FACE RECOGNITION USING FUZZY SYSTEM

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Abstract—**The paper aims at designing a new methodology for face matching and mood detection using fuzzy approach .the matching algorithm has been developed using the fuzzy membership distance products called fuzzy moment descriptors .The fuzzy moment descriptors are estimated mainly using three common image features position,shape and mixed range .This methodology is used instead of existing matching algorithm to reduce template machine time .In the proposed system template matching technique is done invariant to size ,rotation and color of the image .The Existing method are concerned with the comparison of the position of directed edges ,shades and mixed range in an image with the same of another image ,are often prior to error,due to noise .The fuzzy moment descriptors are less sensitive to noise,rotation of images and other external disturbance .The normalization process and sorting of the moment descriptor vector keep the matching process invariant ton size and rotation of the images .This scheme can be applied to facial image database for personal identification .The technique is applicable to mobile games for mood detection by detecting facial expressions**

1.INTRODUCTION:

The need for a system that performs personal identification and recognition has become vital due to the rapid advances in technology in all aspects of our lives. This need was increased by the continuous desire of the human being to guarantee security and privacy. The face recognition system recently gained the attention of many researchers in diverse fields including computer science researchers,neurologists,and psychologists. The process does not require the knowledge of that person in subject,nor does it require his participation in the identification process. This is in contrast to other biometrics such as fingerprint DNA ,hand and palm geometry,and iris recognition.

The face recognition process can be divided into four steps

- Face detection
- Image normalization
- Feature extraction
- Face recognition and verification

Face detection:an image captured by a human face is detected from the cluttered scene.

Image normalization:Here the image should be standardized according to its size,orientation,pose,illumination,scale..etc relative to the image stored in the database .image normalization is the crucial step in the recognition process .the recognition process will not be a successful process unless the properties of the probe image are more or less identical to the features of the image stored in the database.

Feature extraction:Here unique features are extracted to be used for face recognition.

Face recognition and verification:In face recognition the interface is unknown for the system.And the system is responsible for finding a match for the face from the already stored databases.Below figure shows the face recognition flow chart.In verification the input face is claimed to be that of a specific person and the system is the only one responsible to either verify or reject the claimed identity of that input face according to the studies.

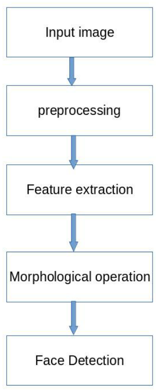

Fig1:face recognition flow chart

In this paper we introduce a new method for face recognition. Here we use fuzzy logic proposed by zadeh in 1965 and develop a fuzzy type-2inference system for face recognition. We use fuzzy logic for face recognition due to the following reasons:Fuzzy logic is a powerful tool and it can handle uncertainties in data .Use of fuzzy logic will lead to better performance and produce better identification results. The use of fuzzy set theory in membership functions allows us to classify and categorize our training data.The use of fuzzy inference systems makes us able to visualize the problem.For better performance and simplicity PCA is used in the feature extraction process. The proposed system is tested on O R L and Yale facial databases and produces better results.In the remainder of the paper we discussed the existing work,and also the proposed system that mentions the fuzzy type2 inference system.

