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Feature Level Fusion of Biometric Images Using Modified Clonal Selection Algorithm

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ABSTRACT

In feature level fusion, biometric features must be combined such that each trait is combined so as to maintain feature-balance. To achieve this, Modified Clonal Selection Algorithm was employed for feature level fusion of Face, Iris and Fingerprints. Modified Clonal Selection Algorithm (MCSA) which is characterized by feature-balance maintenance capability and low computational complexity was developed and implemented for feature level fusion. The standard Tournament Selection Method (TSM) was modified by performing tournaments among neighbours rather than by random selection to reduce the between-group selection pressure associated with the standard TSM. Clonal Selection algorithm was formulated by incorporating the Modified Tournament Selection Method (MTSM) into its selection phase. Quantitative experimental results showed that the systems fused with MCSA have a higher recognition accuracy than those fused with CSA, also with a lower recognition time.

Keywords: Biometrics, Feature level Fusion, Multibiometrics, Modified Clonal Selection Algorithm, Recognition Accuracy, Recognition Time

1. INTRODUCTION

Biometric system is automated recognition of persons based on their physiological and/or behavioural characteristics. (Jain and Ross, 2004; Adedeji, et. al. 2015). Biometric Systems demonstrate some advantages over Conventional Electronic Access Control which include improved security, Flexibility, Cost effectiveness, ease of installation, ease of marketing, high level of performance and so on. (Adegoke, et, al., 2017). Therefore, biometric systems have been adopted in many applications (Kim et. al., 2012). However, unibiometric systems are still limited by factors such as noisy data, inter-class similarities, intra-class variations. Multibiometrics are being used to resolve these problems.

Multibiometrics is the practice of using more than one sources of biometric information to achieve recognition. These different information needs to be fused together in a process called Fusion. Fusion can be achieved at different levels, namely sensor level, feature level, score level and decision level, an overview of multibiometrics and different levels of fusion is presented by Adedeji,et. al. (2018).

Feature level fusion refers to combining different feature vectors that are obtained by either using multiple sensors or employing multiple feature extraction algorithms on the same sensor data (Dapinder and Gaganpreet, 2013). Feature level fusion can be done either at feature extraction stage or feature selection stage

(Awang et. al., 2013). Fusion at feature extraction stage can be achieved either by weighted summation method or by feature concatenation while that of feature selection stage is achievable by the use of nature inspired algorithms.

Clonal Selection Algorithm (CSA) is a special class of Artificial Immune System inspired from the clonal selection principle of AIS. Clonal selection in AIS is the selection of a set of artificial lymphocytes (ALCs) with the highest affinity with non-self pattern (Gong et. al., 2012). Clonal selection principle describes how the immune cells eliminate a foreign antigen and is simple but efficient approximation algorithm for achieving optimum solution. CSA shares many similarities with GA but instead of crossover operator, it uses cloning operator to construct new generation of candidate solutions.

2. LITERATURE REVIEW

Different methods have been applied for feature level fusion of multibiometric systems. These include the works of Feng et. al. (2004) which combined face and palmprint for recognition, by concatenating the features extracted using Principle Component Analysis (PCA) and Independent Component Analysis (ICA) with the nearest neighbor classifier (NNC) and support vector machine (SVM) as the classifier. Wang et. al. (2009) proposed complex vector as the fusion technique of face and iris after the implementation of z-score normalization where by classifier is Fisher Discriminant Analysis (FDA) with Equal Error Rate (EER) of 0.07% and 2.9% for Olivetti Research Laboratory (ORL) and Yale's database respectively.

Rattani et. al. (2006) implemented face and fingerprint bimodal system with Scale Invariant Feature Transform Features (SIFT) applied for face feature extraction and minutiae matching technique for fingerprint. The features are fused by simple concatenation while Delaunay triangulation technique is applied as the matching algorithm with an accuracy of 97.41%.

