Investigation of different feature level fusion methods using iris and fingerprint

[1*]Suneet Narula Garg, [2]Renu Vig, [3]Savita Gupta

[1]Research Scholar, U.I.E.T, Department of Electronics and Communication, Panjab University, India

[2]Professor, U.I.E.T, Department of Electronics and Communication, Panjab University, India

[3]Professor, U.I.E.T, Department of Computer Science and Engineering, Panjab University, India

ABSTRACT

Biometrics becomes very popular area of research due to technology advancement. Most of the security based systems used biometrics for authentication purposes. Multimodal biometrics is more preferable as unimodal has some limitations. In multimodal biometrics more than two modalities are fused and then used. There are different levels of fusion used by multimodal biometrics but feature level fusion gives efficient results. So, this work focuses mainly to analyze the feature level fusion where four different methods Sum, Min, Max and MSUM is used. In this multimodal biometrics system Iris and Fingerprint modalities are used. For feature extraction six different texture features are extracted and then fused by using different methods. To calculate the recognition accuracy 200 samples are tested and comparative analysis of different methods is given in this paper.

Keywords: *Multimodal Biometrics, Texture Features, Feature Level Fusion, Iris, Fingerprint.*

1. Introduction

The identification of the person who they claim to be is done only by Authentication. Authentication is a process comprises individual claiming their individuality, & then offering proof to verify it. Biometrics is one of the technologies that are used to authenticate people by computerized ways which depends on behavioral or anatomical human features. This type of system has potential to perform authentication of people with higher level of assurance. The biometric system is categorized in two types that is Unimodal and Multimodal.

The unimodal biometric employ solitary biometric trait (either behaviour or physical) to recognize user Physiological

biometrics identifiers consist hand geometry, fingerprints, facial features, ear patterns, eye patterns, so on. Behavioural identifiers consist typing patterns, signature, voice, so on. While identifying feature of persons, there is probability for scheme to decide a authentic person as fraud or fraud as authentic. The performance of biometric method employ a particular trait is controlled by some inherent factors. Hence, novel skill was commenced; a grouping of more than one modalities is known as Multimodal Biometric System.

A multimodal biometric method groups more than two features of an individual to be identified together to verify authentication of person. Multi modal biometric methods can considerably enhance identification performance in addition to enhancing population reporting, deterring spoof attacks, enhancing freedom degrees, & minimizing failure-to-enrol rate. And also processing time, storage needs, & computational requirements of a multimodal biometric method could be superior than unimodal biometric method.

Many biometric models organized in real world uses are unimodal that depends on proof of sole information source for authentication (such as: face, fingerprint, voice, so on.). These types of systems are susceptible to various issues like intra-class variations, noisy data, spoofing, non-universality, and inter-class similarities. It lead to significantly high false acceptance rate (FAR) & false rejection rate (FRR), limited discrimination capability, upper bound in performance and permanence lack. Some limitations forced by unimodal biometric methods could be avoided by comprising various information sources to establish uniqueness. This type of system permits incorporation of more than two kinds of biometric methods called as multimodal biometric systems. These type of methods are more reliable because of independent, multiple biometrics.

The grouping of various modalities could give corresponding information and enhance accuracy of overall process of decision making. For instance, grouping of audio-visual characteristics with additional documented information have become more efficient to detect events from team sports video that may otherwise not feasible by utilizing a sole medium. The advantage of multimodal fusion comes with definite complexity and cost in analysis procedure.

2. Related Work

A novel fusion technique to recognize iris based on score and feature that applies voting on Multiple Classifier Selection technique. Voting method is used to achieve final recognition outcome by combining four Discrete Hidden Markov Model classifiers output; right iris based unimodal system, left iris based unimodal system, left-right iris feature fusion based multimodal system & left-right iris likelihood ratio score fusion based multimodal system. To compute performance of proposed technique on the basis of various parameters CASIA-IrisV4 database is used. Results demonstrate versatility of proposed technique (Islam et al., 2014).

Multimodal biometric technique using iris and fingerprint has been developed new feature level fusion algorithm to create combination of unimodal features utilizing Mahalanobis distance method. To train system, extracted features are used by using support vector machine based learning method. To validate and compare the performance of the proposed technique real fingerprint & CASIA iris database are used. Experimental results demonstrate that this technique have high rate of recognition with very small rate of false rejection as compared to existing algorithms (Gawande et al., 2010).

