Tec Empresarial
P-ISSN: 1659-2395; E-ISSN: 1659-3359

REDUCTION OF FALSE ACCEPTANCE RATE IN MULTI-BIOMETRIC SYSTEMS BY WEIGHTED MULTI FEATURE EXTRACTION TECHNIQUE

Kishore Kunal*
Loyola Institute of Business Administration, Nungambakkam, Chennai, Tamil Nadu, India
*Corresponding author email: kishore.sona@gmail.com

ABSTRACT

Today, biometrics is most often employed for a variety of mundane activities, such as mobile authentication process and border crossing. Biometrics is subject to strict accuracy and efficiency standards in high-security circumstances. Multi-biometric techniques that combine the data from many biometric elements have shown to reduce erroneous rates and ameliorate the inherent flaws of the separate biometric systems in order to achieve this goal. Thus, to reduce the false acceptance rate in the multi-biometric system, the proposed approach uses the weighted multi-feature extraction technique. In this multi-feature extraction process, the image is initially segmented into multiple parts. Each part is then treated separately for noise reduction and cancellation. Especially the HSI (Hyper-spectral Image) is broken down into multiple Gaussian pyramid for extracting the multiple scaling features and the noise is eliminated by the usage of averaging filter. Further the extracted features are given weights and are featured to form cluster for each and every feature that is being extracted. This method reduces the error rate and provides more efficiency of the system.

Keywords: Biometrics, Multi-biometric system, false acceptance rate (FAR), weighted multi-feature extraction (W-mf).

INTRODUCTION

Reliable identity governance frameworks are essential due to the rise in contemporary identity fraud and worldwide security issues. In order to achieve it, biometrics has indeed been offered as a replacement to conventional identification techniques like an ID card and a password [1]. In order to distinguish or identify persons scientifically, biometrics is indeed the automated measuring and quantitative analysis of their physical (e.g., fingerprint, face, and iris) or behavior (e.g., voice, posture, and signature) traits [2]. In fact, governments, businesses, and individual people have all embraced biometrics as kind of a vital security tool. Uni-biometric systems are biometric technologies that use only one dimension [3]. Uni-biometric systems are plagued by problems like 1) sensor data that becomes noisy, 2) non-universality, 3) interclass resemblance and intra-class variations becomes high, 4) interoperability is found to be low, and 5) presentation attacks (i.e., deceiving biometrics by proffering real user's trait artifacts [4]), result in high inaccuracy rates. Multi-biometric methods (as shown in figure 1), which combine data from several biometric sources to achieve higher accuracy, can address some of the drawbacks of uni-modal biometric methods [2].

The term "multi-biometric" refers to the utilization of several sources that combine various types of biometric data from many sources for example a person's eyes and fingerprints. The following problems with uni-modal biometrics have been solved by multi-biometrics: non-universality or limited population covering (by lowering the refusal to enlist rate, which increases reach). Figure 1 clearly depicts the functioning of multi-biometric system. It gets more difficult for a fraudster to impersonate a validly enrolled person's various biometric characteristics. Multi-biometric methods effectively handle the issue of noisy information (a voice infection might alter a fingerprint, for example).

