion at feature level provides better authentication results. Practical challenges of fusion at this level were identified by Ross et al. in [36]. The combination of multilayered texture and color of iris creates a pattern which is unique for an individual. Iris recognition proves to be more appropriate for authentication than face recognition because the features of the face undergoes gradual changes over the years, but the texture of the Iris remains unchanged, it has also been experimented that the best current algorithm available for face recognition has failed to recognize a person after a gap of a year because of the changes in the facial features [37]. In case of monozygotic twin’s face recognition often gives erratic results but it is not so for Iris recognition since the texture of the iris is not genetically linked. Being an internal organ protected by the cornea, less vulnerable to damage making it stable over a period, this is one of the important criteria in biometric identification.

Distinct vein pattern has drawn attention in recent years. Among the hand based biometric system, finger print can easily be forged as it is a feature external to the human body. Additionally, a clear condition of the finger surface is required during authentication. Same problems are faced using palm print and knuckle prints. An internal body feature, impossible to replicate and also it does not depend upon the surface conditions of the finger is finger vein and hence it is very likely for the system to generate a reliable result [38-45].

II. ARCHITECTURE AND MODELING

This paper proposes iris and finger vein fusion at feature level with novel ROI selection, feature extraction and SVM classifications techniques. Images are collected from SDUMLA-HMT [46] database. Architecture diagram of the proposed methodology is given in Fig.1.

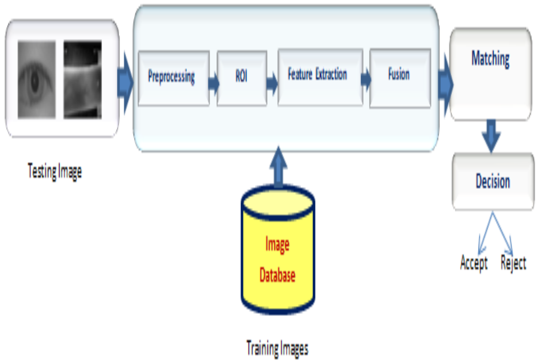


Fig.1. The architecture of the proposed work.

The pre-processing and enhancement module processes image by contrast as well as gray level manipulation, noise reducing, edge sharpening, filtering and binarization techniques. The proposed work is carried out by fusing the iris moment features with finger vein shape features. The work involves only a small portion of iris. ROI is situated inside the iris and external to pupil boundary including 32 X 32 pixels.

Experiments are conducted using training set inclusive of iris images from 100 persons 4 samples each and finger vein images from 100 persons 4 samples each. The testing set is inclusive of 100 irises and 100 finger vein images (1 sample from each person) to accomplish the performance enhancement of multimodal biometric authentication system over unimodal system.

2.1 Finger Vein Feature Extraction

Preprocessing, Region of Interest (ROI) selection and enhancement need to be accomplished before extracting the feature. Sections 2.1.1 and 2.1.2 refer to the detailed description of the steps used for finger vein structure extraction. Fig.2 illustrates the same. The features are extracted from the vein structure.

2.1.1 Preprocessing and ROI selection

Converting the gray scale image to binary is carried out initially via a bi-level thresholding technique. This is a process of classifying the intensity of the image into black and white pixels, the threshold used in the proposed work as given below

$S(x,y)=0$ if <0.2745

$S(x,y)=1$ if $>=0.2745$

Edges of the binary image are highlighted using edge detector to find the finger boundary.

Area opening is performed to remove fewer than P pixels to produce another

binary image, BW2. The steps followed to choose ROI is depicted in Fig. 3.

2.1.2 Enhancement

Enhancement and the refinement of the ROI are carried out to extract the desired features for matching or recognition in the process of authentication. An adaptive method to enhance contrast of the image, which redistributes the brightness of the image is adapted using histogram equalization technique. Segmented image denoising and blur reduction is carried out using wiener filtering. The filter operates by comparing an estimation of the desired noiseless signal with the received signal. Further noise removal and image compression is carried by 'daubechies wavelet transform'. Horizontal component preserves much detail and hence retained for further processing. Morphological erosion followed by dilation operation is performed on the processed image. Thinning is done to observe the vein patterns, mainly used to reduce storage space by removing unnecessary pixels in the image. Fig.4 shows sample dataset finger vein images and its corresponding vein structure.

