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Literature Survey on Development of An Algorithm for Face Recognition using Wavelet Neural Network

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Abstract - Automatic face recognition system is an important component of intelligent human computer interaction systems for biometric. It is an attractive biometric approach, to distinguish one person from another. To perform Automatic face recognition system, the hybrid approach Wavelets face detection and Neural Network based Face Recognition is used. The face recognition accuracy is can be increased using a combination of Wavelet, PCA, and Neural Networks. Preprocessing, feature extraction and classification rules are three crucial issues for face recognition. For preprocessing and feature extraction steps, we apply a combination of wavelet transform and PCA. During the classification stage, the Neural Network (MLP) is explored to achieve a robust decision in presence of wide facial variations.

Index Terms – Face detection, Neural Network, PCA, Face Recognition, Wavelet

I.INTRODUCTION

Over the past few years, the user authentication is increasingly important because the security control is required everywhere. The iris, fingerprint, palm print, and face, etc are playing a crucial role and attracting intensive interests for many researchers. Among them, face recognition is an amicable alternative because the authentication can be completed in a hands-free way without stopping user activities. Also, the face recognition system is economic with the low-cost of cameras and computers. It is extensively feasible to identity authentication, access control, and surveillance, etc. Over the past 20 years, extensive research works on various aspects of face recognition by human and machines [1],[2],[3],[4],[5],[6],[7],[8] have been conducted by psychophysicists, neuroscientist and engineering scientists. Psychophysicists and neuroscientists have studied issues such as uniqueness of faces, how infants perceive faces and organization of memory of faces. While engineering scientist have designed and developed face recognition algorithms. Automatic face recognition by computer can be divided into two approaches [1],[2] namely, content-based and face-based. In content-based approach, recognition is based on the relationship between human facial features such as eyes, mouth, nose, profile silhouettes and face boundary [9],[10],[11], [12].

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The success of this approach relies highly on the accurately is difficult. Every human face has similar facial features, a small derivation in the extraction may introduce a large classification error. Face-based approach [11],[12],[13],[14] attempts to capture and define the face as a whole. The face is treated as a two-dimensional pattern of intensity variation. Under this approach, face is matched through identifying its underlying statistical regularities such as Principal Component Analysis (PCA), Eigenfaces, Linear Discriminant Analysis (LDA) and Neural Network methods. Face Recognition plays an important role in many application areas, such as human-machine interaction, authentication and surveillance. However, the wide-range variations of human face, due to pose, illumination, and expression, result in a highly complex distribution and deteriorate the recognition performance. The different techniques used for face recognition mainly are PCA, Eigenfaces, LDA, Neural network, Template matching and Geometrical Feature Matching and they are discussed below. To overcome the limitations of these methods we are using Wavelet based Neural Networks, a neural network will be used in order to carry out the classification of faces.

II.BASIC OF FACE RECOGNITION

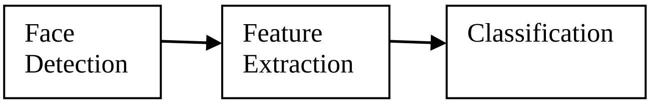

Fig. 1. Block Diagram of a Face Recognition

The first step in face recognition system is to detect the face in an image. The main objective of face detection is to find whether there are any faces in the image or not. If the face is present, then it returns the location of the image and extent of the each face. Pre-processing is done to remove the noise and reliance on the precise registration [15]. The block diagram of a typical face recognition system can be shown with the help of Figure. The face detection and face extraction are carried out simultaneously. The complete process of face recognition can be shown in the Figure 1. There are various factors that makes the face detection is a challenging task. Pose presence or absence of structural components, Facial expression, Occlusion, Image orientation. The facial feature detection is the process to detect the presence and location of features, like nose, eyebrow, eyes, lips, nostrils, mouth, ears, etc.

this is done with the assumptions that there is only a single face in an image. In the Face recognition process the input image is compared with the database. The input image is also called as probe and the database is called as gallery. Then it gives a match report and then the classification is done to identify the sub-population to which new observations belong [16], [17].