Kumar et.al. (2012) presented a multimodal framework based on face and ear modalities. The features were extracted using Haar wavelet and Scale Invariant Feature Transform (SIFT). Integration of their ranks was done with modified Borda count and Logistic regression method. According to their report, logistic regression gave a better result. Nadheen and Poornima (2013) developed a multimodal biometric system using iris and ear, features were extracted from both modalities using Principal Component Analysis and the features were normalized and concatenated. The system showed an improvement over unimodal systems, attaining 93% success rate. Kim et. al (2012) proposed a multimodal biometric system that combines the recognition of the face and both irises to enhance the performance based on Support Vector Machine. Their results showed that the proposed system performs better than face and irises in isolation, and it was also discovered that both irises differ in their performances; hence, could be treated as different biometrics. Intramodal feature level fusion of texture and line features of palmprint was carried by Krishneswari and Arumugam (2012b) using PSO based technique. The resulting feature vector was further reduced via PCA. Experimental results illustrated that the feature level fusion improves the recognition accuracy significantly. A modified GA was employed by Awang et. al. (2013) to maintain feature balance in the feature fusion of face and signature. The accuracy of the system was better than those that use concatenation for fusion. The limitation of this approach is that the fitness function has to be modified anytime another trait is added to the system. Adedeji et. al. (2019) proposed Clonal Selection Algorithm (CSA) for feature Level fusion of multimodal systems. The experimental results showed that the performances of the bimodal systems indicate increase in recognition accuracy compared to their unimodal counterparts.

Clonal Selection Algorithm was modified in Adedeji et. al., (2015) in order to ensure feature balance among the contributing traits. by employing segmented antibody management scheme for solution encoding while selection was based on modified tournament selection. The modification in tournament selection was to reduce between-group selection pressure and at the same time, improve the quality of the solution (Adedeji et. al.,2015).

In this paper, the main objective is to implement MCSA for feature level fusion, and to compare results with CSA. Statistical analysis of the two fusion methods was also carried out.

3.0 METHODOLOGY

3.1 SYSTEM ARCHITECTURAL FRAMEWORK

The system architectural framework is divided into Five (5) major phases namely: image acquisition, image preprocessing, feature extraction, feature fusion, training and classification phase. Each of the phases as shown in Figure 1 is discussed below.

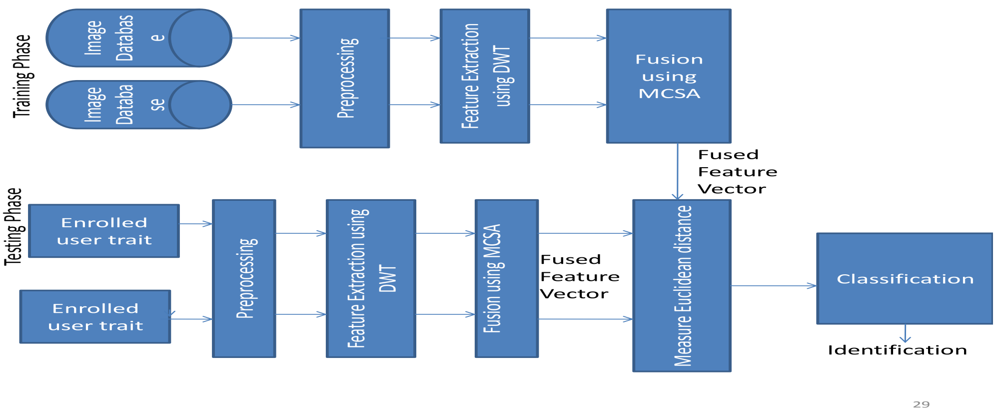

Figure 1: Block diagram of a bimodal biometric system

3.2 IMAGE ACQUISITION

The images (faces, fingerprints and irises) used in this work were acquired from one hundred and fifty-four (154) randomly selected students and staff of Ladoke Akintola University of Technology (LAUTECH). The images were captured though in the software laboratory of the Department of Computer Science and Engineering but not under a controlled environment. The acquisition of faces and eye images were done with CMITECH iris camera while fingerprints were acquired using digital persona fingerprint scanner. There are 6 different images per biometric trait per subject. The facial images were all taken in frontal position with little variation in expression and illumination. However, there are variation in the distance between the subject and the camera.