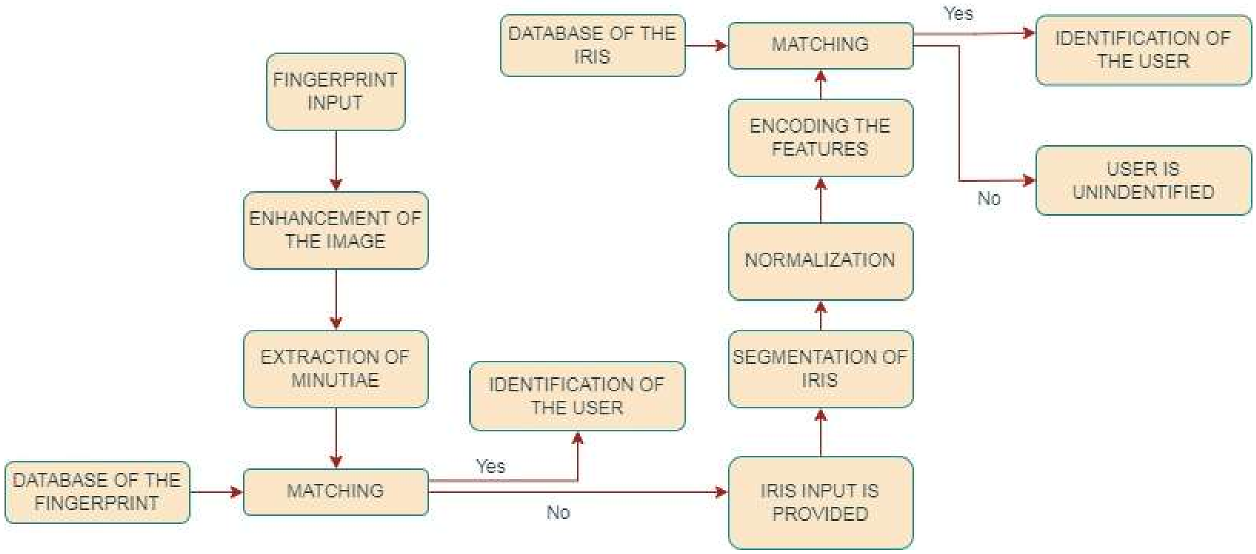

Figure 1. Multi-biometric system’s block diagram

There are five categories of the multi-biometrics and are as follows: [1]

1. **Multiple sensor systems:** This system uses multiple sensors to apprehend same Uni-biometric traits [5]. The outputs of 2-dimensional and 3-dimensional face detection systems, for example, can be merged to improve overall identification accuracy.
2. **Multi-algorithm systems:** It is also known as systems that use a variety of feature that is extracted and/or matching approaches on a single biometric characteristic, such as the fingerprint identification technique in [6] that uses data types depending on minutia and ridges.
3. **Multi-instance system:** It invokes numerous samples of the same biometric characteristics [7].
4. **Multi-modal systems:** It is integrating proof of countless biometric traits of the identical person, such as smart phone user verification through the use of touch stroke, phone mobility, and so on. Combining a number of different biometric features to determine identification is known as a multiple modal approach. Better recognizing rate is one of the many positives of multi-modal systems, which are achieved by merging many modalities. Use of physiological qualities (such as the finger and iris) can boost performance more than use of behavioral features (e.g. lips and voice). The issues with noisy data are also addressed by multi-modal systems.

5. **Multi-sample system:** During the registration and identification phases, several samples and measurements of a single biometric are gathered (e.g., several fingerprint measurements are captured from a single finger).

Feature Extraction:

The technique of turning unprocessed data into numerical elements that can be handled while keeping the data in the primary data set is known as feature extraction. Compared to using machine learning on the original data explicitly, it produces better outcomes. The vital areas of an image are represented as a small feature vector by extracting features for image information. Specialized feature detecting, extraction of features, and feature comparison techniques were formerly used to do this. Deep learning is broadly used for video as well as image processing, and it has gained notoriety for being able to analyze raw picture data without first extracting any features from it. Regardless of the method used, computer vision implementations like image acquisition, object classification as well as detection, and unique content extraction of image all need an efficient depiction of image attributes. This representation can be achieved either indirectly by using the first layers of a profound network or explicitly by using some of the well-established image feature extraction methods.

To overcome the constraint of complexity, feature extraction is thought to be a crucial step in classifying the hyper spectral images [8]. Numerous studies have revealed that multi element classification can significantly enhance the classification efficiency [9].A multi-feature extracting method was presented by centering upon Gaussian pyramid because features of various scales provide complementary but related information for categorization [10]. An integrated methodology that merges spectral data and spatial data at various scales was postulated, and developed two techniques for building integrated concepts. A troupe learning framework SMKB for HSI classification was suggested, which applies adaptive boosting probability method to understand multi-core-based classification models to solve multi-classification issues [11].