2.1.3 Feature Extraction

The finger vein has rich feature information, visible as vein shape. For each vein shapes, features extracted are: area of the shape, contour perimeter, solidity of the shape, major and minor axis lengths, orientation and solidity using connected component of the image. Experiment analysis shows that the prominent features which correctly authenticate a person are area, perimeter, major axis length and minor axis length.

Area is a scalar value representing the overall count of pixels in the region given as:

$$Area(R) = |R|$$

Perimeter region's outer contour length and returned as a scalar. If {X1………..Xn} is boundary list, then perimeter is given by:

$$Perimeter = \sum_{i=1}^{n-1} d_i = \sum_{i=1}^{n-1} |X_i - X_{i+1}|$$

MajorAxisLength is length of the axis when major-axis end points are given. If (x1,y1) and (x2,y2) are the endpoints, the major axis length is given by:

$$MajorAxisLength = \sqrt{(x2 - x1)^2 + (y2 - y1)^2}$$

MinorAxisLength is a scalar value considering the number of pixels between the endpoints of the longest line in the region and remains perpendicular to the major-axis.

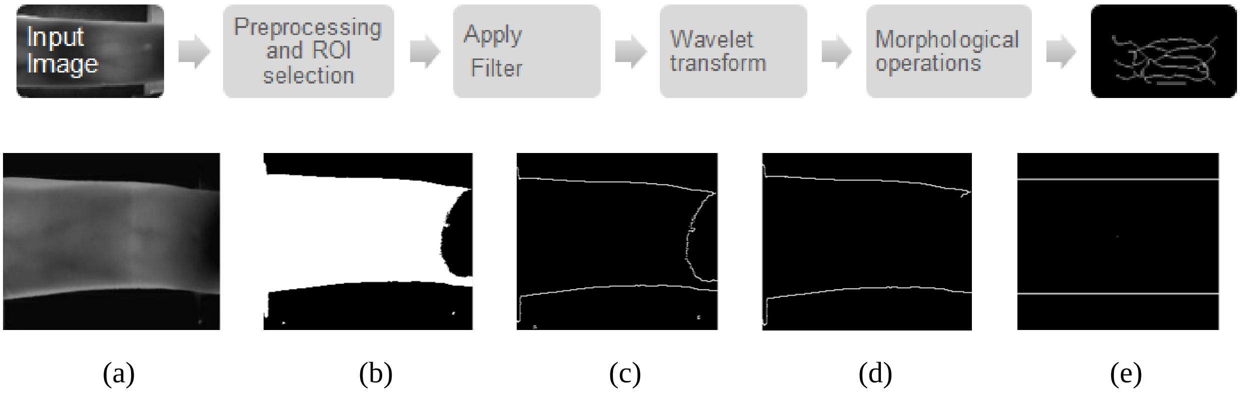


Fig.3. Steps involved in selecting finger vein ROI. (a) Database image. (b) Binary image. (c) Edge detected image. (d) Small objects removed. (e) Selected ROI.

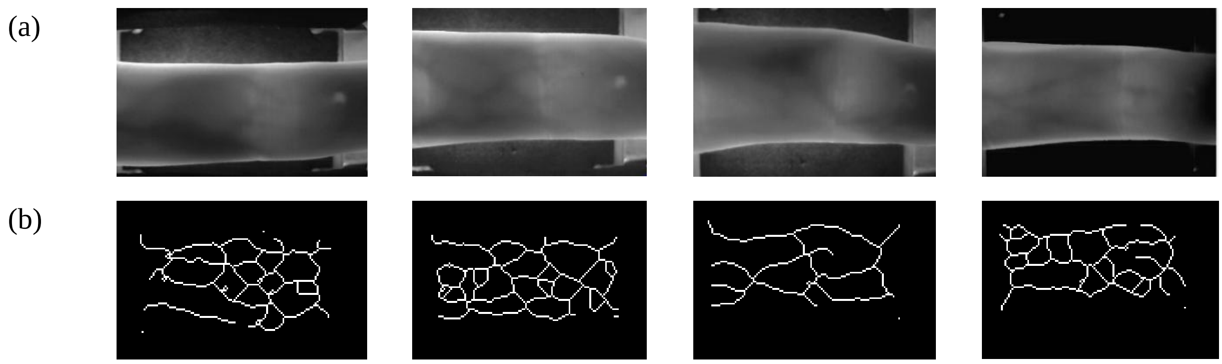


Fig.4. (a) Sample dataset of finger vein images. (b) respective vein structures

2.2 Iris Feature Extraction

The localization of the iris need to be carried out using edge detector. Among many edge detectors available in the literature, canny edge detector is suitable to find the edges. Edge detection is followed by finding the circular structure utilizing circular Hough transform. Section 2.2.1 designates segmentation of the iris followed by the Region of Interest (ROI) extraction using a novel method. The ROI selection is the novel method in this experiment which is less computationally intensive than traditional methods used for iris authentication technique.