A new multimodal multifeature biometric method to recognize humans using two traits; iris and palmprint has been tested. The aim is to analyse integration of multifeature and multimodal biometric technique utilizing feature level fusion for enhanced performance. The main objective of this research work is to enhance the accuracy of recognition. At feature level, features are raw data that comprises of vital information when compared with matching score level fusion. Principal component analysis is used to eliminate the dimensionality of feature sets. Experimental results show significant improvement in accuracy of the proposed technique (Rajagopal et al., 2015).

Investigation and performance comparison from three varied techniques; fuzzy logic, weighted sum rule, classical sum rule for multimodal recognition of fingerprint and iris has been done. Scores from various traits of fingerprint and iris biometric are combined at decision & matching score levels. After normalization, scores combination technique is used (Benaliouche et al., 2014).

Face-iris recognition technique on basis of feature level fusion has been proposed. This research work build unique 2-D Gabor filter for extraction of local features from iris and face images and then change them in energy-orientation variance histogram feature having high distinguishability & low dimensions by using histogram statistics. one-to-n identification and feature level fusion are accomplished by fusion recognition method on basis of support vector machine and principal component analysis. Results show that this proposed technique also provide high accuracy of recognition along with extraction of iris and face features (Huo et al., 2015).

Ensemble algorithm for fusion at feature level in multimodal biometric model has been proposed. In this technique, results of classification is combined from every independent biometric feature to achieve composite classification called as biometric fusion. The efficient fusion technique unites processed information, which is kept for further authentication use (Bhardwaj et al., 2014).

Fusion at feature level to fuse feature vector of ear and iris extracted by technique of principal component analysis that also minimize feature vectors dimension. Matching is done by comparing test fused feature vectors with every training image utilizing measure of distance. This model is developed to analyze improvement in performance of multimodal biometric model upon unimodal biometric model by achieving success rate of 93 percent (Nadheen et al., 2013).

A novel algorithm for dynamic weighting matching on the basis of evaluation of quality of interest features has been tested. This work aimed to study fusion for finger vein and finger print biometrics at level of feature extraction. Initially, finger vein and finger print images are preprocessed by enhancement, filtering, gray-scale normalization, and so on. Efficient sets of feature point are extracted from sources of two-model. Experimental results demonstrate that this method may enhance security & performance of verification (Lin et al., 2011).

Various modalities studies and various methods utilized in different fusion levels with an aim to enhance robustness and performance at every fusion level. A multimodal biometric model unites various biometric traits and gives enhanced recognition than single biometric model (Kaur et al., 2013).

Multimodal biometrics concept that combines various biometric features and take benefit of capability of every biometric to give better performance and enhanced reliability has been proposed. This paper also discussed different fusion levels, significance of feature level fusion (Kaur et al., 2013).

Fusion at level of feature in three varied conditions was discussed. First is fusion of LDA & PCA face coefficients, second is combination of coefficients of LDA related to R,G, & B channels of image of face, third is combination of hand & face modalities. The main aim of this work is to show viability of these type of combinations. Results highlights merits and demerits of performing fusion at these levels (Ross et al., 2005).

The application of multimodal feature-level fusion to authenticate the enhancement in performance of multimodal authentication were implemented. Experimental results demonstrate that multimodal authentication process gives higher performance than single modality (AlMahafzah et al., 2015).

A feature level fusion method called as Discriminant Correlation Analysis (DCA), which incorporates class associations in analysis of feature sets related to correlation has been presented. It performs efficient fusion of features by enhancing pair correlation among two feature sets. This proposed technique may be utilized in recognizing patterns. It is a first method that considers structure of class in feature fusion. This proposed technique has very less complexity in terms of computation, it may be used in real applications. Various experiments are carried out on many biometric datasets. Experimental results demonstrate that proposed technique outperforms existing techniques (Haghighat et al., 2016).