III.LITERATURE REVIEW ON FACE RECOGNITON TECHNIQUES

A. PCA

Sirovich and Kirby [20] first proposed using Karhunen-Loeve (KL) transform to represent human faces. In their method, faces are represented by a linear combination of weighted eigenvector, known as eigenfaces. Turk and Pentland [8] developed a face recognition system using PCA. PCA is used to find a low dimensional representation of data. Some important details of PCA are highlighted as follows [13].

Let $X = \{Xn, n = 1, \ldots\ldots, N\} \in R^{\text{dxd}}$ be an ensemble of vectors. In imaging applications, they are formed by row concatenation of the image data, with dxd being the product of the width and the height of an image. Let be the average vector in the ensemble.

$$E(X) = \frac{1}{N}\sum_{n=1}^{N} X_n$$

After subtracting the average from each element of , we get a modified ensemble of vectors,

$$\overline{X} = \{\overline{X}_n, n = 1,\ldots., N\} \text{ with } \overline{X_n} = X_n - E(X)$$

The auto-covariance matrix M for the ensemble X is defined by

$$M = \operatorname{cov}(\overline{X}) = E(\overline{X} \otimes \overline{X})$$

Where M is d^2xd^2 matrix with elements

$$M(i,j) = \frac{1}{N}\sum \overline{X}_n(i)\overline{X}_n(j), 1 \le i.j \le d^2$$

It is well known from matrix theory that the matrix M is positively definite (or semi-definite) and has only real non-negative eigenvalues [13]. The eigenvectors of the matrix M form an orthonormal basis for R^{dxd}.

This basis is called the K-L basis. Since the auto-covariance matrix for the K-L eigenvectors are diagonal, it follows that the coordinates of the vectors in the sample space X with respect to the K-L basis are un-correlated random variables. Let $\{Y_n, n = 1,\ldots,.N\}$ denote the eigenvectors and let K be the d^2xd^2 matrix whose columns are the vectors $Y_1,\ldots,Y_N$ .The adjoint matrix of the matrix K, which maps the standard coordinates into K-L coordinates, is called the K-L transform. In many applications, the eigenvectors in K are sorted according to the eigenvalues in a descending order. In determining the dxd eigenvalues from M, we have to solve d^2xd^2 matrix.

The PCA of a vector y related to the ensemble X is obtained by projecting vector y onto the subspaces spanned by d' eigenvectors corresponding to the top d' eigenvalues of the autocorrelation matrix M in descending order, where d' is smaller than d. This projection results in a vector containing d' coefficients $a_1,\ldots,a_{d'}$. The vector y is then represented by a linear combination of the eigenvectors with weights $a_1,\ldots,a_{d'}$.

Principal Component Analysis (PCA) [4, 7, 8, 20,] has been proven to be an effective face-based approach. However common PCA-based methods suffer from two limitations, namely, poor discriminatory power and large computational load. It is well known that PCA gives a very good representation of the faces. Given two images of the same person, the similarity measured under PCA representation is very high. Yet, given two images of different persons, the similarity measured is still high. That means PCA representation gets a poor discriminatory power. Swets and Weng [21] also observed this drawback of PCA approach and further improve the discriminability of PCA by adding Linear Discriminant Analysis (LDA). Another problem in PCA-based method is the high computational load in finding the eigenvectors. In view of the limitations in existing PCA-based approach, we proposed a new approach in using PCA – applying PCA on wavelet subband for feature extraction. In the proposed method, an image is decomposed into a number of subbands with different frequency components using the wavelet transform.

