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Fusion of Iris Texture with Finger vein Geometry for Authentication

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Abstract**: *A framework for feature level fusion-based authentication system is proposed in this paper. Feature level fusion improves the robustness and classification accuracy compared to unimodal authentication system. This work is carried in two-folds. The first experiment fuses the translation, rotation and scale (TRS) invariant statistical features of iris with finger vein. The second experiment contemplates geometrical, structural and statistical properties of finger vein with local and statistical features of iris.***

I. INTRODUCTION

An authentication scheme which interprets based on clues from multiple biometric sources is known as a multimodal biometric authentication system [1]. Biometrics being the branch of bioscience deals with verification or identification of a person using physiological or behavioral traits. Since many years unimodal biometric verification was in limelight. Recently multimodal biometric system is under research and many developing countries have implemented such system for the security purpose. Evidences from multiple traits can be fused at various levels namely, at image, sensor, feature, score, decision and at rank level. A unimodal authentication system involving single biometric trait regardless of its advantages encounters various problems. Unfavorable circumstance in capturing a test image such as illumination disparity, interoperability of sensor, noise in the sensed data, malicious attacks and the absence of a needy trait reduces the chances of success or effectiveness of unimodal authentication system. For instance deviation in the acquired image during template creation and test time are pragmatic due to illumination variation, sensor interoperability, weather condition.Impairment of the trait like a faded fingerprint, scar mark or damage of face texture, infected iris would also reduce the authentication accuracy. Hence multimodal authentication system, a branch of multi-biometric system is gradually drawing attention as robust authentication system [2].

Feature level fusion combines the evidences obtained from multiple feature sets extracted from the same subject. The general outline of the authentication system using fusion at feature level comprises of – feature extraction, normalization, feature selection, fusion and classifictionstages.These steps need to be carried out during both enrollment and verification stage. Authentication using multimodal biometric system involves multiple traits, features obtained from individual traits will diverge in their characteristics, range, dimensions and domain. The choice of algorithm used to extract, normalize, trans form and fuse the features must reduce the space and time constraints. Fusing the features at feature level is identified as 'before matching fusion' [3]. Face and Fingerprint traits are fused using DB4 FVC2004 fingerprint and ORL database by Long et al. [4], fusion at feature level carried out using Zernike moments and classification carried out using RBF neural networks. The system observed FAR 4.95%, FRR of 1.12%. A comparative analysis of unimodal system is done to prove the better performance of multimodal system. Gabor texture features from Iris and palmprint [5] are extracted and fused using wavelet-based fusion. KNN classifier shows the recognition accuracy 99.2% and FRR of 1.6%. Face and palmprint Log Gabor transformed features are fused. The dimensionality reduction done using Particle Swarm Optimization (PSO) and compared with AdaBoost method. Kernel Direct Discriminant Analysis (KDDA) classifier is used on virtual multimodal database using face FRGC and PolyU database for palmprint in [6]. Roy et al. [7] integrated of face, iris and gait biometrics at feature level. PSO based feature selection is carried out. Experiments were conducted using AT&T Face dataset, CASIA Version 3 Iris dataset and Gait dataset. Attained GAR of 96.40% and FAR of 0.001%. Face and iris biometric traits are fused [8] at feature level by extracting Log-Gabor transformed features. The extracted features are reduced in dimension using Linear Discriminant Analysis(LDA). Feature selection carried out using Backtracking Search algorithm. The experiment achieved GAR of 98.93% and FAR of 0.01%. Face and gait features are fused using PCA feature extraction method. Experiment observed 90% ,95% and 85% accuracy using Bayesian linear classifier, Bayesian quadratic classifier and Nearest Neighbor classifier in [9]. Huang et al. [10] worked on feature level fusion of face and hand geometry using DCT to extract the face features, distance measure between the hand geometry features. This work finds the classification accuracy using SVM classifier. Huang et al [11] conducted an experiment on semi-supervised dimension reduction while fusing face and gait modals. The database included for face images are AR face CMU PIE and FERET. The USF HumanID gait database is used for experimentation. The work achieved 88.60% of recognition accuracy. Hong et al. [12] fuses multiple features of gait such as mean values obtained from horizontal positive contour, horizontal negative contour, vertical positive contour and vertical

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negativecontour. Classification is done using Euclidean distance measure [12]. Michael et al. [13] carried out feature level fusion utilizing geospatial information and fusions of various features like gray level intensity and Gabor feature were exploited by Zhang et al [14].