2.2.1 Segmentation and ROI selection

The isolation of the iris from the sclera, eyelids and the eyelashes are the important step as they are noise and reduce authentication accuracy. The Hough circular transform is used for the determination of the limbus region and the inner border which separates the iris and the pupil for the accurate isolation of the Iris. Input image for the Hough circular transform is an edge detected image with a suitable threshold. The region which contains the edges in the smoothened image can be found out by calculating the magnitude and the direction of the gradient of the image using Sobel operator.

Since the shape of the Iris is already known to us, Hough circular transform can be cited as one of the most precise method for the determination of the radius and the central coordinates of the pupil and the Iris thereby resulting in an accurate isolation of the Iris. Thus Hough transform is an edge-based segmentation method to find lines or any parametric curve in an image.

Proposed work considers a 32*32 region of the lower portion of the Iris by taking the circumference of the pupil as the starting point, to be the ROI. Two reasons behind the selection of ROI is to reduce the storage space and to choose very less occluded region of Iris by the eyelashes as depicted in Fig.5. Certain enhancement is required to get the precise features during the feature extraction. Contrast enhancement of the ROI is carried out using image histogram equalization. Gaussian filtering is applied to remove the noise as well to retain the edge details. Below Fig.6 represents sample images from the dataset and the procedure followed to extract ROI.

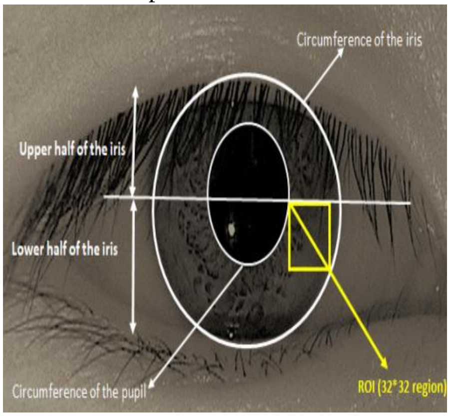
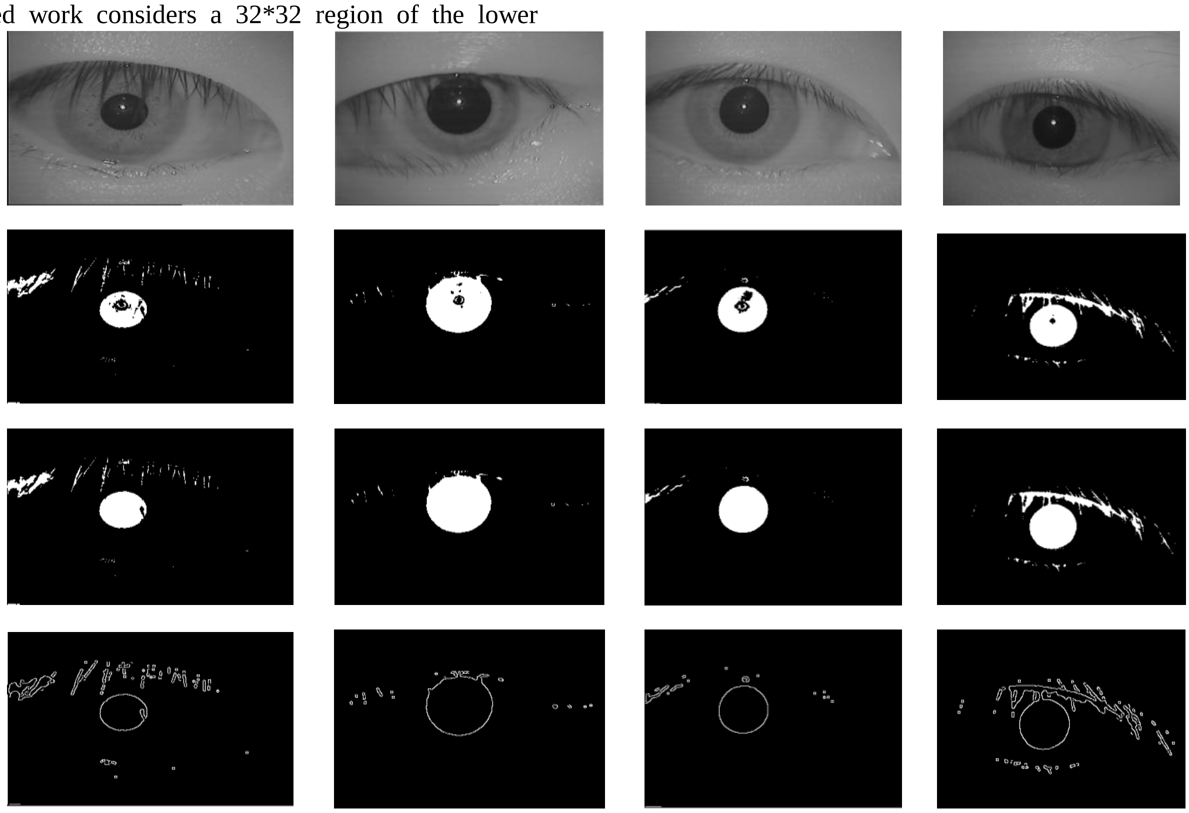