B. EIGENFACES

The Eigenface method is one of the generally used algorithm for face recognition. Karhunen-Loeve is based on the eigenfaces technique in which the Principal Component Analysis (PCA) is used. This method is successfully used to perform dimensionality reduction. Principal Component Analysis is used by face recognition and detection. Mathematically, Eigenfaces are the principal components divide the face into feature vectors. The feature vector information can be obtained from covariance matrix. These Eigenvectors are used to quantify the variation between multiple faces. The faces are characterized by the linear combination of highest Eigenvalues. Each face can be considered as a linear combination of the eigenfaces. The face can be approximated by using the eigenvectors having the largest eigenvalues. The best M eigenfaces define an M dimensional space, which is called as the "face space". [22]

Eigen Values and Eigen Vectors:

In linear algebra, the eigenvectors of a linear operator are non-zero vectors which, when operated on by the operator, result in a scalar multiple of them. The scalar is then called the eigenvalue (λ) [3] associated with the eigenvector(X). Eigen vector is a vector that is scaled by a linear transformation. It is a property of a matrix. When a matrix acts on it, only the vector magnitude is changed not the direction.

$$A X = \lambda X \quad \ldots\ldots\ldots\ldots\ldots (1)$$

Where A is a Vector function.

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Calculations of Eigen Values and Eigen Vectors:

By using (1), we have the equation,

$$(A - \lambda I)X = 0 \ldots\ldots\ldots\ldots\ldots(2)$$

Where I is the n x n Identity matrix. This is a homogeneous system of equations, and from fundamental linear algebra, we know that a nontrivial solution exists if and only if

$$\det\ (A - \lambda I) = 0 \ldots\ldots\ldots\ldots(3)$$

Where det() denotes determinant. When evaluated, becomes a polynomial of degree n. This is known as the characteristic equation of A, and the corresponding polynomial is the characteristic polynomial. The characteristic polynomial is of degree n. If A is n x n, then there are n solutions or n roots of the characteristic polynomial. Thus there are n eigenvalues of A satisfying the equation,

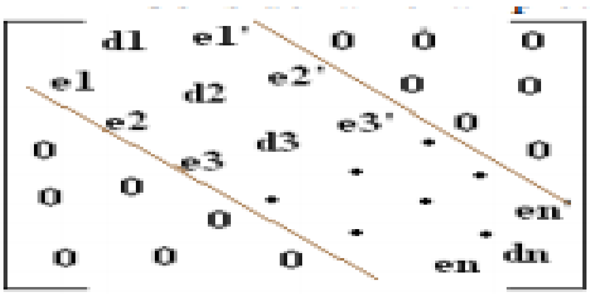
$$AX_i = \lambda X_i \ldots\ldots\ldots\ldots..(4)$$

Where i = 1, 2, 3….n

If the eigenvalues are all distinct, there are n associated linearly independent eigenvectors, whose directions are unique, which span an n dimensional Euclidean space.

Two algorithms called TRED2 () & QL algorithm are used for calculating Eigen Values. In TRED2 algorithm, Covariance Matrix is given as a input. Here Covariance Matrix is converted into Tri-diagonalised form except Upper, Lower & main diagonal elements all other elements are made zero.

Consider an example:



Where $e_1, e_2, \ldots\ldots e_n$ are the Lower diagonal elements and $e_1', e_2' \ldots\ldots e_n'$ are the Upper diagonal elements. This algorithm uses House- Holder Vector form which is n x m matrix (This is a way of Tri-diagonalising the Matrix.). It accepts only symmetric matrix as input.

Working of QL algorithm:

According to the largest value it shifts the elements in a matrix among themselves. (That means Upper and Lower diagonal elements are shifted with respect to main diagonal elements).Hence the number of shifts gives the EigenValues. Higher the Eigen values higher the property of that image and diagonal elements will be in a sorted order. Normalization: It takes max Eigen value of the Eigen Vector and divides each Eigen value by max Eigen value. Basically, eigenface is the eigenvector obtained from PCA. PCA has been widely adopted in human face recognition and face detection since 1987. However, in spite of PCA's popularity, it suffers from two major limitations: poor discriminatory power and large computational load. It is well known that PCA gives a very good approximation in face image. However, in eigenspace, each class is closely packed.