The face and palm print features were represented using isomorphic graphs and portrayed using K-medoids clustering technique. For all accomplishable face and palm print images, the probable pair of graphs were searched using Scale Invariant Feature Transform (SIFT) points. Evaluation was done using K-Nearest Neighbor (K-NN) and correlation coefficient. The result observed using correlation coefficient was a recognition rate of 99.5% and 0% FAR. The K-NN distance measure achieved 99.25% recognition rate with 1.5% FAR [15, 16]. Face and voice traits are fused using the static and dynamic features. This work also performed liveness detection using a framework Multi Level Liveness Verification (MLLV) [17]. The feature level fusion of fingerprint and palmprint were proposed for uneven biometric data distribution in [18] to provide an equal probable discretization with different equal probable segments. This technique attained 0% EER.

Fusion of face and palmprint was carried out by Yan et al. The unconstrained correlation filter trained for a specific modality was designed using Correlation Filter Bank (CFB) technique [19]. Hand shape, finger-print and palm-print were fused in [20]. Coarse level hand shape feature was fused with fine level palm-print /finger-print features for identification. This experimentation yielded EER of 1.6 [20]. The Log Gabor transformed features of face and palm were concatenated to form a fused feature vector and PSO method was applied for reducing feature vector size [21].

Face and ear features were performed using the kernel based non-intrusive fusion by utilizing connection relationship. The accuracy recorded as 94.52% [22, 23]. Iris feature was used as watermark on the host face image with large population coverage, the overall accuracy of the system recorded as 99.50%. Unimodal comparison is also done with 86.3% and 94.1% for face and iris modalities respectively. [24, 25]. The phase congruence extract of face with Gabor transformation extract of palmprint texture by Fu et al. [26]. The visual and audio systems outputs were fused, and classification was done using Radial Basis Function (RBF) neural network. The work achieved a recognition rate of 94.4% [27]. The reduced feature point sets of face and finger print compatible for concatenations were achieved. The fusion features extracted from face and finger print were classified based on Delaunay triangulation by Rattani et al. [28]. The unimodal as well as multimodal fusion of face and hand traits were carried out by Ross et al using Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) coefficients of face and hand modalities. The feature selection scheme was used to remove redundant feature values [29].

II. PROPOSED FRAMEWORK

The experiment includes two phases: enrollment and testing phase. During enrollment various features from iris and finger vein are extracted, normalized, fused and stored as template set. Testing stage involves same steps as mentioned in the enrollment stage followed by applying classification algorithm to identify whether the probed sample is ‘genuine’ or ‘imposter’. Multiple features are extracted from iris and finger vein using multiple algorithms. Multiple instances of the same trait are also considered for classification. The resulting feature-level fused descriptors are fed into SVM and KNN classification models. Authentication accuracy of unimodal iris and unimodal finger vein is also procured to realize the elevated authentication accuracy of fused patterns. Subsequent sections reveal the feature extraction techniques of both iris and finger vein attributes followed by the details of the experiments. This work is carried out using SDUMLA_HMT multimodal database [31] utilizing iris and finger vein images. The preprocessing, enhancement and Region of Interest (ROI) segmentation are detailed in our previous work [30]. This paper deals with feature extraction, fusion, normalization and classification stages of multimodal biometric authentication. Fig.1 shows the sample iris and finger vein images from the SDUMLA_HMT database.

III. IRIS FEATURE EXTRACTION METHODS

This section discusses iris statistical features and local extraction methods. The statistical feature is obtained using Hu invariant moments. The local features are extracted using a novel method called as Iris Global Local Feature Extraction(IGLFE) [30] technique.