LITERATURE SURVEY

Selection of the features has been widely utilized to save computation time and increase precision. RELIEF [12], a well-liked method, applies weights to specific features based on the variances in nearest neighbor pair values. This method was extended further by understanding weights of features in piece-space and continuously removing useless features. It started off like evolution by creating an SVM classifier with every parameter that was available and then iteratively eliminating any elements that would have a negligible impact on the ability to make choices. As a result, many employed a ravenous continuous forward evaluation technique to identify a subset of features and support vectors that the SVM arrangement had obtained by making use of all available components. For the face identification, the most instructive features were chosen using multi-class SVM. With the suggested SVM-DFS, sorting can be improved without sacrificing matching precision. It was proposed for discrimination of subject part identification and it uses contingent risks as closest neighbor's separation measure. A method for selecting the most discriminatory object component classifiers in light of probability ratio and common data was proposed later.

The two biometric modalities that are used the most frequently in the literature are fingertip and face [13], both of which are taken into account in this work. Three categories of fingerprint recognition algorithms can always be made:

1) **Matching based on correlation:** Using the pixel strengths, the correlation amongst two fingerprint photos is calculated to determine how similar they are. For instance, an advanced correlation filter was suggested to be used as in [14].
2) **Matching based on minutiae:** The most well-known and often used method of fingerprint comparison is minutiae-based. The algorithms take into account how many pairs of tiny details from two fingerprint scans match. The method put out by the authors of [15] involves directly extracting details from the grey-scale photographs by following the crest lines.
3) **Matching based on non-minutiae:** Over the past ten years, non-minutiae characteristics in fingerprint methods have received a lot of attention. Non-minutiae match procedures can be loosely categorized as
   a. *Local image descriptions:* for example, the authors recommended the usage of localized Gaussian pattern as well as fuzzy localized directional pattern for fingertip matching [16].
   b. *Gabor filter based descriptions:* the authors retrieved the texture features with the use of Gabor filter around every core point [17].
   c. *Transform-based descriptions:* a localized texture analysis technique employing the discrete cosine transformation for fingertip matching was presented [18].
   d. *Machine/DL-based approaches:* e.g. Non-linear back propagation neural network (BPNN) was used with the invariant element features for fingertip identification and verification [19].
   e. *Hybrid Methods:* It combines more than one of the aforementioned techniques. E.g. the approach described in the study [20] makes advantage of local binary sequence characteristics and minutiae.

SYSTEM MODEL

The proposed work for reducing the false acceptance rate (FAR) by using weighted feature extraction has the following process. Firstly, each image should be split into several identical regions or sub-images. Secondly, the noise removal is performed using an averaging filter for every sub-image. Thirdly, the Gaussian pyramid is being used to identify the features. In which 8 features have been chosen at random and every feature is assigned with a weighted value. Lastly, build a cluster using the k Means Algorithm for every feature that has been chosen. The largest cluster is provided with the highest weightage. Two features with the maximum weight values will be chosen from each sub-image.

Dividing the Image into Sub-Images:

The main goal of this study is to develop an algorithm that, in ideal circumstances, chooses a subset with k features out of N image features. To acquire the maximum possible precision in detecting and selecting the key features, the image is split into 8 sub-images, each of which is then worked on individually. This subset is applied to the entire image beyond exception. Eight sub-images (Ai), each with 64 x 64 pixels, were created from the original 512 x 512 images.

Reducing the noise from the Image:

The method for reducing noise out of a digital image is noise removal. Enhancing the clarity of an image is indeed the main goal of noise removal. Images typically lose quality due to noise during transmission or the acquisition process. Combing in the spatial domain depends on positioning and its neighbors.

The easiest and least complicated method for actualizing image smoothing, or reducing the level of power variation between adjacent pixels, is the average filter. Additionally, it is frequently used to reduce noise from the image. The second step involves separating and using the Average Filter to eliminate the noise from the Sub Image. The idea behind this step's filtration is to change the value of each processing pixel in an input frame with the averages of its surrounding pixels, including itself. It repeatedly deletes the pixel values that do not accurately reflect their neighborhood. Convolution filter and average filter are relatively analogous. When calculating the mean, this filter additionally uses the kernel to indicate the size and shape of the area to be sampled. The image head information for the resulting image is set by the Average Filter after reading the input image.

The smoothing method is applied, the resulting image is set as source for the subsequent iteration if it is not the final iteration, and the final image is written once all iterations have been completed. The mean procedure calculates the average or mean of all the neighboring or adjacent pixel values. The centre pixel receives the resultant value.