3.3 IMAGE PREPROCESSING

The image preprocessing involves enhancement of the image. However, before preprocessing, all images were converted to JPEG format using Microsoft Picture Manager. This is done to compress the image so as to reduce the memory consumption during experiments. After conversion, each face image was 57.4Kb, iris 41Kb and thumbprint was 34.6Kb but the image resolution still remains the same. After this, geometric normalization was done to convert the images to the same resolution since they have different resolution. For face images, the images were first automatically cropped from original size of 720x960 to a reduced size using the Adaboost algorithm. The cropping was done to retain only the face region with the extinction of areas such as ear and fore-head without distortion. The images were then resized to 100x100 pixels for uniformity. Meanwhile for iris and thumbprint images, they were only resized to 100x100 pixel level. Sample cropped and resized images are shown in Figures 2a-c

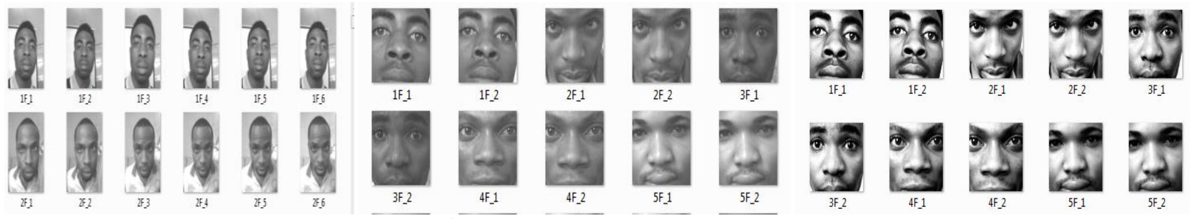

Figure2: Sample Faces:(a) original faces;(b)Cropped and resized Faces; (c) Histogram Equalized Faces

Figure2: Sample Fingerprints:(a) original Thumbprint;(b)Cropped and resized Thumbprint; (c) Histogram Equalized Thumbprint

3.4. FEATURE EXTRACTION

This stage describes the extraction of unique characteristics which can represent an image. The goal of feature extraction is to pick up a set of features, which can maximize the recognition rate with the least number of elements. Discrete Wavelet Transform (DWT) was adopted for a transformation based feature extraction. Two level decomposition was performed on the preprocessed images. The DWT coefficient matrices extracted forms an efficient representation of the images in a lower dimension space. The output of DWT was converted to feature vector which serves as input to the fusion stage of the multimodal systems.

3.4.1 Feature Fusion using the Modified Clonal Selection Algorithm (MCSA)

Fusion of extracted features was carried out by applying modified Clonal Selection Algorithm as detailed in Adedeji et. al. 2015. The algorithm is given below:

Step 1: Initialize the algorithm parameters of MCSA

Step 2: Generate Initial antibody population

Step 3: Selection Phase

Group population S into a set of N groups.

For y = 1 to N

Return the best individual from each group to form the new population.

Step 4: Clone the selected antibodies segment by segment.

Step 5: Mutate the cloned antibodies segment by segment.

Step 6: Evaluate the affinity of the mutated antibodies.

Step 7: Repeat steps 3 to 6 until the stopping criteria is satisfied.

3.4.2. Parameter setting of MCSA algorithm

Central Composite Design (CCD) of design expert 6.0.8.was used to optimize the composition of the three parameters of MCSA. The parameters are Antibody population size, Clonal factor and Mutate factor

Taking the range for population size to be from 20 to 80 antibodies, clonal factor to be from 0.1 to 0.7 and mutate factor from 2.00 to 5.00 (Gong et, al., 2012), the design of experiment for the parameters is given in Table1. Twenty (20) experimental runs were generated by the design expert. The responses desired are average testing time measured in seconds and recognition accuracy measured in percentage as shown in Table 2.