A new technique of fusion utilizing biometric of iris-online signature at space of feature level has been proposed. Pre-processed iris image and signature dynamics are used to extract biometric features. This paper also proposed various schemes of fusion at feature level. To minimize the fusion scheme complexity, binary particle swarm optimization process is used. This paper also analyses how accuracy improves by integrating various biometric data (Almayyan et al., 2011).

Effective fusion at feature level of ear and iris images utilizing SIFT descriptors that separately extract ear and iris features has been implemented. These extracted features are combined in a single feature vector known as fused template. Synthetic multimodal biometrics database is used to execute proposed method. This fusion of ear & iris authentication system at feature level outperforms separate authentication systems of ear and iris (Ghoualmi et al., 2015).

A fusion of features of face and features of handwritten online signature at feature level has been proposed. High dimensionality of combined features are eliminated by using LDA in phase of feature extraction. This paper also applied fusion of features in phase of feature selection. This scheme provides high recognition rate with 97.50% accuracy as compared to previous techniques (Awang et al., 2013).

A new technique of fusion at feature level on basis of kernel Fisher discriminant analysis and also applied fusion of profile face and ear biometrics has been implemented. Recognition on basis of ear is a novel technique of authentication. This technique is effective for fusion at feature level and multimodal recognition on the basis of profile face and ear. This system performs better than unimodal system on the basis of profile face and ear (Xu et al., 2007).

Multimodal biometrics for palmprint and face images utilizing fusion methods at feature level has been introduced. To extract discriminant features gabor based image processing is used and to minimize dimension of modalities, principal component analysis (PCA) and linear discriminant analysis (LDA) are utilized. LDA output features are combined serially and Euclidian distance classifier is used for classification. This technique enhance rate of recognition than single modalities biometric (Ahmad et al., 2014).

3. Methodology Used

This work presents a Feature Level Fusion using different methods with Iris and Fingerprint Modalities. In this work, an image samples are used for both fingerprint and iris modalities. Feature Extraction of these samples has been done and then feature vectors of both the modalities are fused using different fusion methods. These fused values are saved in database and then it will use for recognition purpose. The detail of the Algorithm is given below.

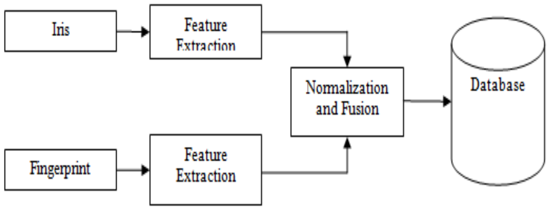

Figure 1: Feature Level Fusion using Iris and Fingerprint

3.1 Biometric Modality

The selection of biometric trait for security method use based on use; weaknesses & strengths of Iris and Fingerprint Modalities are summarized in the table below.

Table 1: Strength and Weaknesses of Iris and Fingerprint

	Fingerprint	Iris
Distinctiveness	High	High
Permanence	High	High
How well trait can be sensed	Medium	Medium
Speed and cost efficiency of system	High	High
Willingness of people to have trait used	Medium	Low
Difficulty of spoofing the trait	High	High
False reject rate*	0.4 %	1.1 - 1.4 %
False accept rate*	0.1 %	0.1 %

Error rates depend on sensors used, testing environment, & composition of clients in population.

3.2 Database Used

For this work, database of 200 samples for both Iris and Fingerprint has been used. Out of these 200 samples, 100 samples are collected from IITD database and 100 from CASIA database for both Iris and Fingerprint. This database contains 2 samples for each fingerprint and iris from a single person. It means this dataset contains the sample from 100 different users where each user contributes 2 samples each for both Iris and Fingerprint.

3.3 Wavelet based Decomposition

In this work, Hybrid Wavelet is utilized to decompose image and 5-level decomposition is done. The pictures are thought to be networks with N lines and M segments. At each level of disintegration the flat information is sifted, and after that the estimate and points of interest delivered from this are separated on sections. At each level, four sub pictures are gotten, the estimation, the vertical detail, the even detail and the askew detail.

3.4 Feature Extraction

In this work Texture features such as Contrast, Homogeneity, Coarseness, Energy, Directionality, and Entropy has been utilized which comes under statistical approach (Mirmohamadsadeghi et al., 2014) as described in Table 2.