Gaussian pyramid-based multi-scale feature extracting technique:

The proposed approach suggests a weighted ballot and Gaussian pyramid-based multi-scale feature extracting technique. To be more precise, we first utilize Gaussian pyramid deconstruction to divide the image into many distinct resolution images in order to extract features of various scales. The classifier is then trained using the training sets, and we finally get the classification outcome based on each unique learner plus their coefficient of the weight.

To have a low rank because the same type of sample typically exhibits near spectral features. The nuclear norm typically relaxes the ranking of S_c

$$R_c = rank(S_c)\ ||S_c|| \qquad (1)$$

$$R_c = \sum_i \sigma_i(S_c) \qquad (2)$$

where c is the number of classes, an i (S_c) stands for the unique values of S_c, and R_c is indeed the nuclear standard of S_c. The S_c is given by

$$S_c = [S_{ij}]\begin{bmatrix} SAD(X_1, X_2) & \dots & SAD(X_1, X_n) \\ \vdots & \ddots & \vdots \\ SAD(X_n, X_1) & \dots & SAD(X_n, X_{n-1}) \end{bmatrix} \in b^{n*(n-1)} \qquad (3)$$

Higher R_c indicates lower "quality" in sample whereas lower R_c indicates higher "quality". You can figure out how much I_l weighs by

$$\omega_t = \left(\frac{1}{C}\sum_{c=1}^{C} R_c\right)^{-1} \qquad (4)$$

For every test case, the logistic regression (LR) classifier calculates the class absolute probability. Let h_l signify the classifiers in I_l and let h_l^c (x) ∈ [0, 1] h denote the likelihood that the sample x will be classified as c. The labels for x are then obtained using the weighted vote approach as follows:

$$H(x) = arc\ max \sum_{l=I}^{L} \omega_l h_l^c(x) \qquad (5)$$

Where H(x) is the label of x that is being predicted.

Algorithm of the Proposed Work:

The following is the algorithm of the proposed work for reducing the false acceptance rate (FAR) by using weighted feature extraction.

Step 1: Each image should be split into several identical regions or sub-images.
Step 2: Noise removal is performed using an averaging filter for every sub-image.
Step 3: The Gaussian pyramid is being used to identify the features.
Step 4: Choose 8 features at random.
Step 5: Assign a weighted value for every feature.
Step 6: Building a cluster using the k Means Algorithm for every feature that has been chosen.
Step 7: Give the most weight to the feature with the largest cluster.
Step 8: Two features with the maximum weight values will be chosen from each sub-image.

this phase. Eight features are chosen at random from the feature collection, and the K-Means approach is used to create a clustering for every one of these characteristics. The value of a trait depends on the cluster. Each Sub Image generated eight clusters, and the two characteristics with the greatest weighting factor will be chosen. The weight value is equal to the number of attributes in the cluster. This approach will ultimately extract 16 features from the entire image.

RESULT AND DISCUSSION

The fact that match ratings from many matchers might not be uniform is one of the difficulties in merging match ratings. Take a look at the results from the two facial matchers in the Face collection. Figure 2, shows the ROCs again for face C and left as well as right indexing fingertip matcher scores from the initial BSSR1 data. The figure also shows the outcomes of combining the left and right index fingertip scores, the right index fingertip scores for face C, and the combined index fingerprint scores for face C. The conclusions are based on applying the best linear combining approach that is optimized for FAR = 10-4 in all three scenarios. Fusion outperformed employing a single modality significantly for the data under study. Additionally, combining face C and right hand fingerprint data has a higher TAR than combining left index fingerprint and right hand fingerprint data. The table 1 provides the consolidated value of the proposed method.