2.DESCRIPTION OF THE EXISTING PARADIGM

The problem of face recognition has long been an ongoing subject of research. In all that ongoing research in the field,we still cannot find a proliferated research point. A wide variety of approaches have been introduced and implemented and have proven to be successful. The major problems faced in the research are high variability in facial ages,due to pose variations,image illumination factor. Face recognition technology has a wide range of algorithms that has been proposed .Feature based facial recognition approach is one of them. The theme behind the algorithm is to use the geometric characteristics among the facial features like eyenoise .it proved that it has less accuracy according to studies .another approach is appearance based facial recognition .The approach uses the features based on pixel intensity. Researchers concluded that statistical similarities between people introduce a novel identification .The appearance based method has naturally proven to have a higher efficiency than the feature based method. Some template matching techniques use principal component analysis(PCA)technique and linear discriminant analysis(LDA). PCA is based on the second order statistics of the image set and it does not address high order dependencies .There for kernel PCA have been proposed .This technique is able to compute the higher order statistics without the time and memory complexity. A fuzzy fisherface has been introduced for feature extraction and face recognition .Fuzzy fisherface computer within class scatter matrix and between class scatter matrix by incorporating class membership of the binary labelled faces. It has been proven to be effective .Recently the face recognition system improves the performance by incorporating spatially structured features into a histogram based face recognition framework. Some other techniques use neural network classification. neural network system have proven to have a good performance even the input images are noisy or when the portions of the images are missing .neural network use in face recognition to solve the three problem:gender classification,face recognition and facial expressions .while other research works have succeeded in improving feature extraction tools using fuzzy logic and others have combined fuzzy logic along with other computational intelligence approach to build a high performing classifier.in our approach we focused solely on fuzzy inference for the recognition phase.the basic thought behind fuzzy logic for use as the inference engine for the recognition is that it is able to mimic the way of human thinking process.The recognition process is an everyday activity of human.The human being is able to identify a particular person he sees based on the facial features of that subjected person.The human perceives the features compare them with a database of features representing persons that he meets knowns in his life.Based on that Clarkson the human is able to identify the subject person.Another interesting thing about using fuzzy logic that use PCA for the feature extraction tool.The PCA can mimic the human thought process.It also able to mimic the human recognition process.since a human being does not recognize a person because of specific features of that person.For instance,we do not remember that a specific person had a small nose,large ears and short hair,but a more complex and a more general process takes place instead.The human being is able to remember the general appearance of a certain face without remembering specific details about certain facial features. appearance based facial recognition methods have an advantage over feature based facial recognition method.And it has proven to have a better performance than feature based methods. similarly ,this is how our proposed system work,we compare the features with the features of the person stored within our database. The details of the proposed system is discussed in next section

3.The Proposed Methodology

There are tons of uncertainties that we are able to encounter within the application of face recognition. Such uncertainties are variations that might be introduced to a person's face image that would require handling so on to make the system robust and capable of accepting those variations. Those variations make it almost impossible to capture two images of the same person that would not involve some significant differences between them. Some of those variations are; the person's pose angle (or, equivalently, camera viewpoint) in the image, whether he is wearing glasses or not, and the fact that the shape and the glasses themselves could be changed, a person's moustache, smile, hair color and elegance , wrinkles, fringe, make-up, and eye direction within the image. Not to mention the natural changes which are introduced to any human by time; like the change in skin color and the natural changes in his looks and features by the effect of age. And of course the variation in the illumination conditions of the image plays a major role. All of the above variations in one person's image are uncertainties introduced to a system. Such uncertainties - if not well accounted for - shall in the case of face recognition result in an improper identification of a person in subject. Consequently, it's imperative that a system - in our case a face recognition system - be ready to handle such uncertainties. From this argument; the very fact that several variations (i.e. uncertainties) could occur within facial images of an equivalent person, we came in favor of symbolic logic as a tool to perform our face recognition process. In this section, we present the PCA as a feature extraction tool then we discuss the detailed design of the proposed fuzzy logic-based inference system .Figure 1 depicts a diagram illustrating the proposed type-2 fuzzy inference system.As are often seen in the below figure,the system consist of two units,namely the training unit and there for the testing unit.