Table 1: High and Low Values used for the composition of the three parameters

Parameters	Level	
	Low	**High**
Population Size	20.00	80.00
Clonal Factor	0.1	0.7
Mutate Factor	2.00	5.00

Table 2: Design Summary for the Responses Considered for the three parameters of MCSA

Response	Name	Unit	Transformation	Model
Y1	Time	sec	None	Linear
Y2	Accuracy	%	None	Linear

3.4.3. Affinity function

The affinity function is associated with each antibody and it represents the quality of the solution. The goal of multibiometric system is to reduce inter-class similarities and increase intra-class similarities. Therefore, the affinity function used in this research work was adopted from the work of Aly, Onsi, Salama and Mahmoud (2013). The main objectives of the affinity function are:

(i) Maximize the between-class scatter (Sb) among the different classes.
(ii) Minimize the within-class scatter (Sw) in the same class.
(iii)Improve the recognition rate of the system.

Suppose there are C classes, yi is the ith vector, Mi the number of samples within class i, where i = 1, 2, …C. μi the mean vector of class I, and μ be the total mean vector of samples. The within-class scatter matrix is represented as:

$$S_w = \sum_{i=1}^{c}\sum_{j=1}^{M_i}(y_i - \mu_i)(y_i - \mu_i)^T \qquad 1$$

While the between-class matrix is given as:

$$S_b = \sum_{i=1}^{c}(\mu_i - \mu)(\mu_i - \mu)^T \qquad 2$$

Where $\mu = {}^{1}/_{c} \sum_{i=1}^{c} \mu_i$

Finally, the affinity function is computed by maximizing the between-class scatter matrix while minimizing the within-class scatter and is performed by:

Affinity function = maximize $\frac{\det(S_b)}{\det(S_w)}$) 4

3.5 Classification

The fused features were classified using Euclidean Distance (ED) as shown in equation (5):

$$ED = d(p, q) = \sqrt{\frac{1}{M}\sum_{i=1}^{M}(p_i - q_i)^2} \qquad 5$$

Where M = dimension of the feature vector; p_(i)= stored feature vector; q_i = the test feature vector.

Performance metrics employed for evaluation are Average Recognition Accuracy, Total Training Time and Average recognition time. Each of the systems was trained with a total of 800 images while 400 imaes were used for testing.

4.0 EXPERIMENTAL RESULTS AND DISCUSSIONS

Results reported in this work is in three (3) categories. They are as discussed below:

4.1 Result of Parameter Setting of the developed Algorithm (MCSA)

CSA is a parametric algorithm whose performance depends on the proper setting of its parameters. In order to properly tune its three parameters (clonal factor, mutate factor and population size) and to get an optimal combination, Central Composite Design (CCD) of the design expert 6.0.8 was used. No blocks were selected and linear model was chosen as the design model. The responses considered were average recognition time (measured in seconds) and average accuracy (measured in percentage). The design generated twenty (20) experimental runs and the results obtained showed that no transformation was done for the two responses considered.

The parameter setting experiments were carried out for multibiometric system using a combination of face, left thumb, right thumb, left iris and right iris. This combination is chosen to cater for both multimodal and multi-instance systems. A total of 100 images were used for the experiments to determine the effect of those three parameters on both the recognition time and accuracy. The results of responses from experimental data were given in Table 3. From the results, it could be seen that different values of the algorithm parameters gave different responses in terms of recognition time and accuracy. Experimental run 17 generated the lowest recognition time of 15.06seconds with an accuracy of 97.84% while experimental run 20 generated the highest testing time of 16.47seconds with an accuracy of 95.43%. Therefore, from the results of the parameter tuning, the population size was set to 50.00, clonal factor to 0.7 and mutate factor was set to 3.5 for the developed algorithm

(MCSA). No result for experimental runs 4 and 14 because one of the parameters was set to a negative value by the software. Likewise in experimental run 6 population size was assigned a real number (100.45), therefore, no result was given because population size must be an even whole number (Zhang et. al., 2007).

