International Journal of Trend in Scientific Research and Development (IJTSRD)
Volume 3 Issue 5, August 2019 Available Online: www.ijtsrd.com e-ISSN: 2456 – 6470

An Improved Self Organizing Feature Map Classifier for Multimodal Biometric Recognition System

Olabode, A. O; Amusan, D. G; Ajao, T. A

Department of Computer Science and Engineering,
Ladoke Akintola University of Technology, Ogbomoso, Nigeria

How to cite this paper: Olabode, A. O | Amusan, D. G | Ajao, T. A "An Improved Self Organizing Feature Map Classifier for Multimodal Biometric Recognition System" Published in International Journal of Trend in Scientific Research and Development (ijtsrd), ISSN: 2456-6470, Volume-3 | Issue-5, August 2019, pp.1399-1402, **https://doi.org/10.31142/ijtsrd26458**

IJTSRD26458

Copyright © 2019 by author(s) and International Journal of Trend in Scientific Research and Development Journal. This is an Open Access article distributed under the terms of the Creative Commons Attribution License (CC BY 4.0) (http://creativecommons.org/licenses/by/4.0)

ABSTRACT

Multimodal biometric system is a system that is viable in authentication and capable of carrying the robustness of the system. Most existing biometric systems (ear-fingerprint and face-ear) suffer varying challenges such as large variability, high dimensionality, small sample size and average recognition time. These lead to the degrading performance and accuracy of the system. Sequel to this, multimodal biometric system was developed to overcome those challenges. The system was implemented in MATLAB environment. Am improved self –organizing feature map was used to classify the fused features into known and unknown. The performance of the developed multimodal was evaluated based on sensitivity, recognition accuracy and time.

KEYWORDS: *Multimodal Biometric System, Self organizing feature map.*

I. Introduction

Multimodal biometric recognition system has drawn the attention of various researchers because of the increased high level of security and authentication it provides over the existing biometric system. Multimodal recognition system has a comparative advantage over the individual biometric system in terms of difficulty to hack and manipulate. Multimodal biometrics system combines two or more recognition systems into one singular system to overcome the limitations of individual biometrics (Ramadan *et al.,* 2015).

However, different biometrics features or traits collected from different sources of same person such as face, ear, fingerprint, palmprint, iris, voiceprint, signatures and DNA can be used in developing multimodal biometrics system and each biometric trait has its distinctive application, need and benefits.

This study considered the ear, fingerprint and face biometric system to develop a robust multimodal biometric system (face-ear-fingerprints) for maximum accuracy and recognition time. The multimodal biometric system overcomes challenges encountered by individual biometric system such as large variability, high dimensionality, small sample size and average recognition time. This study used an improved self-organizing feature as a classifier technique and its performance is evaluated using sensitivity, recognition accuracy and recognition time. The rest of the paper is organized as follows; Section II presents the review of the related works. The analysis and methodology procedures are described in Section III. Section IV described the results and discussion. Conclusion and recommendations are described in Section V.

II. Review of related works

Biometric recognition system has many publications to its credit. Several authors have worked extensively on individual biometric system such as iris, ear, face and fingerprint. However, despite all these effort there is degrading in the performance of the biometric system and recognition accuracy. There is need to increased level of security and authentication to have a robust biometric system. Chang *et al.* (2003) compared ear recognition with face recognition using a standard principal components analysis (PCA) technique known as the "eigen-face" approach on face and ear images acquired at the University of South Florida. The results showed that recognition performance was not significantly different for the two modalities; with 71.6% and 70.5% accuracies obtained in the baseline experiment for ear and face recognition respectively.

Shubhandi and Manohah (2012) proposed an artificial multi-biometrics approach to fingerprint and face biometrics. The study presented an efficient fingerprint and face recognition algorithm combining ridge based matching for the fingerprint and eigenface approach for the face. The study shows improved performance in terms of recognition accuracy. Ujwalla *et al.* (2013) proposed a system with combination of Iris, finger print, face and palm geometry. Probabilistic Neural Network and Radial Basis Function NN classifier were used in identification phase for obtaining precision in decision of adaptive and cascade classifier. The Back Propagation neural network classifier (BPNN) was used in verification phase to classify user as genuine or imposter. The result showed 98.8% of accuracy.