False Acceptance Rate (FAR)	Multi-biometric system	True Acceptance Rate (TAR)
	Face A	68
	Face B	70
	Face C	0.90
	Left Index	0.88
0.01	Right Index	0.91

	Left and Right Index	0.95
	Right Index with Face C	0.98
	Right and Left index with Face C	1.00
	Fingerprint A	70
	Fingerprint B	83
0.1	Face A	72
	Face B	75
	Face C	0.95
	Left Index	0.90
	Right Index	0.91
	Left and Right Index	0.99
	Right Index with Face C	0.98
	Right and Left index with Face C	1.00
	Fingerprint A	80
	Fingerprint B	83
1	Face A	80
	Face B	83
	Face C	1.00
	Left Index	1.00
	Right Index	0.8
	Left and Right Index	1.00
	Right Index with Face C	1.00
	Right and Left index with Face C	1.00
	Fingerprint A	82
	Fingerprint B	90

Table 1. Consolidated values of all the metric from the proposed method.

The TAR is approximately 97.5% at FAR = 10-4 whenever face C plus right index fingertip data are combined, as opposed to 92.5% when combining the more precise left indexing fingertip scores with the right indexing fingertip scores. Since the multi-biometric (facial and fingertip scores) information for the mates is mutually independent (r_2 = 0.0008), a large improvement was anticipated. The ROC obtained by combining the face C data with both the left and right index fingerprints demonstrates substantially enhanced improvement. For instance, compared to merely fusing the right index fingertip score also with face C score, the FRR, that would be 1 minus the TAR, is lowered by nearly 50% at FAR = 10-4 [28].