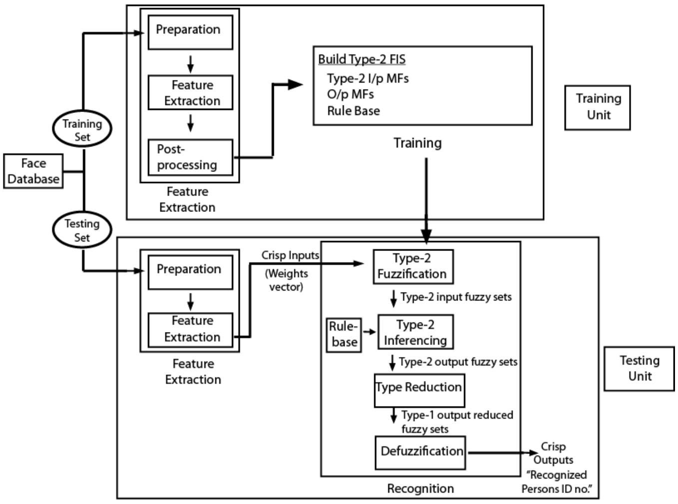

Fig2:fuzzy inference system

We first start by the training unit of the system. We have a selected set of facial images that play the role of the training set. Those images are fed to the feature extraction module where the many features are extracted from the facial images. After which, we compute certain values of interest that enter as input to the next module; the training module .In this module, we simply build up the fuzzy inference system by using the computed values where we create the different membership functions for the inputs and outputs as well as build the rule base. The system is now trained and ready to accept new facial images to identify them. The testing unit consists of two modules; namely, the (1) feature extraction module and the (2)recognition module. In the testing unit, a set of testing images goes through the feature extraction module first, where significant values are computed and are fed into the recognition module. The crisp inputs undergo type-2 Fuzzification where we compute two different membership values one for every membership set we've (that is, lower and higher membership sets).This step is followed by feeding the produced type-2 fuzzy values into the type-2 inferencing where each rule in the rule base is fired twice, once using the lower M F and once using the upper M F, and consequently producing two firing strengths (lower and upper firing strengths). We have the option of choosing either that all rules would have the same weight during the inference process, or each rule will affect the inferencing by a different weight than the other according to one of two algorithms; (1) assigning the latent value of the rule's antecedent feature, (2) calculating an absolute mean value for the antecedent feature from the feature's values in the training data. In the aggregation step of the activated rules, we aggregate all rules fired by the lower M F s together and all rules fired by the higher M F s together. For each output set (for each person), we sum all activated rules indicating this output set. After this, we go through all the output sets and we choose for the next type reduction and Defuzzification step three output sets; the person set with the maximum total firing strengths using the upper firing strengths values only, the person set with the Utmost total firing strengths using the lower firing strengths values only, and therefore the person set with the utmost total firing strengths using the typical of both the upper and lower firing strengths values. In the following sections, we present more details about the training unit and our symbolic logic Controller (F LC).

3.1 The training unit

The system's training unit consists of two modules; the feature extraction module and therefore the training module. In the feature extraction module, we start by a preparation step, where we prepare the set of coaching images to place them during a standard format. We do this by first resizing the pictures to quarter of its size followed by reshaping them to be a row vector. Afterwards, within the feature extraction step,we perform dimensionality reduction and have extraction on the group of coaching images of all persons. This is done by extracting a group of Eigen faces (that is, the significant features), producing the new feature space (Turk et al, 1991). This new space will be used afterwards in the testing unit to project each test image onto it to perform the recognition process. Next, we perform a post-processing step, where we compute the means and the standard deviation matrices out of the resultant extracted features. These matrices contain the mean and the standard deviation values of all corresponding features of all training images of a certain person. These matrices are needed later to be fed into the training module .It is worth to note here that as a result of the projection operation onto the face-space, the faces that's projected are often characterized by a weighted sum of the eigen faces. Therefore, to acknowledge a particular face, it's only required to match such a group of weights with the set of weights of known persons. In a more abstract way, what we are required to try to do is just compare the position of the face projected on the face space with the positions of the known individuals previously projected onto the same face space. PCA is understood for its simplicity and good performance within the feature extraction process allowing us to specialise in evaluating the performance of symbolic logic on the second phase of our system (i.e. recognition of faces, which is the main aim behind our research#41;, rather than diverting our focus to a complicated feature extraction technique .In the training module, we actually start building our fuzzy logic Controller. The approach we take in this research is based on applying the recognition process on each feature of the extracted set of features of a certain facial image. Imagine that each facial image has a set of features that represent it, we take each of those features and we find out to which person it more likely belongs to. This is done by calculating the membership of this feature to each membership set of each person. The highest calculated membership value to a certain membership set denotes that this person has the highest probability of representing this feature. In the end, the system takes a decision of which person it recognized based on the highest number of extracted features represented by the same person set .In designing our FLC, we have two parts; (1) The input of the system, (2) The rule base and (3) the output of the system.

More details about each part are discussed within the following subsections.