Table 3 Result of Responses from Experimental Data using MCSA

Run	Factors Population Size	Clonal Factor	Mutate Factor	Responses Average Recognition Time (sec)	Average Accuracy (%)
1	50.00	0.40	0.98	15.65	96.00
2	80.00	0.70	3..50	16.40	97.40
3	20.00	0.10	2.00	15.10	97.40
4	50.00	-0.10	3.50		
5	50.00	0.40	3.50	16.09	97.40
6	100.45	0.40	3.50		
7	80.00	0,60	2.00	15.35	95.80
8	50.00	0.40	3.50	15.28	97.32
9	50.00	0.40	3.50	15.14	97.32
10	50.00	0.90	3.50	15.27	97.24
11	20.00	0.10	5.00	15.15	94.98
12	20.00	0.70	5.00	16.01	96.60
13	80.00	0.70	5.00	15.33	96.94
14	-0.45	0.40	3.50		
15	20.00	0.70	2.00	15.16	97.42
16	50.00	0.40	3.50	15.43	97.28
17	50.00	0.70	3.50	**15.06**	**97.84**
18	80.00	0.10	5.00	16.12	96.60
19	50.00	0.40	3.50	15.19	95.87
20	50.00	0.40	6.02	16.47	95.45

4.2. Results of the Performance Evaluation of the Developed Multimodal Biometric Systems

Three bimodal and one trimodal biometric systems were developed in this work, they are Iris-Fingerprint (IR-FI), Face-Iris (FA-IR), Face-Fingerprint (FA-FI) and Face-Fingerprint-Iris (FA-FI-IR). Features were extracted separately from each biometric modality using DWT while fusion of the features was done with MCSA. The summary of results obtained is shown in Table 4.

Table 4: Summary of Experimental Results

Biometric System	Average Recognition Accuracy (%)	Total Training Time (s)	Average Recognition Time (s)
IR-FI	91.33	2230.00	4.16
FA-IR	93.25	3527.02	7.16
FA-FI	88.13	3140.00	8.80
FA-FI-IR	94.33	4064.00	9.99

The second column of Table 4 revealed the accuracy of the systems. Face-Iris (FA-IR) bimodal system with MCSA has the highest accuracy of 93.25% and out of all the bimodal systems considered while Face-Fingerprint (FA-FI) has the least accuracy (88.13%). This result implies that high discriminating features contained in iris, when combined with features from other biometric traits will enhance the recognition accuracy of the system than face and fingerprint. also from the results, one can observe that bimodal systems that have fingerprints as one of the modalities, have relatively low ARA, this may be connected to poor fingerprint images since the database used were not captured in a controlled environment.

The results for the training time indicate that Iris-Fingerprint (IR-FI) bimodal system has the least training time while the highest training time was recorded with the trimodal system. This is because the trimodal system has more features to be trained than the bimodal ones. It can also be noted that bimodal systems containing face as one of the traits have relatively high training time. This is an indication that face contains more features to be trained than Iris and Fingerprint. Similarly, the Average recognition time follows the same trend.

The results in table 4 are then compared with their counterparts systems when CSA was used for fusion without the modifications as reported in Adedeji et. al., 2019. The comparison is given in Table 5.

Table 5

Biometric System	Average Accuracy CSA	Recognition (%) MCSA	Total Time CSA	Training (s) MCSA	Average Time CSA	Recognition (s) MCSA
IR-FI	89.50	91.33	3050.06	2230.00	5.35	4.16
FA-IR	89.63	93.25	3926.18	3527.02	8.39	7.16
FA-FI	88.25	88.43	3256.96	3140.00	10.08	8.80
FA-FI-IR	92.25	94.33	4256.44	4064.00	11.33	9.99

From Table 5, It was discovered that the accuracy of Face-Iris (FA-IR) bimodal system with MCSA has the highest accuracy of 93.25% and out of all the bimodal systems considered while Face-Fingerprint (FA-FI) has the least accuracy (88.43%) when MCSA was used for fusion. Comparing this with the results gotten when CSA was used for fusion, one can see that fusion with MCSA produces systems with higher recognition accuracies. This implies that MCSA was able to select high discriminating features during fusion than CSA which indicates its capability to locate optimum solution than CSA. It was also observed that MCSA utilizes less time for training than CSA, which further signifies MCSA was able to locate optimum solution faster than CSA.