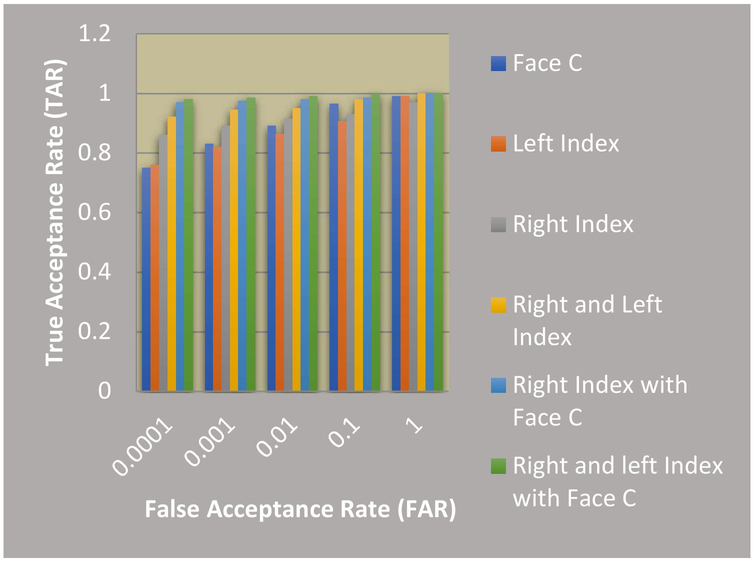

Figure 2. FAR vs. TAR for the proposed multi-biometric system

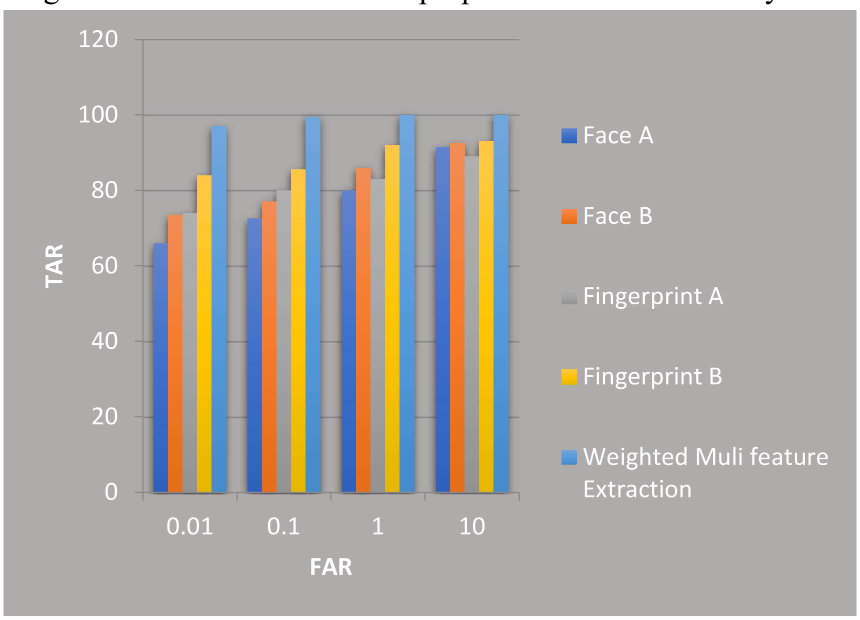

Figure 3. FAR vs. TAR for all four types of modalities

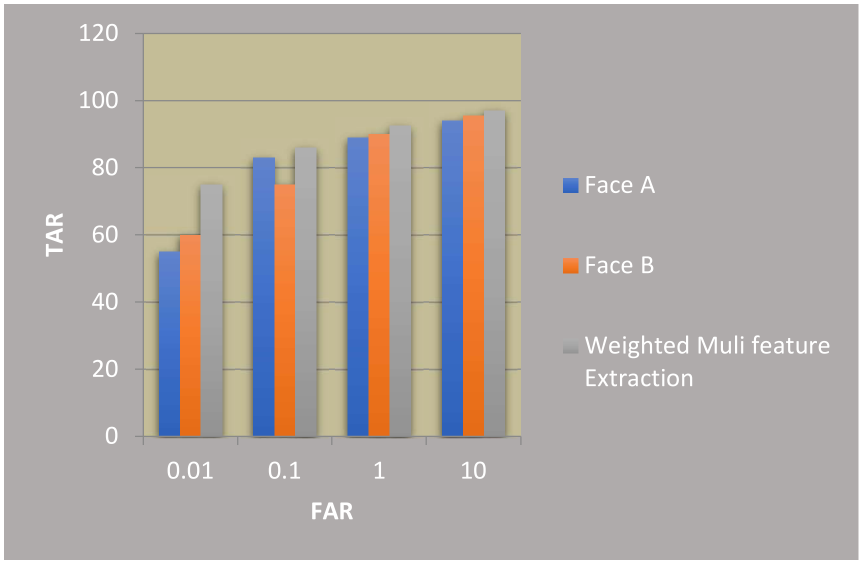

Figure 4. FAR vs. TAR only for both the face index modalities

In figure 3, it can be shown that the matched performance provided by both clustering algorithms is noticeably superior to that of the strongest single modality in every database. Additionally, it notes that there is no correlation between the top single modality in any database and the other modalities. The correlations values with face A, B, and finger A paradigms, respectively are -0:02, -0:06, & 0:43 for the legitimate cases & 0:04, 0:02, as well as 0:14 for the imposter cases for the Multi-modal collection (the best single modalities is finger B). Since the greatest modality dominates the fusion. The proposed method is examined for the fusion outcomes of 1 and 2 faces of the Multi-modal collection in order to assess the efficacy as seen Figure 4. In the two collections, this pair exhibited the strongest association of any other pair (0:75 and 0:29 as an output for the genuine as well as impostor scores, respectively). It was noted that especially in this instance, there is no appreciable efficiency difference between both the product as well as copula fusion rules.

CONCLUSION

A couple of the issues seen in uni-modal biometric methods are resolved by multi-biometric technologies. In addition to enhancing matching performance, they solve the non-universality and also spoofing issues. The most common level of information integration for multi-biometric systems is fusion at the matched score level, where the scores produced by the multiple matchers are combined. When uncorrelated qualities are applied in a multimodal system, productivity gains are noticeable. In this study, a developed technique for locating the key components of any image is described. After dividing the image into 8 Sub Images, the Gaussian Pyramid picture features were obtained for this objective. Furthermore, predetermined features have been clustered and given a weight value using the K- Means Procedure. The weighted features are treated in this approach as the basic and essential components of the image. The findings demonstrate that this approach can accurately identify all significant aspects without missing any, and it ensures that noise or unimportant features will be ignored. This technique predicts the features that are appropriate for matching and categorizing images.

REFERENCE:

[1] Bhanu, B., Govindaraju, V.: 'Multi-biometrics for human identification' (Cambridge University Press, USA, 2011).

[2] Jain, A.K., Ross, A.A., Nandakumar, K.: 'Introduction to biometrics' (Springer Science & Business Media, Secaucus, NJ, USA, 2011).

[3] Akhtar, Z., Hadid, A., Nixon, M., et al.: 'Biometrics: in search of identity and security (Q & A)', IEEE Multimedia, 2018, 25, (3), pp. 22–35.