C. LDA

LDA is one, the most successfully widely used method for face recognition. It is based on appearance method. In 1930 R.A Fisher developed linear/fisher discriminant analysis for face recognition.[24],[25] It shows successful result in the face recognition process. LDA method demonstrated in (Belhumeur et al., 1997; Zhao et al., 1999; Chen et al., 2000; Yu and Yang, 2001; Liu and Wechsler., 2002; Lu et al., 2003a, b; Ye and Li., 2004)[26]. All used LDA to find set of basis images which maximizes the ratio of between-class scatter to within-class scatter. The disadvantage of LDA is that within the class the scatter matrix is always single, since the number of pixels in images is larger than the number of images so it can increase detection of error rate if there is a variation in pose and lighting condition within same images. LDA finds the vectors in the underlying space that best discriminate among classes. For all samples of all classes the between-class scatter matrix SB and the within-class scatter matrix SW are defined by:

$$S_B = \sum_{i=1}^{c} M_i.(x_i - \mu).(x_i - \mu)^T$$

Where Mi is the number of training samples in class i, c is the number of distinct classes, μi is the mean vector of samples belonging to class i and Xi represents the set of samples belonging to class i With xk being the k-th image of that class. SW represents the scatter of features around the mean of each face class and SB represents the scatter of features around the overall mean for all face classes. The LDA method is able to take advantage of within-class information, minimising variation within each class, yet still maximising class separation. Like the eigenface construction process, the first step of the fisherface tecnique is take each (NxM) image array and reshape into a ((N*M)x1) vector. Fisherface is similar to Eigenface but with enhancement of better classification of different classes image. We have better accuracy in facial expression than Eigen face approach. Besides, Fisherface removes the first three principal components which are responsible for light intensity changes; it is more invariant to light intensity[23]. The disadvantages of Fisherface are that it is more complex than Eigenface to finding the projection of face space. Calculation of ratio of between-class scatter to within-class scatter requires a lot of processing time. Besides, due to the need of better classification, the dimension of projection in face space is not as compact as Eigenface, results in larger storage of the face and more processing time in recognition[23].

D. NEURAL NETWORK

The neural networks are used in many applications like pattern recognition problems, character recognition, object recognition, and autonomous robot driving. A neuron is the basic element of any artificial neural network (ANN). It works as:

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$$h_j = \sum_k w_{jk}^{(i)} x_k$$

Where x_k are input signals, $w_{jk}^{(i)}$ are the weights of synaptic connections between neurons of i and 1 + i layers. The output signal of the j-th neuron is $y_j = g(h_j)$, where the activation function g(x) is either a threshold function, or a sigmoid type function, like

$$g(x) = \frac{1}{1+e^{-x}}$$

In the case of a threshold function and, say two classes, the perceptron attributes the vector i x to the first class, if $\sum_j w_{ij}^{(2)} h_j \geq 0$ or to the second class, otherwise. Such a scheme admits the following geometric interpretation.The hyperplane given by equation $\sum_j w_{ij}^{(2)} h_j = 0$,divided the space on two halfspace corresponding to classes in question. If the number of classes is more than two, then several dividing hyperplanes will be defined during the training process. For the input vector of the classified features $\overline{X_i}$ MLP brings in correspondence an output vector Y_i .The transformation $\overline{X_i} \Rightarrow \overline{Y_i}$ is completely described by the matrix of synaptic weights to be found as a solution of any concrete problem. Let us have some training sample as a set of pairs of vectors $\{\{\overline{X}_i^{(m)}\},\{\overline{Z}_i^{(M)}\}\}$ .The ML training is accomplished by minimization of so-called energy function