Fig. 5. Iris region if interest for feature extraction

(a)
(b)
(c)
(d)



(e)

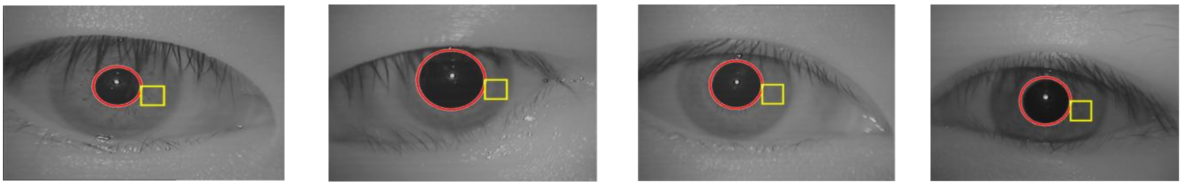


Fig.6. (a) sample dataset images. (b) binary image. (c) Filled with small holes. (d) edge detected image. (e) Respective ROI extracted image

2.2.2 Feature Extraction

A small region involving 32*32 pixels located inside the iris is of interest in the experiment is further intended for obtaining the Hu moment is then used for fusion. Shape descriptors using moments uniquely characterize an image [47]. The normalized central moments η_{pq} are calculated using central moments μ_{pq} of order pq using formula:

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}} \quad \gamma = \frac{p+q}{2}+1$$

This work uses central moments of order 3 to generate seven Hu moments as given in Fig. 7.

Feature Fusion

Feature extraction modules from both the traits are followed by feature fusion with reduced dimensions. Among all the features obtained from finger vein prominent features are area of the identified region, its perimeter, major and minor axis lengths are used for fusion. Hu moments from the iris are serially fused with finger vein features. Fused features from each person is used for classification. Table 1 shows sample fused features of 5 persons, where each row representing the iris Hu-moments followed by finger vein shape features. It is observed that 5^{th} , 6^{th} and 7^{th} order Hu moments of iris has more contribution in decision making when combined with all finger vein features as shown in Table 2.

3. Implementation and Performance Analysis

The database includes data from 106 individuals. The SDUMLA-HMT [46] database comprises multimodal biometric traits involving face images from 7 view angles, finger vein images

of from left and right hand inclusive of index, middle and ring fingers. Gait videos are captured at 6 different angles, iris images of both left and right eye and fingerprint images got with 5 different sensors. Every finger vein image is in "bmp" format with 320×240 pixels in size. The iris dataset has 10 iris images from every subject, 5 samples each for left and right eyes. Each iris image is 768 × 576 pixels in size with 256 gray-level "bmp" format. The total sizes of iris and finger vein databases are about 0.5G Bytes and 0.85G Bytes in total. Experiment has been conducted using MatLab2015a.

The training set per person is composed of 4 images from iris and finger vein traits. Testing dataset included single image per person per trait. SVM classifier with quadratic kernel is used to take decision during authentication process. The experiments witnessed 98% authentication accuracy. The performance of the classifier is visualized using Receiver Operating Curve (ROC) as in Fig.8. The Area Under Curve

(AUC) attained is 1. The experiment is carried out with various SVM kernels, namely linear, quadratic and cubic kernels. Among the kernels, quadratic kernel perceived best results. The experiments are also conducted to prove that multimodal biometric authentication outperforms in comparison with unimodal system. Unimodal authentication system witnessed 76% and 89% accuracy utilizing iris and finger vein traits respectively.