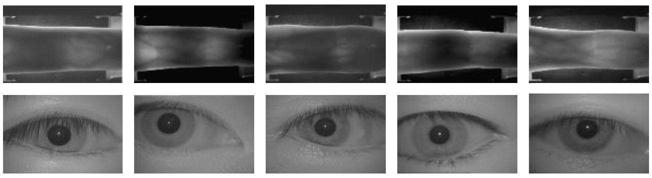

Fig 1. Sample finger vein and iris images from the database

3.1 STATISTICAL FEATURE EXTRACTION

The global and comprehensive details of the image can be fetched using moments. Moments are mathematically proved to be invariant to various transformations. Proposed work utilizes moments to quantify, distinguish and elucidate the shape of extracted ROI of an image. An image is modelled using distribution function g (x, y) in its continuous form as an integral:

$$M_{ab} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x^a \, y^b \, g(x,y)dxdy \text{ where } a, b=0,1,2\ldots.. \quad (1)$$

This function M_{ab} delivers the $(a+b)^{th}$ order regular moments over the image g(x,y). For discrete functions i.e for a digital image the moment is defined as follows:

$$M_{ij} = \sum_{x=1}^{N}\sum_{y=1}^{N} x^i \, y^j \, g(x,y) \quad (2)$$

Hence from equation (2) ‘M_{00}’ refers to sum of the intensities of the image. The moment equation (2) is mutable when g(x,y) encounters translation, rotation and scaling. Moments which are invariant to translation is known as central moments which are calculated about the centroid and is comprehended as,

$$\mu_{ab} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} (x-\bar{x})^a (y-\bar{y})^b f(x,y)dxdy$$

$$\bar{x} = \frac{M_{10}}{M_{00}}, \ \bar{y} = \frac{M_{01}}{M_{00}} \quad \text{wherea,b=0,1,2,......} \qquad (3)$$

The centroid of the image is given as

For discrete functions, the central moment can be written as (4). The regular moment in (2) whose center is shifted to coincide with the centroid ($\bar{x}$, $\bar{y}$), gives the central moment equation. Hence the central moments are invariant to translation.

$$\mu_{ab} = \sum_{x=1}^{N}\sum_{y=1}^{N}(x-\mu_x)^a (y-\mu_y)^b g(x,y) \qquad (4)$$

In probability theory and statistics, the horizontal distribution of the intensity is characterized by calculating 1st order central moment μ_{10} mean, 2nd order μ_{20} variance (σ^2) ,3rd order (μ_{30}) is skewness and 4th order (μ_{40}) is kurtosis. The higher order central moments i.e. 3rd and 4th order is used for iris ROI image characterization. The third order moment measuring the symmetry of the intensity distribution, the 4th moment kurtosis are employed in the iris feature set. Skewness is the statistical property which describes the extent of symmetricity of a function. Skew value zero indicates intensity is evenly distributed over the mean. A positive skew indicates intensity distribution is towards the right side of the mean and if the intensity distribution is towards the left of the mean, it is a negative skew. In image processing Kurtosis refers to noise and resolution, high kurtosis mentions low noise and low resolution.

$$\mu_{30} = \frac{1/n \sum_1^n (x_i-\bar{x})^3}{\sigma^3}, \quad \mu_{40} = \frac{1/n \sum_1^n (x_i-\bar{x})^4}{\sigma^4} \qquad (5)$$

Normalizing the central moments given in equation (4) will yield scale invariance property and can be termed as normalized central moments as given in the below formula:

$$N_{ab} = \frac{\mu_{ab}}{\mu_{00}^{\alpha}} \quad \text{Where } \alpha = \frac{a+b+2}{2} \text{ and a+b=2, 3, …} \qquad (6)$$

Based on this normalized central moments Hu's seven moment invariants can be computed, as follows:

$$m_1 = N_{20} + N_{02}$$

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

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

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

$$m_5 = (N_{30} - 3N_{12})(N_{30} + N_{12})[(N_{30} + N_{12})^2 - 3(N_{21} + N_{03})^2] + (3N_{21} - N_{03})$$
$$(N_{21} + N_{03})[3(N_{21} - N_{03})[3(N_{30} + N_{12})^2 - (N_{21} + N_{03})^2]$$

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

$$m_7 = (3N_{21} - N_{03})(N_{30} + N_{12})[(N_{30} + N_{12})^2 - 3(N_{21} + N_{03})^2] - (N_{30} - 3N_{12})$$
$$(N_{21} + N_{03})[3(N_{30} + N_{12})^2 - (N_{21} + N_{03})^2]$$
(7)

The seven Hu moments m_1 *to* m_7 given in (7) are invariant to translation, rotation and scaling (TRS) are considered as iris features in the first experiment. Algorithm 1 entitles the steps followed in iris features extraction.