Table 2: Texture Features

Texture Feature	Description	Formula Used
Coarseness	To spot biggest size at which texture occurs, even where minor micro texture occurs[21]	$S_{opt}(x,y) = 2^{k_{opt}}$
Contrast	To acquire dynamic series of grey states in image, along with polarisation of allocation of white & black.	$F_{con} = \sigma/(\alpha_4)^n$
Directionality	To compute entire directionality degree	Histogram will imitate the directionality degree
Homogeneity	To compute uniformity of non-zero entries in GLCM [7]	$\text{Homogeneity} = \sum_{i,j} \frac{1}{1-(i-j)^2} p(i,j)$
Entropy	To compute spatial disorder.	$\text{Entropy} = \sum_{i,j} p(i,j)\log(p(i,j))$
Energy	It is a measure of local homogeneity.	$\text{Energy} = \sum_{i,j} p(i,j)^2$

These Features identifies various characteristics of the samples used. In this work, all these features are calculated for both Iris and Fingerprint Samples. These features values may be similar or nearly equal for the samples that are of the same person. The extracted features of some samples for both Iris and Fingerprint are given in Table 3. These features will be used for further analysis.

Table 3: Extracted Texture Feature for Iris and Fingerprint

Iris Modality						
Sample	Coarseness	Contrast	Directionality	Entropy	Homogeneity	Energy
Sample_1	47.8697	48.7723	0.55187	7.3025	0.031167	1.5665e-005
Sample_2	48.8055	39.4728	0.88498	7.2263	0.030805	1.5337e-005
Sample_3	46.6678	50.0022	0.69037	7.4821	0.030819	1.6447e-005
Sample_4	48.0809	51.3934	0.73422	7.4595	0.031434	1.6329e-005
Sample_5	46.2396	61.9728	0.43447	7.7094	0.030459	1.6918e-005
Fingerprint Modality						
Sample	Coarseness	Contrast	Directionality	Entropy	Homogeneity	Energy
Sample_1	48.6166	66.1937	1.8122e-009	5.5267	0.090372	3.7441e-005
Sample_2	49.2744	53.2497	0.062914	2.6996	0.076883	2.6207e-005
Sample_3	49.155	53.3646	0.074633	4.5559	0.090591	3.456e-005
Sample_4	45.3557	78.0402	0.98182	3.1875	0.091157	4.014e-005
Sample_5	49.0421	53.6284	0.69293	2.5219	0.09241	3.4323e-005

3.5 Level of Fusion:

In Multimodal biometrics, there are four different level of fusion named as decision level, sensor level, matching score level, & feature extraction level (Gupta et al., 2015). Sensor and feature level are referred to as pre-mapping fusion while matching score and decision level are referred to as post-mapping fusion (Lin et al., 2011). In pre-mapping fusion, the data is incorporated before classifiers are used, while in post-mapping fusion; the data is incorporated after mapping to decision space/matching score.

- **Sensor Level Fusion**

The information procured from detecting the same biometric trait with two or more sensors are combined. Combination at this kind of level is required to improve biometric acknowledgment exactness (Bhardwaj et al., 2014; Kaur et al., 2013), it can't be utilized for multimodal biometrics in light of inconsistency of information from various modalities (Bhardwaj et al., 2014). **Example:** sense speech signal with two microphones at same time.

- **Feature Level Fusion**

Combination at this level could be connected to removal of various components from identical methodology or distinctive multimodalities (Bhardwaj et al., 2014). It is expressed in (Bhardwaj et al., 2014; Kaur et al., 2013) that combination at element level is relied upon to execute improved in examination with combination at score & choice level. The fundamental reason is that element level consists wealthier data regarding crude biometric information. In any condition, such a combination sort is not generally doable (Bhardwaj et al., 2014; Kaur et al., 2013). **Example:** Concatenating feature vectors extracted from fingerprint & face modalities.

- **Match Score Level Fusion**

At this level, it is possible to connect scores obtained from identical biometric trademark or distinctive ones. These type of scores are gotten, for example, on premise of vicinity of highlight vectors to their related reference data. The common score is transmitted to choice module (Rajagopal et al., 2015). Presently, this provides an feeling of being most precious combination state because of its great straightforwardness and execution (Kaur et al., 2013; Ross et al., 2005) This combination level may be partitioned in two classes: mix and arrangement. In preceding methodology, a scalar melded score is obtained through information coordinating scores normalization into similar reach and after that combining these type of standardized scores. In last method, information coordinating scores are considered as info components for brief moment level instance grouping problem among two classes of impostor & customer (Almahafaz et al., 2015).