3.2The system input

The input to our FLC contains two components; the primary may be a matrix containing the training data for our rule base, this matrix consists of two vectors per everyone one containing the mean values of each feature from this person's training images and the second containing the standard deviations of these values. This matrix is employed to construct our rule base. At running time period, the input to the FLC consists of 1 vector containing the feature values for the image we would like to acknowledge to match it with the rule base. We have a preparation unit to handle the feature extraction from the training images and to project any new image we want to recognize on the same feature space (i.e. using the same eigenfaces for the training images) and to resize/reshape the image if necessary to match the training images in order to facilitate comparison. The membership functions used in the fuzzification unit are constructed in the training process .Each fuzzy set corresponds to and defines one of the extracted features from the training images of the persons making up the facial database. That is to say, the number of membership functions defining the linguistic variables is linearly proportional to the final number of extracted features that we use for training. Each of those linguistic variables is defined by a set of linguistic labels that corresponds to the set of persons we have in our facial database. That is to say, the number of membership functions representing those linguistic labels is linearly proportional to the number of "unique" persons that make up our facial database .Our type-2 fuzzy set input is formed from an infinite number of type-1 fuzzy sets. All those type-1fuzzy sets make up what is called the footprint of uncertainty (FOU). In our case, we'll only be having two embedded type-1 fuzzy sets. We were ready to develop that dimension within the fuzzy sets using two approaches, and that we afterward show the results of testing each of these approaches and we compare the resultant recognition accuracy. The FOU is made by one among two ways; one is by applying the quality deviation value of all images of one person. This approach is responsible to accommodate for the specific variations between the images of a certain person at hand. While the other is applying the SD value of all images of all persons. This approach is to accommodate for the general variations that exist between different persons. We will call the first approach specific person SD and we will call the second General SD.for the upper and lower MFs, we have used Gaussian membership. The Gaussian MF is created by two values; the mean and therefore the variance . Figure 2 shows our Gaussian shaped type-2 input membership function .We also calculate the centroids of the output membership sets. We calculate two centroids per linguistic labels, namely; the left and right centroids of the both the lower and upper membership sets.

3.1.2 The rule base

The rule base of our system may be a very intuitive and dynamic one. By dynamic we mean the number of rules depend upon the amount of persons and therefore the number of features, when an individual is added to the database, a variety of rules like double the amount of features, F1,2,.. n is added to the rule base. One set of rules for the upper MFs and another for the lower Mfs . Eqn 1 shows the general form of our rules for the upper MFs and rules of the lower MFs are constructed during a similar fashion .What these rules simply say is: if the value for feature-1 from the image we are trying to understand is a member of person-1's feature-1 membership set, then the rule will determine the output that the picture belongs to person-1, and the same with every feature and every person. In the end the outputs of all the rules will aggregate (sum). We do this separately for the upper and lower firing strengths .The results of the aggregation process may be a set of type-2 output fuzzy sets. After which those output values undergo the sort reduction and defuzzification phase where they're reduced to become type-1 output fuzzy sets then defuzzified to get one crisp output value representing the recognized person's id number. We applied two different mechanisms; (1) the Karnik-Mendel (KM) type reduction technique which can end in two centroids (left and right centroids), and then defuzzified by averaging the two resultant centroids, (2) using our own version of the type-1

modified height defuzzifier (Gabr et al, 2011). To apply it on type-2, we use the typical firing strengths multiplied by the centroid at each accepted output set and then we divide that by the sum of average firing strengths .For the upper MFs (upper firing strengths);

If F 1 is in P 1 THEN output is P 1

If F 2 is in P 1 THEN output is P 1

...

If F n is in P 1 THEN output is P 1

If F 1 is in P 2 THEN output is P 2

If F 2 is in P 2 THEN output is P 2

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If F n is in P 2 THEN output is P 2

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If F n is in P n THEN output is P n

4.1 The Yale Facial Database Results

In the first experiment, we compare between type-1 and type-2 FIS when varying the amount of eigenfaces /features. type-2 FIS gives a far better recognition performance when having lower numbers of features. This indicates that type-2 features a better ability to handle uncertainties resulting from a low number of features representing the facial image.In the second experiment, we investigate the performance of our FIS system when the number of training images decreases. In this experiment, we used 58 features (eigenfaces). It could be observed that the performance (eigenfaces) showing the highest recognition rate for their algorithm is 100. T It also can be seen that because the number of coaching images decreases, the performance of both systems decreases.In another experiment, we compare our results against the entire fuzzy LDA (CFLDA) (Yang et al, 2008) that used Yale databases as we did here. It is worth mentioning that we are the sole research that have accounted for all possible combinations of coaching and testing images, making our results more representative and reliable. While this compared approach (CFLDA) performs its testing only on a few combinations of testing and training images, specifically on the first n images, where n is equal to 3 and 4 -as mentioned in their research-. This means that the result could be influenced by the choice of images.