Snehlata *et al.* (2014) proposed an implementation of person identification fusing face, ear and iris biometric modalities. They used PCA based neural network classifier for feature extraction from the face and ear images and hamming distance for calculating iris templates. The results showed an improvement over the existing result when the modalities are combined, but the limitation is there was no separate test with non-neutral data and also recognition time was not reported. Ismaila *et al.* (2018) implemented unsupervised learning algorithm in multi-modal biometric system that made used of palmprint and thumbprint for its suitability. The performance of the self-organizing feature map and back-propagation neural network was evaluated and compared. The back-propagation neural network produced recognition accuracy rate of 93.7 while self-organizing feature map yielded recognition accuracy rate of 93.5.

III. METHODOLOGY

The developed multimodal biometric system was implemented using MATLAB R2015a and run on Windows 10 professional 64-bit operating system, Intel(R) Core(TM) i3-2370M CPU @ 2.40GHz, 4GB Random Access Memory and 500GB hard disk drive with accurate speed for better performance of the developed system. The methodology involved the acquisition of image datasets, the preprocessing of the acquired images, the extraction of features, fusion of the features and classification of the extracted features using self-feature map.

Images acquisition

The face, ear and fingerprints of 120 subjects were captured in the same lightening conditions with no illumination changes in the size 1200 x 1600 pixels. Six images were captured for 120 subjects with total dataset of 2160 images. One thousand two hundred and sixty (1260) images were used in training the system and the remaining 900 images were used to test the system and finally saved in jpeg format.

Image preprocessing

Image pre-processing was carried out by converting face, ear and fingerprint images into grayscale using histogram equalization method**.** The average face, ear and fingerprint vector were calculated and subtracted from the original image vectors. This removed noise and other unwanted element from the images. Each of the grayscale images are expressed and stored in form of matrix in MATLAB which eventually converted to **v**ector image**s** for further processing.

Normalization removed any common features that all the images shared together, so that each image was left with unique features. The common features were discovered by finding the average dataset vector of the whole training set (face, ear and fingerprint images). Then, the average image vector was subtracted from each of the dataset vectors which resulted to normalized (face, ear and fingerprint) vector using histogram equalization.

Feature extraction using principal component analysis

Principal component analysis was used for dimensionality reduction by converting the set of correlated images into set of uncorrelated eigenvectors**.** PCA eigenvector method considered each pixel in an image as a separate dimension, that is, N x N image has N^2 pixels or N^2 dimensions. To calculate eigenvector, there was a need to calculate the covariance metric for dimensional reduction**.** The eigenvectors were sorted according to their corresponding eigenvalues from high to low. The eigenvector corresponding to zero**,** the eigenvalues were discarded while those associated with non-zero eigenvalues were kept**.**

Feature level Fusion

The feature set originated from three different sources (face, ear and finger) were initially pre-processed and the extracted features from each of the dataset formed a feature vector. These features from each of the dataset were then concatenated to form a new feature vector. Concatenation of feature set increased the dimensionality of the fused feature vector. Feature level fusion was used in this study because it is can fuse incompatible feature vectors from multiple modalities.

Training and testing of Multimodal Biometric System using SOFM

The input vectors were presented to the network based on the initial weights that was chosen at random and the neuron with weights closest to the input image vector was declared as the winner. Then, weights of all of the neurons in the neighborhood of the winning neuron were adjusted by an amount inversely proportional to the Euclidean distance.

During the training phase, the data acquisition, pre-processing, feature extraction process and feature concatenation process took place concurrently and the fused image sample was presented to the SOFM at a stretch. For each node, the number of "wins" was recorded along with the label of the input sample. The weight vectors for the nodes were updated as described in the learning phase. By the end of the stage, each node of the SOFM recorded t w o values, that is, it generated the total number of winning times for "known fused images" in image database, and the total number of winning times for "unknown fused images" in image database.

During the testing phase, SOFM classified individual image based on correctly or incorrectly identified images. The fused input vector was compared with all nodes of the SOFM and the best match found based on minimum Euclidean distance and was further subjected to some selected threshold values such as 0.24, 0.35, 0.47 and 0.58. The final output of the classified image was displayed as known or unknown and the results were recorded as illustrated in Figure 1.

The steps for Self-Organizing Feature Map algorithm considered in this study were as follows;

1. Each node's weights was initialized.
2. A vector was chosen at random from the set of training data and presented to the network.
3. Every node in the network was examined to calculate which ones' weights are most like the input vector. The winning node is commonly known as the Best Matching Unit (BMU).
4. The radius of the neighborhood of the BMU was calculated. This value started large. Typically it was set to be the radius of the network, diminishing each time-step.
5. Any nodes found within the radius of the BMU, calculated in (iv.), was adjusted to make them more like the input vector (Equation 2.17 and Equation 2.18). The closer a node is to the BMU, the more its' weights are altered (Equation 2.19).
6. Repeat (ii) for N iterations.