[4] Akhtar, Z.: 'Security of multimodal biometric systems against spoof attacks'. PhD thesis, Department of Electrical Electronic Engineering, University of Cagliari, Italy, 2012.

[5] Guo, K., Wu, S., Xu, Y.: 'Face recognition using both visible light image and near-infrared image and a deep network', CAAI Trans. Intell. Technol., 2017, 2, (1), pp. 39–47.

[6] Fierrez Aguilar, J., Chen, Y., Ortega Garcia, J., et al. 'Incorporating image quality in multi-algorithm fingerprint verification'. Int. Conf. on Biometrics, Hong Kong, China, 2006, pp. 213–220.

[7] Mehrotra, H., Vatsa, M., Singh, R., et al.: 'Biometric match score fusion using RVM: A case study in multi-unit iris recognition'. IEEE Computer Society Conf. on Computer Vision and Pattern Recognition Workshops (CVPRW), Providence, RI, USA, 2012, pp. 65–70.

[8] J. M. Bioucas-Dias, A. Plaza, G. Camps-Valls, P. Scheunders, N. Nasrabadi and J. Chanussot, "Hyper spectral remote sensing data analysis and future challenges", IEEE Geosci. Remote Sens. Mag., vol. 1, no. 2, pp. 6-36, Jun. 2013.

[9] Pan B , Shi Z , Xu X . Hierarchical Guidance Filtering-Based Ensemble Classification for Hyper spectral Images [J]. IEEE Transactions on Geoence and Remote Sensing, 2017:4177-4189.

[10] Tu, B.; Li, N.; Fang, L.; He, D.; Ghamisi, P. Hyper spectral Image Classification with Multi-Scale Feature Extraction. Remote Sens. 2019, 11, 534.

[11] Qi C, Zhou Z B , Hu L , et al. A Framework of Multiple Kernel Ensemble Learning for Hyperspectral Classification[C]// Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People, & Smart World Congress. IEEE, 2017.

[12] K. Kira and L. A. Rendell. The feature selection problem: Traditional methods and a new algorithm. In AAAI, pages129–134, 1992.

[13] Akhtar, Z., Hadid, A., Nixon, M., et al.: 'Biometrics: in search of identity and security (Q & A)', IEEE Multimedia, 2018, 25, (3), pp. 22–35

[14] Crihalmeanu, S., Ross, A., Schuckers, S., et al.: 'A protocol for multi-biometric data acquisition, storage and dissemination'. Technical Report, WVU, Lane Department of Computer Science and Electrical Engineering, 2007

[15] Phillips, P.J., Flynn, P.J., Beveridge, J.R., et al.: 'Overview of the multiple biometrics grand challenge', In: Advances in biometrics (Springer, Berlin, Heidelberg, 2009), pp. 705–714

[16] McCool, C., Marcel, S., Hadid, A., et al.: 'Bi-modal person recognition on a mobile phone: using mobile phone data'. 2012 IEEE Int. Conf. on Multimedia and Expo Workshops, Melbourne, Australia, 2012, pp. 635–640

[17] Sequeira, A.F., Monteiro, J.C., Rebelo, A., et al.: 'Mobbio A multimodal database captured with a portable handheld device'. 2014 Int. Conf. on Computer Vision Theory and Applications (VISAPP), Lisbon, Portugal, vol. 3, 2014, pp. 133–139

[18] Sequeira, A.F., Chen, L., Ferryman, J., et al.: 'Protect multimodal db: fusion evaluation on a novel multimodal biometrics dataset envisaging border control'. 2018 Int. Conf. of the Biometrics Special Interest Group (BIOSIG), Darmstadt, Germany, 2018, pp. 1–5

[19] Cheniti, M., Boukezzoula, N.E., Akhtar, Z.: 'Symmetric sum-based biometric score fusion', IET Biometrics, 2018, 7, (5), pp. 391–395

[20] Chaa, M., Boukezzoula, N.E., Attia, A.: 'Score-level fusion of two dimensional and three-dimensional palm print for personal recognition systems', J. Electron. Imaging, 2017, 26, pp. 12–26