The results for the average recognition time of the systems shows that there is a reduction in recognition time for all the systems when MCSA was used for fusion. The least average recognition time of 4.16 seconds was gotten with MCSA contrary to 5.35 seconds when CSA was employed for fusion. However, the average recognition time obtained from all the systems is less than the 60seconds benchmark prescribed by Phillips (Phillips et. al., 1998). This implies that that both fusion techniques can be employed in real life situations.

4.3. Statistical Analysis of Results of Fusion using MCSA and CSA

Inferential statistical analysis using Paired Sampled t-test was done to analyze the results obtained for accuracy, training time and recognition time respectively for MCSA and CSA. The paired sampled t-test was performed on the null hypothesis (H0) that there is no significant difference between the result of fusion with MCSA and CSA against the alternative that there is a significant difference (H1), at 5% level of significance. The hypothesis is defined below;

H0: There is no significant difference between MCSA and CSA algorithm

H1: There is a significant difference between MCSA and CSA algorithm

The test was performed by tabulating the results obtained from fusion using MCSA and CSA for accuracy, total training time and average recognition time. The tests were performed separately for accuracy, training time and recognition time to determine the level of significance for each case. Summary of the results obtained is presented in Table 6.

Table 6: Summary of Results of the T-test for MCSA and CSA

Parameter	t	Degree of Freedom (*df*)	*P*-value	Comment
Accuracy	2.684	5	0.044	Significant
Total Training Time	-2.860	5	0.035	Significant
Average Recognition Time	-33.668	5	0.000	Significant

From the table 6, the p-value for accuracy, training time and recognition time are 0.044, 0.035 and 0.000 respectively. Since the p-value in each of the cases is less than 0.05, therefore the null hypothesis is rejected thus, the test revealed that there is significant difference between the results recorded when MCSA was used for fusion ($m = 91.96$, $SD = 2.29$) compared to CSA ($m = 89.65$, $SD = 1.91$), $t(5) = 2.684$, $p = 0.044$. the t-test result validates the fact that MCSA outperformed CSA in terms of accuracy, training time and recognition time.

This indicates that MCSA has a better explorative and exploitative ability than CSA and was able to reach a more quality solution than CSA. This however, may be linked to the fact that MCSA considers not only the best antibodies but also the weak ones during selection as compared to CSA which uses only the good antibodies to drive the search into the next generation. This is a further confirmation of the fact that selecting only the best antibodies during the selection phase has the tendency to lead the search to a local optimum rather than a global one. On the other side, in line with the work of Gong et. al. (2011) selecting less fit antibodies together with some highly fitted ones is a good way to improve the quality of solution from an evolutionary algorithm.

This result also validates that MCSA utilized less time for training than CSA. The reduction in time experienced when MCSA was employed for fusion may be linked to the removal of sorting module from MCSA, which makes use of modified tournament selection where antibodies were not sorted before tournament is performed. This confirms further that sorting increases the time complexity of an algorithm.

5. CONCLUSION AND FUTURE WORK

In this work, different parallel multimodal biometric systems were proposed. The purpose of the research is to implement MCSA for fusion and to investigate the effect of the modification of CSA on the overall performance of the biometric systems. DWT was used both to reduce the dimension of the images and at the same time, extract the discriminating features to represent the traits while the features were fused at the feature selection phase using MCSA. The results obtained showed that MCSA can be used for feature level fusion of biometric systems. Also, statistical test results validated that MCSA outperformed CSA in all the metrics considered. Based on the results obtained from the experiments carried out, MCSA is recommended as a better alternative for feature level fusion. Future research interest hopes to carry out comparative analysis on the performances of bimodal and bi-instance biometric systems.