$$E = \sum_m \sum_i (Y_i^{(m)} - X_i^{(m)})^2 \Rightarrow \min .$$

by weights $w_{jk}^{(i)}$ as minimization parameters. Such the EBP method is usually realized by the gradient descent method. The number of units (neuron) in the input layer is equal to the number of image pixel. The number of units in the hidden layer is unknown and it can be determine with trial and error algorithm and the number of output units is equal to the number of classes (number of different person in database). The main objective of the neural network in the face recognition is the feasibility of training a system to capture the complex class of face patterns. To get the best performance by the neural network, it has to be extensively tuned number of layers, number of nodes, learning rates, etc. The neural networks are non linear in the network so it is widely used technique for face recognition. So, the feature extraction step may be more efficient than the Principal Component Analysis. It provides partial invariance to translation, rotation, scale, and deformation. The disadvantage of the neural network approach is that when the number of classes increases. [28],[29]. A new approach to face detection with wavelets & feed forward neural network was presented. The method used wavelet transform and feed forward neural network for both finding feature points and extracting feature vectors.[30],[31].

E.TEMPLATE MATCHING

In template matching, we can exploit other face templates from different prospects to characterize single face. Primarily, grey levels that match the face image can also be processed in proper format (Bichsel, 1991). In Bruneli and Poggio (1993) the Pop and Bruneli is available for all aspects of developing automatic four template features i.e., eyes, nose, mouth, face and selecting the entire set. Template based algorithms are more expensive and cannot be easily processed. However, the recognition process is easily handled between the given template and input image. The complexity arises only during the extraction of template. A simple version of template matching is that a test image represented as a two-dimensional array of intensity values is compared using a suitable metric, such as the Euclidean distance, with a single template representing the whole face. There are several other more sophisticated versions of template matching on face recognition. One can use more than one face template from different viewpoints to represent an individual's face. A face from a single viewpoint can also be represented by a set of multiple distinctive smaller templates. The face image of gray levels may also be properly processed before matching. In Bruneli and Poggio automatically selected a set of four features templates, i.e., the eyes, nose, mouth, and the whole face, for all of the available faces. They compared the performance of their geometrical matching algorithm and template matching algorithm on the same database of faces which contains 188 images of 47 individuals. The template matching was superior in recognition (100 percent recognition rate) to geometrical matching (90 percent recognition rate) and was also simpler. Since the principal components (also known as eigenfaces or eigenfeatures) are linear combinations of the templates in the data basis, the technique cannot achieve better results than correlation, but it may be less computationally expensive .One drawback of template matching is its computational complexity. Another problem lies in the description of these templates. Since the recognition system has to be tolerant to certain discrepancies between the template and the test image, this tolerance might average out the differences that make individual faces unique[17],[18].

F.GEOMETRICAL FEATURE MATCHING

Geometrical feature matching techniques are based on the computation of a set of geometrical features from the picture of a face. The overall configuration can be described by a vector which representing the position and size of the main facial features like eyes and eyebrows, nose, mouth, and an outline of face. The primary works on automated face recognition by using geometrical features was done in 1973. Their system achieved 75% recognition rate on a database of 20 people using two images per person, one as the model and the other as the test image. In 1993 R. Bruneli and T. Poggio, automatically extracted a set of geometrical features from the picture of a face, such as nose width and length, mouth position and chin shape. There were 35 features extracted form a 35 dimensional vector.

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The recognition was then performed with a Bayes classifier. They achieved recognition rate 90% on a database of 47 people.[17] I.J. Cox el at. introduced a mixture-distance technique which achieved 95% recognition rate on a query database of 685 individuals. Each face was represented by 30 manually extracted distances.[20] Reference [21] used Gabor wavelet decomposition to detect feature points for each face image which reduced the storage requirement for the database. Typically, 35-45 feature points per face were generated. Two cost values, the topological cost, and similarity cost, were evaluated. The recognition accuracy of the right person was 86% and 94% of the correct person's faces were in the top three candidate matches. In summary, geometrical feature matching based on precisely measured distances between features may be useful for finding matches in a large database. However, it will be dependent on the accuracy of the feature location algorithms. Disadvantage of current automated face feature location algorithms do not provide a high degree of accuracy and require considerable computational time[19].So to overcome limitations of these techniques we use Wavelet Neural Networks.