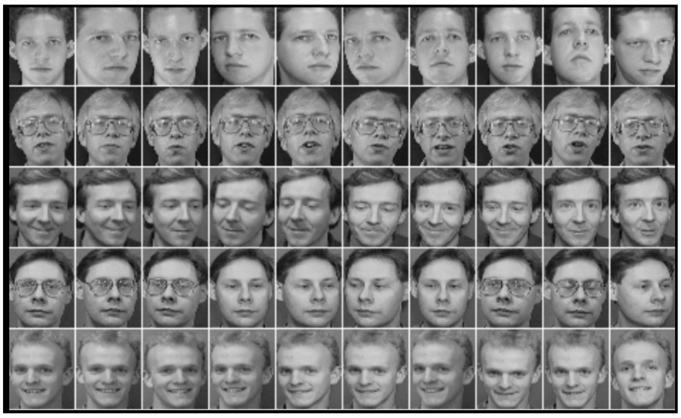

Fig 3 : yale facial database

It is important to say that Since the authors used PCA also as LDA in the feature extraction step, while we only used the PCA, then the comparison between their approach and our proposed approach wouldn't be fully valid. This is because the features extraction method ”LDA " raises the separability power making the popularity process an easier one and therefore the error rate decreases, not because the popularity technique is necessarily better but because the features extracted might be simpler to recognize. images per person were chosen for training while the remaining 20 images were overlooked for testing.Experiments are repeated by extracting 80, 60, 40 and 20 eigenfaces. In this comparison as well,since the authors used PCA as well as LDA in the feature extraction step, while we only used the PCA,then the comparison between their approach and our proposed approach wouldn't be fully valid. If we plan to compare their recognition results with our proposed algorithm's results, we will perform the comparison on the smallest number of LDA features, in order that both algorithms would have only the PCA as a feature extraction method. In this case, the number of principal components of our type-2 system exceeds that of type-1. It also can be seen that because the number of coaching images decreases, the performance of both systems decreases. In another experiment, we compare our results against the entire fuzzy LDA (CFLDA) that used Yale databases as we did here. Table 1 shows the popularity of the CFDA, type-1 fuzzy and type-2 fuzzy algorithms. It is worth mentioning that we are the sole research that have accounted for all possible combinations of coaching and testing images, making our results more representative and reliable. 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Experiments are repeated by extracting 80, 60, 40 and 20 eigenfaces. In this comparison as well,since the authors used PCA as well as LDA in the feature extraction step, while we only used the PCA,then the comparison between their approach and our proposed approach wouldn't be fully valid. Here, the popularity increases because the number of PCA and LDA features increase. If we plan to compare their recognition results with our proposed algorithm's results, we will perform the comparison on the smallest number of LDA features, in order that both algorithms would have only the PCA as a feature extraction method. In this case, the number of principal components of our type-2 system exceeds that of type-1. It also can be seen that because the number of coaching images decreases, the performance of both systems decreases. In another experiment, we compare our results against the entire fuzzy LDA (CFLDA) (Yang et al, 2008) that used Yale databases as we did here. 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4. Conclusion

In this paper we propose a facial recognition system based solely on type-2 fuzzy logic. Based on the evaluation of our system, we confirmed that type-2 fuzzy logic yields better recognition results than its corresponding type-1. This indeed has been proven when we compared the recognition rates of both approaches, and the more interesting fact is that the higher recognition rates of type-2 were spotted when there exist more uncertainties in the data at hand s.Our system is a novel implementation with a large room for improvement and has yielded very promising results so far. We have compared our approach with various previous face recognition methods and have proven to have high recognition rates under different types of experiments. We conclude that the developed fuzzy type-2 FIS can prove to be efficient when a facial recognition system is required in an environment with various uncertainties, whether coming from the variation within a certain person or the similarities that occur between different people, or the absence of enough training images or features representing a certain facial image at hand.For future work, the Eigenface algorithm for feature extraction could be replaced with other feature extraction algorithms like LDA. LDA -unlike PCA- maximizes the between class scatter matrix and minimizes the within class scatter matrix, which in turn yields a higher performance when extracting the most significant features, resulting in a higher recognition rate for our system. We could also use both PCA followed by LDA in the features extraction method, which enhances the capability of LDA and PCA when each is used alone, and therefore we will enhance the performance of the system.

REFERENCES:

[1] Zhao, W., Chellappa, R., Phillips, P.J., & Rosenfeld, A. (2003). Face recognition: A literature survey. ACM Computing Survey, 35, 399–458.