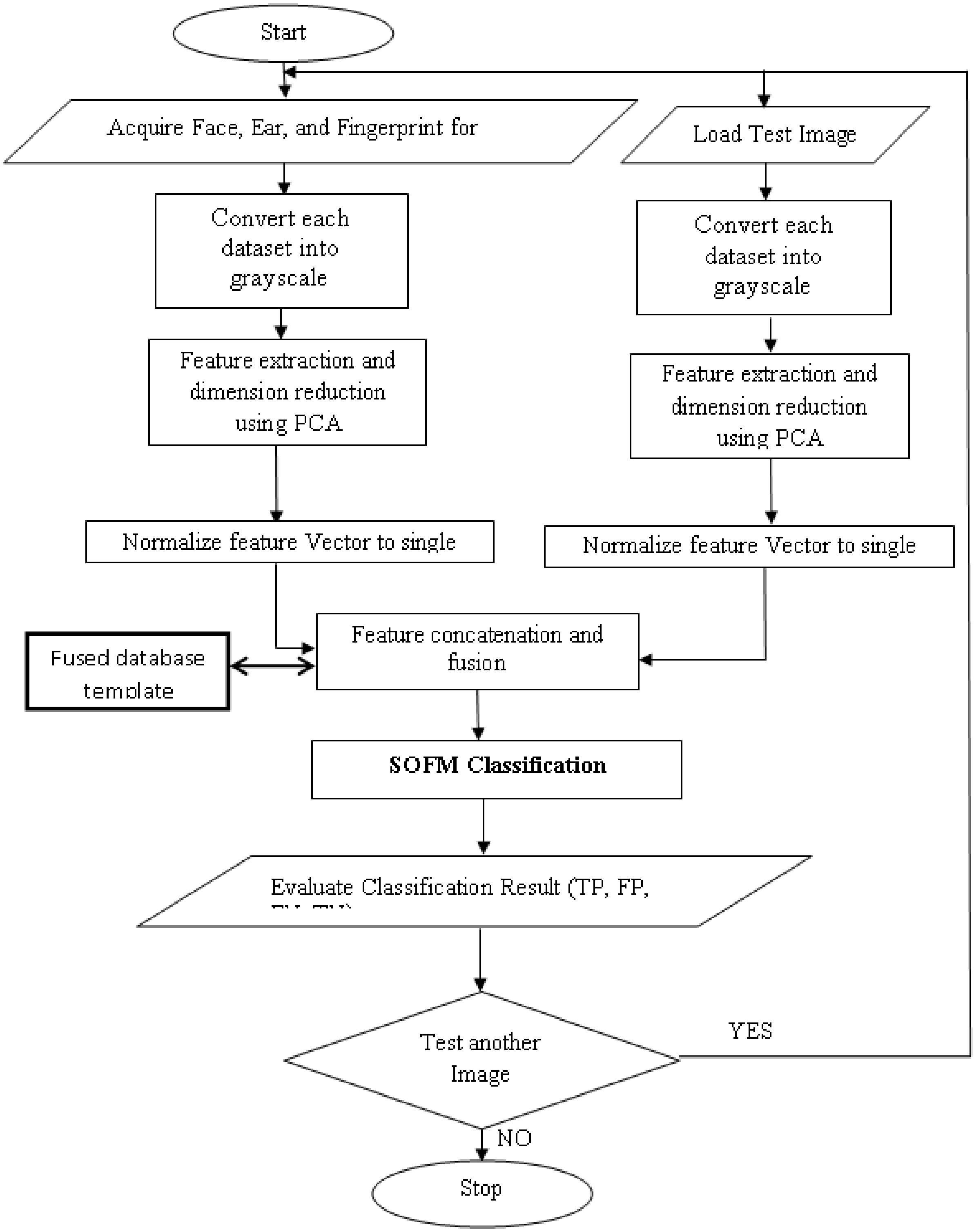

Figure 1:Flowchart showing trained and tested of selected images with Self Organizing Feature Map

IV. RESULTS AND DISCUSSION

The performance of multimodal system with respect to SOFM was evaluated based on false positive rate, sensitivity, specificity, recognition accuracy and recognition time. The accuracy generated by SOFM was analyzed by using ear-fingerprint, face-fingerprints, face-ear and face-ear-fingerprints dataset features at different threshold values of 0.24, 0.35, 0.47 and 0.58 as illustrated in Tables 1-4. The results obtained at different threshold values showed that SOFM perform better at 0.58 threshold value than the rest of the values. The results of the experiments with SOFM were presented in Table1, Table 2, Table 3 and Table 4 based on false positive rate, sensitivity, specificity, recognition accuracy and recognition time.