G. WAVELET NEURAL NETWORKS

Wavelets have been successfully used in image processing. Wavelets are functions that satisfy certain mathematical requirements and are used in presenting data or other functions, similar to sines and cosines in the Fourier transform. However, it represents data at different scales or resolutions, which distinguishes it from the Fourier transform. The structure of a wavelet neural network is very similar to that of a (1+ 1/2) layer neural network. That is, a feed-forward neural network, taking one or more inputs, with one hidden layer and whose output layer consists of one or more linear combiners or summers is shown in fig.2. The hidden layer consists of neurons, whose activation functions are drawn from a wavelet basis. These wavelet neurons are usually referred to as wavelons[18]. A wavelet-based method is developed so as to overcome the limitations of the above techniques mentioned; furthermore, we have utilized a neural network in order to carry out the classification of faces. This consist two stages, namely training step in which the feature extraction, dimension reduction and adjusting the weight of neural networks have been performed and the recognition step to identify the unknown face image. The training stage includes the feature extraction of reference images and the adjustment of neural network parameters. The extracting feature identifies the representational basis for images in the domain of interest.

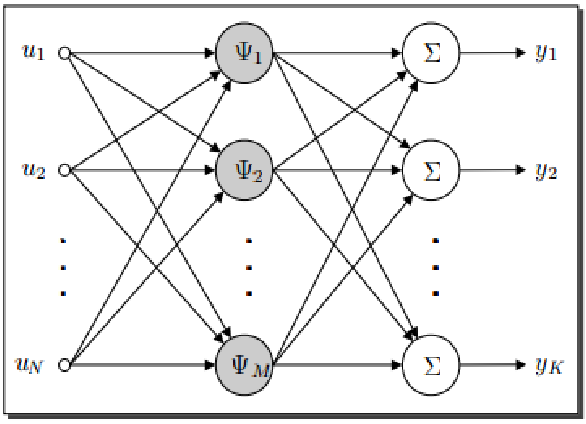

Fig. 2 Structure of a Wavelet Neural Network

Subsequently, the recognition stage translates the input unknown image according to the representational basis, identified in the training stage. There are three significant steps in the training stage. In the first step, wavelet transform (WT) is applied to decompose reference images; consequently, sub-images in the form of 16x16 pixels obtained by three level wavelet decomposition are selected. In the next step, Principal Component Analysis (PCA) is performed on the sub-images to obtain a set of representational basis by the selection of d'eigenvectors corresponding with the largest eigenvalues and sub-space projection. Finally, the feature vectors of reference images obtained by previous steps are used so as to train neural networks using back propagation algorithm. Processing in the recognition stage is similar to the training stage, except that recognition stage also incorporates steps to match the input unknown images with those reference images in the database by neural network. When an unknown face-image is presented to the recognition stage, WT and PCA are applied to transform the unknown face-image into the representational basis identified in the recognition stage, and the classification is achieved by trained neural networks [19].

IV.CONCLUSION

A wavelet-based method is developed so as to overcome the limitations of the PCA, EigenFaces, LDA etc. techniques.In this paper we have presented some techniques used for face recognition with their advantages and disadvantages, for preprocessing and feature extraction stages, we apply a of wavelet transform. During the classification phase, the Neural network is explored for robust decision in the presence of wide facial variations. In summary, no existing technique is free from limitations. Further efforts are required to improve the performances of face recognition techniques, especially in the wide range of environments encountered in real world.