- **Decision Level Fusion**

In this method, a different choice is occupied for every biometric sort at a late phase. This truly confines premise for improving the framework exactness by combination procedure. Along these lines, combination at such a level is the minimum effective (Haghighat et al., 2016).

There are so many work has been done on various level of fusion by using different modalities in multimodal biometrics. Table 4 describes the level of fusion of used by different authors for different modalities. From where it is found that, feature level fusion gives the best results as compare to other fusion levels and recently need to be explored. So, in this work, a feature level fusion has been selected and tested using different methods of fusion and is described in the next section.

3.6 Methods of Feature Level Fusion

In this work, feature level fusion is used. The performance of this level is analyzed using different fusion methods as described in table 5. These methods are here used to fuse texture features of the modalities. In this work, Iris & Fingerprint modalities are used and then their texture features are fused using these methods.

Table 5: Methods for Feature Level Fusion

Method	Definition	Formula
SUM based Fusion	The fused Feature vector is calculated by accumulating feature vector for each involved modality.	$f_{sum} = \sum_{i=1}^{N} F_i$
MIN based Fusion	Minimum rule method chooses the feature vector with minimum value of modalities involved.	$f_{min} = min(F_1, F_2, F_3, \dots\dots. F_N)$
MAX based Fusion	Maximum rule method chooses the feature vector having the largest value of the modalities involved.	$f_{max} = max(F_1, F_2, F_3, \dots\dots. F_N)$
MSUM based Fusion	The fused Feature vector is computed by calculating mean value after adding the feature vector for all modalities involved.	$f_{MSUM} = \frac{1}{N}\sum_{i=1}^{N} F_i$

4. PERFORMANCE ANALYSIS

This Work is to simulate feature level fusion on multimodal biometrics where iris and fingerprint modalities are used. In this different texture feature are extracted for all the samples and then fusion is done by using four different methods named as sum, min, max and msum. To implement this work, MATLAB simulator is used and database of 200 samples for both Iris and Fingerprint are collected from IITD and CASIA datasets. Analysis is done on these samples and results are calculated by using the performance metrics: False acceptance rate, false rejection rate and Accuracy.

False Acceptance Rate: The probability that system inaccurately coordinates info instance to non-coordinating layout in database. It gauges percent of invalid inputs which are acknowledged inaccurately (Proenc et al., 2014). If there is occurrence of similitude scale, individual is sham in genuine, coordinating score is greater than edge, and after that he is dealt with as honest to goodness that builds FAR and henceforth execution likewise relies on the determination of limit worth. Contingent upon the decision of the order limit, amongst all and none of the impostor examples are dishonestly acknowledged by the framework. The edge depending portion of the erroneously acknowledged examples isolated by the quantity of all impostor examples is called False Acceptance Rate (FAR). Its worth is one, on the off chance that all impostor examples are erroneously acknowledged and zero, if none of the impostor examples is acknowledged. The calculated false acceptance rate for 200 samples is as shown in Fig 2.

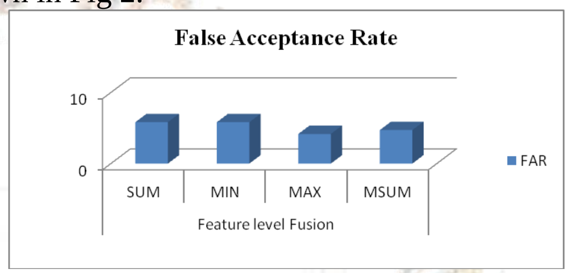

Figure 2: False Acceptance Rate using different Methods

False Rejection Rate: The probability that framework neglects to differentiate a match among info design & coordinating layout in database. It gauges legitimate percentage inputs that are inaccurately dismisses. Presently how about we change to the customer designs. Like the impostor scores, the customer example's scores shift around a specific mean quality (Dubey et al., 2016). The mean score of the customer examples is higher than the mean estimation of the impostor designs, as appeared in the left of the accompanying two pictures. On the off chance that a grouping edge that is too high is connected to the order scores, a portion of the customer examples are erroneously dismisses. Contingent upon the estimation of the edge, amongst none and the majority of the customer examples will be dishonestly dismisses. The division of the quantity of rejected customer designs isolated by the aggregate number of customer examples is called False Rejection Rate (FRR). As indicated by the FAR, its quality lies in the middle of zero and one. The calculated false rejection rate for 200 samples is as shown in Fig 2.