III. CONCLUSION

Principal contribution of the paper is to derive shape attributes of the finger vein and iris traits by reducing computation complexity. The work demonstrates that the Hu-moments of iris and shape features of finger vein are encouraging as discriminating features for authentication. The investigation also demonstrates that multimodal biometric authentication technique outperforms than Unimodal biometric authentication system. The work also satisfies the below requirements in accordance with Hong L and Jain A.K [48]: (a) speed: takes less time as the features are reduced and fused from each modality (b) accuracy: estimation of accuracy is done by choosing prominent features. The proposed framework attains 98% authentication accuracy and suitable for secured authentication environment.

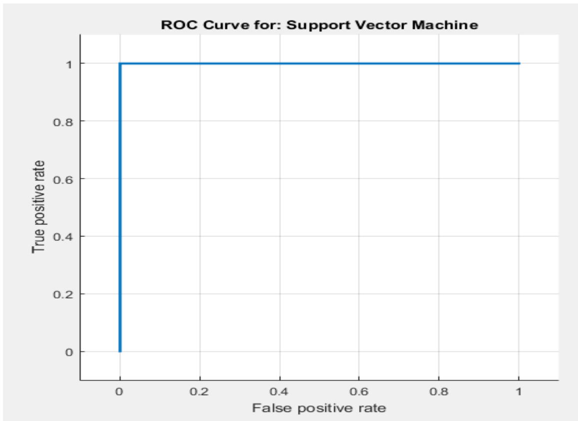


Fig.8. ROC curve for SVM classifier with quadratic kernel

$$m_1 = \eta_{20} + \eta_{02}$$

$$m_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2$$

$$m_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$$

$$m_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$$

$$m_5 = (\eta_{03} - 3\eta_{12})(\eta_{30} + \eta_{12})\left[(\eta_{03} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2\right] + (3\eta_{21} + \eta_{03})(\eta_{21} + \eta_{03})\left[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right]$$

$$m_6 = (\eta_{20} - \eta_{02})\left[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})$$

$$m_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})\left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2\right] - (\eta_{30} + 3\eta_{12})(\eta_{21} + \eta_{03})\left[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right]$$

Fig.7. The seven Hu-moments

Table 1. Sample values after feature fusion: each row representing the features from single person

Iris Features							Finger vein shape features			
1st order Moment	2nd order Moment	3rd order Moment	4th order Moment	5th order Moment	6th order Moment	7th order Moment	Area	Major Axis Length	Peri-meter	Minor Axis Length
0.001134	5.52E-08	1.99E-11	2.97E-11	-4.02E-22	6.74E-15	1.23E-21	403.5817	126.9978	463	46.31336
0.001208	2.84E-08	1.04E-10	2.11E-11	-3.56E-22	7.78E-16	-5.81E-22	398.4668	120.6978	458	56.69778
0.001148	7.22E-08	1.26E-10	1.03E-11	-1.96E-23	-2.13E-15	1.75E-22	374.3333	115.5556	474	40.55555
0.001486	2.37E-08	8.23E-11	4.13E-11	-2.16E-21	-5.58E-15	-4.93E-22	384.7004	125.1395	480	54.13951
0.001193	1.23E-07	2.40E-11	2.11E-13	-1.11E-25	-5.73E-17	1.33E-25	365.493	111.5662	495	39.5662

Table 2. Result and analysis

	Iris Hu moments (Left Iris)	Finger vein shape features (Left Middle Finger)	Classifier (kernel)	Accuracy
1.	ALL	NONE	SVM (Linear)	68%
2.	6^{th} & 7^{th} order	ALL	SVM (Gaussian)	80%
3.	5^{th} & 6^{th} order	ALL	KNN(n=3)	86%
4.	5^{th} & 6^{th} order	ALL	KNN(n=5)	90%
5.	ALL 7 orders	ALL	SVM (Linear)	92%
6.	4^{th},5^{th},6^{th} &7^{th} order	ALL	SVM (Linear)	94%
7.	5^{th} ,6^{th} & 7^{th} order	ALL	SVM (Linear)	94%
8.	**6^{th} &7^{th} order**	**ALL**	**SVM(Quadratic)**	**98%**

ACKNOWLEDGEMENT

Authors would like to express thanks to the MLA Group of Shandong University for providing SDUMLA-HMT Database.

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