[2] Introna, L., & Nissenbaum, H. (2009). Facial recognition technology, a survey of policy and implementation issues. Technical Report, The Center for Catastrophe Preparedness and Response.

[3] Turk, M., & Pentland, A. (1991). Eigenfaces for recognition. Journal of Cognitive Neuroscience, 3, 1, 71–86.

[4] Bartlett, M.S., Lades, H.M., & Sejnowski, T.J. (1998). Independent component representations for face recognition. Proceedings of the SPIE, 3299, 528–539.

[5] Belhumeur, P.N., Hespanha, J.P., & Kriegman, D.J. (1997). Eigenfaces vs. Fisherfaces:Recognition using class specific linear projection. IEEE Trans. Pattern Analysis and Machine Intelligence, 19, 7, 711–720.

[6] Swets, D.L., & Weng, J. (1996). Using discriminant eigenfeatures for image retrieval. IEEETrans. Pattern Analysis and Machine Intelligence, 18, 8, 831–836.

[7] Robinson, M., Escarra, M., Krueger, J., & Kochelek, D. (2004). Introduction: Face recognition using Eigenfaces. Technical Report, Rice University.

[8] Chen, Y., Jiang, S., & Abraham, A. (2005). Face Recognition Using DCT and Hybrid Flexible Neural Tree. Proceeding of the Int. Conf on neural network and Brain, 1459-1463.

[9] Makhsoos, N.T., Ebrahimpour, R., & Hajiany, A. (2009). Face Recognition Based on the Neuro-Fuzzy System. Int. Journal of Computer Science and Network Security, 9, 4, 319-326.

[10] Zadeh, L.A. (1965). Fuzzy sets, Information and Control, 8, 3, 338-353.

[11] Samaria, F., & Harter, A.C. (1994). Parameterisation of a Stochastic Model for Human Face Identification. Proceedings of 2nd IEEE Workshop on Applications of Computer Vision (Dec1994), Sarasota FL.

[12] Zhao, W., Chellappa, R., & Krishnaswamy, A. (1998). Discriminant analysis of principal components for face recognition. Proc. of the 3rd IEEE International Conference on Face and Gesture Recognition (14-16 April 1998), Nara, Japan, 336-341.

[13] Wright, J., Yang, A.Y., Ganesh, A., Sastry, S., & Ma, Y. (2008). Robust Face Recognition via Sparse Representation. IEEE Trans. On Pattern Analysis and Machine Intelligence, 31, 210-225.

[14] Kim, K.I., Jung, K., & Kim, H.J. (2002). Face recognition using kernel principal component analysis. IEEE Signal Processing Letter, 9, 2, 40-42.

[15] Yang, W., Yan, H., Wang, J., & Yang, J. (2008). Face Recognition Using Complete Fuzzy LDA. Proceedings of Int. Conf. Pattern Recognition, 1-4.

[16] Kotropoulos, C., Pitas, I., Fischer, S. & Duc, B. (1997). Face Authentication using Morphological Dynamic Link Architecture. Proceedings of the First International Conference on Audio- and Video-based Biometric Person Authentication, 169-176.

[17] Wiskott, L., Fellous, J.M., Kruger, N., & Malsburg, C. (1999). Face Recognition by Elastic Bunch Graph Matching. In Intelligent Biometric Techniques in Fingerprint and Face Recognition, eds. L.C. Jain et al., publ. CRC Press, Chapter 11, 355-396.

Wright, J., Yang, A.Y., Ganesh, A., Sastry, S.S., & Ma, Y. (2008). Robust Face Recognition Via Sparse Representation. IEEE Trans. on pattern analysis and machine intelligence, 31,210-225.

[18] Sahoolizadeh, A.H., Heidari, B.Z., & Dehghani, C.H. (2008). A New Face Recognition Method using PCA, LDA and Neural Network. International Journal of Electrical and Electronics Engineering.

[19] Thomas A.A., & Wilscy, M. (2010). Face Recognition using Simplified Fuzzy Artmap. Signal and Image Processing: An International Journal, 1, 2.

[20] Gabr, H., & Hemayed, E. E. (2011). A Fuzzy Type-1 Facial Recognition System. CiiT

[21] International Journal of Fuzzy Systems, 3, 8, 306-312.

[22] Zhou, H., Sadka, A.H. (2011). Combining Perceptual Features With Diffusion Distance for Face Recognition. IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews, 41, 5, 577-588.