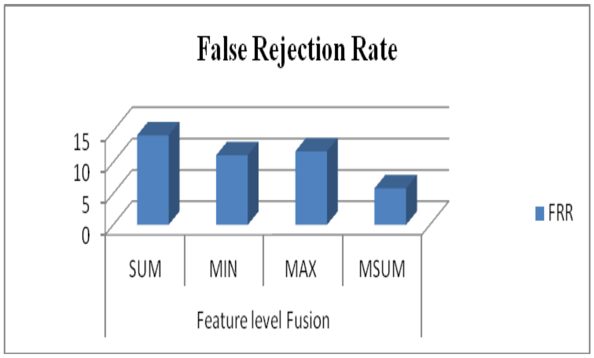

Figure 3: False Rejection Rate using different Methods

Recognition Accuracy: The accuracy of method improves if value of FAR, FRR reduces. The accuracy of recognition of biometric method is computed as:

$$Accuracy = 100 - \left(\frac{FAR + FRR}{2}\right)$$

Table 6 gives the measured parameters for the selected samples of Iris and Fingerprint using various methods for Feature Level Fusion. These results shows that FAR and FRR is least for MSUM based Fusion method as show in Fig 2 and 3 and hence it is very clear that the recognition accuracy of the MSUM based Feature level fusion in more than the other methods as shown in Fig 4.

Table 6: Performance Metrics

Performance Metrics	SUM	MIN	MAX	MSUM
FAR	5.820106	5.820106	4.166667	4.712042
FRR	14.28571	11.11111	11.73184	5.820106
ACCURACY	89.94709	91.53439	92.05074	94.73393

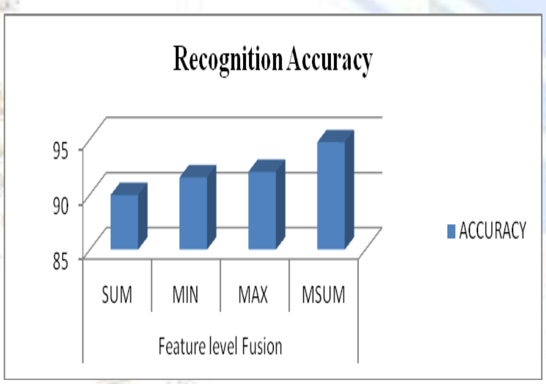

Figure 4: Recognition Accuracy using different Methods

5. CONCLUSION AND FUTURE SCOPE

This work focuses on feature level fusion utilizing texture features of Iris and Figerprint modalities in Multimodal Biometric System. In this four techniques Sum, Min, Max and MSUM is used to analyze performance of feature level fusion and also to find the best method by comparing their recognition rate. The results of this multimodal biometrics system has been analyzed using 200 samples of both the modalities where six different texture feature are first extracted and these all textures features are then fused using each of the given methods. FAR, FRR and Recognition accuracy is used as performance metrics in this work. The comparative analysis of all these fusion methods shows that the MSUM based feature level fusion achieves better recognition rate that is 94% in compare to other methods. The future work is to include other features so that more important information of the images will be extracted.

REFRENCES:

M. Ahmad, W. L. Woo, and S. S. Dlay, (2010) Multimodal Biometric Fusion at Feature Level: Face and Palmprint", Communication Systems Networks and Digital Signal Processing, 801–805.

R. Islam, (2014) Feature and Score Fusion Based Multiple Classifier Selection for Iris Recognition, Comput. Intell. Neurosci., 1–11.