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REFERENCES

1. Jain A. K and Ross A. (2004): Multibiometric systems, Communications of the ACM. Special issue on Multimodal Interfaces. 47(1):34-40.
2. Adedeji O. T., Falohun A. S., Alade O. M., Omidiora E. O., Olabiyisi S. O. (2015): Development of a Modified Clonal Selection Algorithm for Feature Level Fusion of Multibiometric Systems. LAUTECH Journal of Engineering and Technology (LAUJET). 9(2): 80-85.
3. Adegoke B. O., Ojo J. A. Falohun A. S., Adedeji O. T. and Omidiora E. O. (2017): Comparative Analysis of Two Biometric Access Control Systems. LAUTECH Journal of Engineering and Technology (LAUJET). 11(1): 93-98. Nigeria
4. Adedeji O. T., Falohun A. S., Alade O. M., Omidiora E. O., Olabiyisi S. O. (2018). Comparative Analysis of Face, Iris and Fingerprint Recognition Systems. World Journal of Engineering Research and Technology (WJERT). 4(4):160-167.
5. Kim Y. G., Shin K. Y., Lee E. C. and Park K. R., (2012). Multimodal Biometric Sytem based on the Recognition of faces and Both Irises. International Journal of Advanced Robotic Systems. 9(65):1-6.
6. Adedeji O.T, Falohun A.S., Alade O.M. and Amusan E.A (2018): Overview of Multibiometric Systems. International Research Journal of Computer Science. ISSN: 2393-9842. 9(5):459-466.
7. Dapinder K. and Gaganpreet K. (2013). Level of fusion in Multimodal Biometrics: a Review. International journal of Advanced Research in Computer Science and Software Engineering. 3(2): 242-246.
8. Awang S., Yusof R., Zamzuri M. F. and Arfa R. (2013). Feature Level Fusion of Face and Signature using a Modified Feature Selection Technique. International Conference on Signal-Image Technology

and Internet-Based Systems, (IEEE-Computer Society): 706-713.
9. Gong T., Li L., Guo C. and Gong X. (2012). Novel Clonal Selection Algorithm: Improving Selection Operator. International Journal of Multimedia and Ubiquitous Engineering, 7(2):323-328.
10. De Castro L. N. and Von Zuben F. J. (2002). Learning and Optimization using the Clonal Selection Principle. IEEE Transaction on Evolutionary Computation, 6(3):239-251.
11. Feng, G., Dong K., Hu D. and Zhang D. (2004). When Faces are combined with palmprints: A novel Biometric fusion Strategy. In proceedings of First International conference. ICBA 2004 Springer:701-707.
12. Wang Z., Wang E., Wang S., and Ding Q. (2011). Multimodal Biometric System Using Face-Iris Fusion Feature. Journal of Computers. 6(1): 931-938.
13. Rattani A., Kisku D. R., Bicego M and Tistarelli M. (2007). Feature Level Fusion of Face and Fingerprint Biometrics. First IEEE International Conference on Biometrics: theory, Applications and Systems.
14. Kumar A. and Zhang D. (2012). Combining fingerprint, palmprint and hand-shape for user authentication. In Pattern Recognition 18th International conference (IEEE). 4(1):549-552.
15. Nahdeen F. M. and Poornima S. (2013): Feature Level Fusion in Multimodal Biometric Authentication System. International Journal of Computer Applications. 69(18): 36 – 40.
16. Krishneswari, K. and Arumugam, S. (2012b). Intramodal feature fusion based on PSO for palmprint authentication. International Journal on Image and Video Processing. 2(4): 435-440.
17. Adedeji O. T., Falohun A. S,, Alade O. M., Omidiora E. O., Olabiyisi S. O. 2019. Clonal Selection Algorithm for feature level fusion of multibiometric systems. Anale. Seria Informatica. 17(1): 69-75.
18. Zhang, L., Zhong, Y., Huang, B., Gong, J, and Li, P. (2007). Dimensionality Reduction Based on Clonal Selection for Hyperspectral Imagery. IEEE Transaction on Geoscience and Remote Sensing. 45(12):4172-4186
19. Phillips P. J., Wechsler H., Huang J. and Rauss P. J. (1998): The FERET database and Evaluation Procedure for Face Recognition Algorithms. Image and Vision Computing. 16(5):295-306.

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