3.2 IRIS LOCAL FEATURE EXTRACTION

This section describes reducing the dimensionality of extracted ROI. Local Binary Pattern(LBP) provide the texture feature of processed image by working on each pixel. If the feature extraction stage itself consumes more processor time during the authentication stage, the time efficiency of the developed algorithm reduces. Similarly, storage space for ROI can be reduced by converting LBP details into its encoded version. Hence this thesis proposes time and space efficient

Algorithm 1: Iris_HU_moments_extraction

Step1: [get ROI]

For each iris image I in the dataset

obtain ROI of iris IR_i

Step2: [extract Hu moments using 4.7]

For each IR_iimage in the dataset

Obtain Hu moments {$m_{1i}, m_{2i}, m_{2i}, m_{3i}, m_{4i}, m_{5i}, m_{6i}, m_{7i}$}

algorithm for iris feature extraction. As discussed in chapter 3, iris ROI is a 32x32 vector. Utilizing this vector becomes computationally intensive for matching purpose. Initially mean and standard deviation of the entire ROI is found and referred as global pattern. Now the LBP code vector is divided into 16 blocks, each block of equal size (8x8) vectors. These small blocks serve the local information in encoding iris features. The LBP code is now reduced empirically to 1x 64 vector by comparing the local patterns with the Global pattern.

IV. FINGER VEIN FEATURE EXTRACTION

This section gives an insight into finger vein statistical, structural and geometrical feature extraction methods used in the experimentation. The statistical feature is Hu moment as mentioned in the section 3.1. Diameter is the number of pixels along a straight line across a circular or a spherical profile passing through the center. Centroid is the geometric center of a profile. The centroid C(x,y) of a profile or the ROI having N vertices can be computed as follows:

$$\frac{1}{N}\sum_{i=1}^{N} x_i \ y = \frac{1}{N}\sum_{i=1}^{N} y_i \qquad (8)$$

Where, N is the number of pixels in the binary image and, xi and yi are the coordinates of the pixels present in the binary image.

Axis of least inertia preserves the orientation of a profile. It is defined as a line for which the integral of the distance from the line to the points on the profile boundary is minimum. The parametric equation of axis of least inertia can be given as

$$x\sin\theta - y\cos\theta = 0 \qquad (9)$$

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Where θ is the slope angle given as:

$$\theta = \alpha + \frac{\pi}{2} \quad if \ \frac{d^2 I}{d\alpha^2} < 0 \text{ and } \theta = \alpha$$

otherwise (10)

Where α is the angle between the x-axis and the axis of least inertia, which can be calculated as follows:

Inertia I is given by the formula

$$I = \frac{1}{2}(a+c) - \frac{1}{2}(a-c)\cos(2\alpha) - \frac{1}{2} b\sin(2\alpha) \qquad (11)$$

On double differentiation of the above equation with respect to α we get,

$$\frac{dI}{d\alpha} = (a-c)\sin(2\alpha) - b\cos(2\alpha) \qquad (12)$$

$$\frac{d^2 I}{d\alpha^2} = 2(a-c)\cos(2\alpha) + 2b\sin(2\alpha) \qquad (13)$$

If $\frac{dI}{d\alpha} = 0$ then, $\alpha = \frac{1}{2}\tan^{-1}\left(\frac{b}{a-c}\right) \quad , \alpha \in \left(\frac{-\pi}{2}, \frac{\pi}{2}\right)$

Eccentricity is a structural property which describes the aspect ratio of an image. It is defined as the ratio of the length of major axis to the length of minor axis.