U. Gawande, M. Zaveri, and A. Kapur, (2010) A Novel Algorithm for Feature Level Fusion Using SVM Classifier for Multibiometrics-Based Person Identification, Appl. Comput. Intell. Soft Comput., 1–11.

G. Rajagopal and R. Palaniswamy, (2015) Performance Evaluation of Multimodal Multifeature Authentication System Using K NN Classification, Sci. World J., 1–9.

H. Benaliouche and M. Touahria, (2014) Comparative Study of Multimodal Biometric Recognition by Fusion of Iris and Fingerprint, Sci. World J., 1–13.

G. Huo, Y. Liu, X. Zhu, H. Dong, and F. He (2015) Face – iris multimodal biometric scheme based on feature level fusion, J. Electron. Imaging, 24(6), 1–10.

S. Bhardwaj (2014) An Algorithm for Feature Level Fusion in Multimodal Biometric System, Int. J. Adv. Res. Comput. Eng. Technol., 3(10), 3499–3503.

M. F. Nadheen and S. Poornima(2013) Feature Level Fusion in Multimodal Biometric Authentication System, Int. J. Comput. Appl., 69(18), 36–40.

K. Lin, F. Han, Y. Yang, and Z. Zhang, (2011), Finger Vein Biometrics, Springer, 348–355.

D. Kaur and G. Kaur(2013) Level of Fusion in Multimodal Biometrics: a Review, Int. J. Adv. Res. Comput. Sci. Softw. Eng., 3(2), 242–246.

S. Kaur and P. Sharma, (2013) Analysis of Multimodal Biometrics by Feature Level Fusion: A Review, Int. J. Adv. Res. Comput. Sci. Softw. Eng., 3(7), 1388–1392.

A. Ross and R. Govindarajan (2005), Feature Level Fusion Using Hand and Face Biometrics, SPIE Confernce on Biometric Technolofy for Human Identification, 5779, 196–204.

H. Almahafzah and Z. Alrawashdeh, (2015) Feature Level Fusion the Performance of Multimodal Biometric Systems, Int. J. Comput. Appl., 123(11), 37–43.

M. Haghighat, M. Abdel-mottaleb, and W. Alhalabi (2016) Discriminant correlation analysis for feature level fusion with application to multimodal biometrics, IEEE, International Conference on Acoustics, Speech and Signal Processing, 1866 – 1870.

W. Almayyan, H. S. Own, and H. Zedan, (2011) A Comparative Evalution of Feature Level Based Fusion Schemes for Multimodal Biometric Authentication, IEEE, Hybrid Intelligent Systems, 22–27.

L. Ghoualmi, S. Chikhi, and A. Draa, (2015) A SIFT-Based Feature Level Fusion of Iris and Ear Biometrics, Springer, 102–112.

S. Awang, (2013) Feature Level Fusion of Face and Signature using a Modified Feature Selection Technique, IEEE, Computer Society Conference on Signal Image Technology and Internet Baised System, 706–713.

X. Xu, Z. Mu, and L. I. Yuan, (2007), Feature-level fusion method based on kfda for multimodal recognition fusing ear and profile face, IEEE, Conference on Wavelet Analysis abd Pattern Recognition, 1304–1310.

M. I. Ahmad, M. Z. Ilyas, M. N. Isa, and R. Ngadiran, (2014) Information Fusion of Face and Palmprint Multimodal Biometrics, IEEE, Region 10 Symposium, 635–639.

L. Mirmohamadsadeghi and A. Drygajlo, (2014) Palm vein recognition with local texture patterns, IET Biometrics, 3(4), 198–206.

N. Bagri and P. K. Johari, (2015) A Comparative Study on Feature Extraction using Texture and Shape for Content Based Image Retrieval, 80, 41–52.

D. Gupta, (2015) Multimodel Biometric System: Fusion Techniques and Their Comparison, RAECS IEEE, 1–4.

H. Proenc, (2014) Ocular Biometrics by Score-Level Fusion of Disparate Experts, IEEE, Trans. Image Process., 23(11), 5082 – 5093.

R. K. Dubey, J. Goh, and V. L. L. Thing, (2016) Fingerprint Liveness Detection From Single Image Using Low Level Features and Shape Analysis , IEEE, Trans. Inf. Forensics Secur., 11(7), 1461 – 1475.