The recognition accuracy at multimodal level with SOFM generated 94% of 0.24, 95% of 0.35, 96% of 0.47 and 97% of 0.58. The average recognition time produced at multimodal level are 97.05s at 0.24, 92.10s at 0.35, 92.05 s at 0.47 and 91.60s at 0.58. In terms of false positive rate, SOFM generated 8 at 0.24, 8 at 0.35, 6 at 0.47 and 4 at 0.58, while sensitivity and specificity were on increase when subjected to threshold values of 0.24, 0.35, 0.47 and 0.58.

Table 1: EAR-FINGERPRINT

Threshold	TP	FP	FN	TN	FPR (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Recognition Time (Sec)
0.24	50	5	0	45	10	100.00	90.00	95.00	98.20
0.35	49	5	1	45	10	98.00	90.00	94.00	92.85
0.47	48	3	2	47	6	96.00	94.00	95.00	92.20
0.58	47	3	3	47	6	94.00	94.00	94.00	91.00

Table 2: FACE-FINGERPRINT

Threshold	TP	FP	FN	TN	FPR (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Recognition Time (Sec)
0.24	48	7	2	43	14	96.00	86.00	91.00	95.05
0.35	48	5	2	45	10	96.00	90.00	93.00	92.90
0.47	48	3	2	47	6	96.00	94.00	95.00	91.15
0.58	47	3	3	47	6	94.00	94.00	94.00	91.30

Table 3: FACE-EAR

Threshold	TP	FP	FN	TN	FPR (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Recognition Time (Sec)
0.24	48	7	2	43	14	96.00	86.00	91.00	96.65
0.35	47	6	3	44	12	94.00	88.00	91.00	91.65
0.47	46	4	4	46	8	92.00	92.00	92.00	91.65
0.58	46	5	4	45	10	92.00	90.00	91.00	91.35

Table 4: FACE-EAR-FINGERPRINT (MULTIMODAL LEVEL)

Threshold	TP	FP	FN	TN	FPR (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Recognition Time (Sec)
0.24	50	4	0	46	8	100.00	92.00	94.00	97.05
0.35	49	4	1	46	8	98.00	92.00	95.00	92.10
0.47	48	3	2	48	6	98.00	94.00	96.00	92.05
0.58	49	2	3	48	4	96.00	96.00	97.00	91.60

V. CONCLUSION AND RECOMMENDATION

Am improved SOFM classified faster in terms of recognition accuracy, recognition time, specificity and sensitivity for multimodal biometric systems over the existing techniques due to the fact that the images acquired were concatenated into a single fused vector making it easier for classification. This has contributed greatly in the areas of e-passports, border control and e-learning. Future works can be carried out by comparing and evaluate the performance of other neural network techniques.

REFERENCES

[1] Chang , K., Bowyer, K. W., Sarkar, S., and Victor, B. (2003). "Comparison and Combination of Ear and Face Images in Appearance-based Biometrics," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 25 pp. 1160-1165.

[2] Ismaila W. Oladimeji, Shittu Jaleel K., Ismaila Folasade. M, Ajayi Ayomide O, (2018): *"Performance Evaluation Of Unsupervised Learning Algorithm In Biometric Based Fraud Prevention System"* Journal of Engineering Research and Application ISSN : 2248-9622 Vol. 8, Issue 10 (Part -I) Oct 2018, pp 62-67

[3] Ramadan Gad, Ayman El-Sayed, Nawal El-Fishawy, M. Zorkany, (2015): "Multi-Biometric Systems: A State of the Art Survey and Research Directions" (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 6, No. 6, pp.128–138.

[4] Shubhandi D. C. and Manohah (2012): *BaliMulti-Biometric Approaches to Face and Fingerprint Biometrics*: International Journal of Engineering Research and Technology Vol. 1 Issue 5 ISSN: 2278-0181, July-2012.

[5] Snehlata Barde, Zadgaonkar A. S, Sinha G. R. (2014), "Multimodal Biometrics using Face, Ear and Iris Modalities" International Journal of Computer Applications, Recent Advances in Information Technology. 21(5): pp. 0975 – 8887.

[6] Ujwalla Gawande and Kamal Hajari (2013) *"international Journal of Applied Information Systems"* (IJAIS) –ISSN: 2249-0868 Foundation of Computer Science FCS, New York, USA Volume 6 –No.2, September 2013–www.ijais.org