Circularity is the measure of roundness of an image, which can be calculated by the following formula:

Algorithm 2: Feature_Fusion

Input: *Iris features vector* $I_f = \{I_1, I_2, \ldots I_n\}$ *and*

Finger vein features vector $FV_f = \{FV_1, FV_2, \ldots FV_n\}$

Output: *Fused features of iris and finger vein* $Fused_f$

Step 1: *Normalize the extracted features from each modality using z-score normalization* $Z_i = \frac{x_i - \mu}{\sigma}$ *where* μ *is mean of all features,* x_i *is* i^{th} *feature in the feature vector and* σ *is standard deviation.*

Calculate $Z(I_f)$ *and* $Z(FV_f)$ *using the above formula*

Step 2: *Concatenate the normalized z-scores from each modality*

$Fused_f = Z(I_f) \cup Z(FV_f)$

$$circularity = \frac{perimeter^2}{4 * \pi * Area} \qquad (15)$$

Solidity is defined as the ratio of the area of the shape to the area of the convex hull of the shape, hence it is the measure of extent of convexity or concavity of a shape.

V. FEATURE FUSION

Algorithm 2 gives an outline of how feature fusion is carried out. The extracted iris statistical and local features are normalized before fusion using z-score normalization technique. Similarly finger vein statistical features, structural and geometrical features as mentioned in (8) to (15) and Hu moments are normalized using z-score normalization. Fused features are verified using Support Vector Machine (SVM) classification.

VI. RESULT AND ANALYSIS

The result of experiment with the fusion of homogenous features i.e. moment features of both iris and finger vein traits are shown in table 1. The TRS invariant moment features are extracted, normalized using z-score normalization, fused features are classified using SVM classifier.

Table 1: Result showing the fusion of moment features of iris and finger vein

Iris Hu moments (right Iris)	Finger vein Hu moments (Left ring Finger)	Classifier (kernel)	Accuracy
ALL	NONE	SVM (Linear)	68%
NONE	ALL	SVM (Linear)	80%
5^{th}& 6^{th} order	ALL	KNN(n=3)	86%
5^{th}& 6^{th} order	ALL	KNN(n=5)	90%
ALL 7 orders	ALL	SVM (Linear)	92%
4^{th},5^{th},6^{th}&7^{th} order	ALL	SVM (Linear)	94%
5^{th} ,6^{th}& 7^{th} order	ALL	SVM (Linear)	94%

The next experiment considers finger vein statistical property– Hu moments; geometrical features like axis of least inertia and eccentricity; structural features – area, perimeter, centroid, diameter, solidity and circularity features. Iris statistical property- Hu moment, skewness and kurtosis; local -multi-encoded LBP features. Results exhibit elevated performance with the increased number of features are demonstrated by this experiment. Authentication accuracy achieved here with all iris and finger vein features using SVM, Gaussian kernel is 99.48%.

VII. CONCLUSION

The work illustrates the feature level fusion of iris and finger vein traits for multimodal biometric authentication.

The experiments were conducted in two-folds. The first experiment fuses the Translation,

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rotation and scale invariant features of both iris and finger vein to attain classification accuracy of 94%. Through the next experiment, heterogenouscombination including iris statistical and local features with finger vein geometry feature were combined demonstrating increased classification accuracy of 99.48%.

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REFERANCES

1. A. A. Ross, K. Nandakumar, A. K. Jain, Handbook of Multibiometrics , vol. 6. ,Springer, online, 2006
2. Ross, Arun, and Norman Poh. "Multibiometric systems: Overview, case studies, and open issues." Handbook of Remote Biometrics.Springer, London, 2009.273-292.
3. A. Ross, K. Nandakumar, and A. K. Jain, ‘‘Introduction to multibiometrics,’’ in Handbook of Biometrics, Springer, 2008, pp. 271–292
4. Long TB, Hanh T. Multimodal biometric person authentication using fingerprint, face features. In Pacific Rim International Conference on Artificial Intelligence 2012, pp. 613-624
5. R. Gayathri and P. Ramamoorthy, ‘‘Feature level fusion of palmprint and iris,’’ IJCSI Int. J. Comput.Sci. Issues, vol. 9, no. 4, pp. 194–203, 2012.
6. Raghavendra R., Dorizzi B., Rao A., Hemantha K.G. ‘‘PSO versus AdaBoost for feature selection in multimodal biometrics,’’ in Proc. IEEE 3rd Int. Conference on Biometrics, Theory, Applications and Systems (BTAS’09), 2009, pp. 1–7.
7. Roy K., Kamel M.S. (2012) Multibiometric System Using Level Set Method and Particle Swarm Optimization. In: Campilho A., Kamel M. (eds) Image Analysis and Recognition. ICIAR 2012. Lecture Notes in Computer Science, vol 7325. Springer,pp 20-29
8. OmidSharifi, Maryam Eskandari, Optimal Face-Iris Multimodal Fusion Scheme, Symmetry 2016, Volume 8, issue 6, 48, https://doi.org/10.3390/sym8060048
9. Y. Huang, D. Xu, and F. Nie, ‘‘Patch distribution compatible semisu-pervised dimension reduction for face and human gait recognition,’’ IEEE Trans. Circuits Syst. Video Technol., vol. 22, no. 3, pp. 479–488, Mar. 2012.
10. E.-S. M. El-Alfy and G. M. BinMakhashen, ‘‘Improved personal identification using face and hand geometry fusion and support vector machines,’’ in Networked Digital Technologies (Communications in Computer and Information Science), vol. 294, R. Benlamri, Ed. Berlin, Germany: Springer, Apr. 2012, pp. 253–261.
11. Y. Huang, D. Xu, and F. Nie, ‘‘Patch distribution compatible semi supervised dimension reduction for face and human gait recognition,’’ IEEE Trans. Circuits Syst. Video Technol., vol. 22, no. 3, pp. 479–488, Mar. 2012.
12. Sungjun Hong, Heesung Lee, Sung Je An, Euntai Kim, “Fusion of multiple gait features for human identification”, in International Conference on Control, Automation and Systems, ,pp 2121 – 2125, 2008.
13. Michael A. O’brien, John M I, “Information fusion for feature extraction & the development of Geospatial information”, in Proceedings of the 7th International Conference on Information Fusion, pp 976—982, 2008.
14. Wenchao Zhang, Shiguang Shan, Wen Gao, Yizheng Chang, Bo Cao, Peng Yang, “Information fusion in Face identification”, Proceedings of the 17th International Conference on Pattern Recognition, 2004, Vol 3, pp 950 – 953 ,2004.
15. DakshinaRanjanKisku, Phalguni Gupta, JamunaKanta Sing, “Multi biometrics feature level fusion by graph clustering”, in international Journal of Security and Its Applications, Vol. 5, No. 2, pp. 61-74, 2011.
16. DakshinaRanjanKisku, Phalguni Gupta, JamunaKanta Sing, “Feature Level Fusion of Face and Palmprint Biometrics by Isomorphic Graph-based Improved K-Medoids Partitioning”, in proc. of Advances in Computer Science and Information Technology, pp 70-81 , June 2010.
17. Chetty G, Wagner M, “Multilevel liveness verification for Face-voice biometric authentication”, in Biometrics Symposium: Special Session on Research at the Biometric Consortium Conference, pp 1 – 6, 2006.
18. Yong Jian Chin, Thian Song Ong, Teoh A.B.J, Goh M.K.O, “Multimodal Biometrics based bit extraction method for template security” in 6th IEEE Conference on Industrial Electronics and Applications, pp 1971 – 1976,2011.
19. Yan Yan, Yu-Jin Zhang, “Multimodal Biometric fusion using correlation filter bank”, in 19th International Conference on Pattern Recognition, pp 1-4, 2008
20. Yan Hui, Long Duo, “Personal identification based on multi-modal hand-print features”, in proc. of the 7th World Congress Intelligent Control and Automation, pp 7649 - 7652 ,2008.
21. Raghavendra R, Dorizzi B, Rao A; Hemantha G.K, “PSO VsAdaBoost for Feature Selection in Multimodal Biometrics”, in proc. of IEEE 3rd International Conference on Biometrics Theory, Applications and Systems, pp 1 - 7, 2009.

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