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REFERENCES

1. R. Chellappa, C. L. Wilson and S. Sirohey, "Human and machine recognition of faces: a survey," Proceedings of the IEEE, Vol. 83, No. 5, 705-740, May 2001.
2. G. Chow and X. Li, "Towards a system for automatic facial feature detection," Pattern Recognition, Vol. 26, No. 12, 1739-1755, 1998.
3. F. Goudail, E. Lange, T. Iwamoto, K. Kyuma and N. Otsu, "Face recognition system using local autocorrelations and multiscale integration," IEEE Trans. PAMI, Vol. 18, No. 10, 1024-1028, 2002.
4. K. M. Lam and H. Yan, "Locating and extracting the eye in human face images", Pattern Recognition, Vol. 29, No.5 771-779, 2011.
5. D. Valentin, H. Abdi, A. J. O'Toole and G. W. Cottrell, "Connectionist models of face processing: A Survey," Pattern Recognition, Vol. 27, 1209-1230, 2005.
6. A. L. Yuille, P. W. Hallinan and D. S. Cohen," Feature extraction from faces using deformable templates," Int. J. of Computer Vision, Vol. 8, No. 2, 99-111, 2008.
7. M. Kirby and L. Sirovich," Application of the Karhunen- Loeve procedure for the characterization of human faces, "IEEE Trans. PAMI., Vol. 12, 103-108, 2009.
8. M. Turk and A. Pentland," Eigenfaces for recognition, "J. Cognitive Neuroscience, Vol. 3, 71-86., 2001.
9. M. V. Wickerhauser, Large-rank "approximate component analysis with wavelets for signal feature discrimination and the inversion of complicated maps, "J. Chemical Information and Computer Sciences, Vol. 34, No. 5, 1036-1046, 1999.
10. A. J. O'Toole, H. Abdi, K. A. Deffenbacher and D. Valentin, "A low-dimensional representation of faces in the higher dimensions of the space, "J. Opt. Soc. Am., A, Vol. 10, 405-411, 2012.
11. A. Pentland, B. Moghaddam and T. Starner," View-based and modular eigenspaces for face recognition," Proc. IEEE Conf. Computer vision and Pattern Recognition, Seattle, June, 84-91, 1998.
12. H. A. Rowley, S. Baluja and T. Kanade, "Neural network- based face detection," IEEE Transaction on PAMI, Vol. 20, No. 1,23-38, 2002.
13. E.M.-Tzanakou, E. Uyeda, R. Ray, A Sharma, R. Ramanujan and J. Dong, "Comparison of neural network algorithm for face recognition," Simulation, 64, 1, 15-27, 2009.
14. D. Valentin, H. Abdi and A. J. O'Toole, "Principal component and neural network analyses of face images: Explorations into the nature of information available for classifying faces by sex," In C. Dowling, F. S. Roberts, P. Theuns, Progress in mathematical psychology, Hillsdale: Erlbaum, (in press, 2000)
15. Y. Meyer, "Wavelets: Algorithms and Applications," SIAM Press, Philadelphia, 2011.
16. Jigar M. Pandya, Devang Rathod, Jigna J. Jadav," A Survey of Face Recognition approach", International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622 www.ijera.com Vol. 3, Issue 1, January -February 2013, pp.632-635.
17. Jyoti S. Bedre ,Shubhangi Sapkal, "Comparative Study of Face Recognition Techniques: A Review", Emerging Trends in Computer Science and Information Technology 2012(ETCSIT2012) Proceedings published in International Journal of Computer Applications® (IJCA) 12
18. M. Berthold & D. Hand, Intelligent Data Analysis, 2nd ed., Springer, 2013.
19. E. C. Cho & Vir V. Phoha S. Sitharama Iyengar, Foundations of Wavelet Networks and Applications, Chapman & Hall/CRC, 2012.
20. L.Sirovich and M. Kirby, "Low-dimensional procedure for the characterization of human faces," J. Opt. Soc. Am. A, Vol. 4, No. 3, 519-524, 1998.
21. D. L. Swets and J. J. Weng, "Using discriminant eigenfeatures for image retrieval," IEEE Trans. PAMI., Vol. 18, No. 8, 831-836, 1996.
22. A. S. Tolba, A.H. El-Baz, and A.A. El-Harby, " Face Recognition: A Literature Review", International Journal of Signal Processing 2:2 2006.
23. Sushma Jaiswal, Dr. (Smt.) Sarita Singh Bhadauria, Dr. Rakesh Singh Jadon," COMPARISON BETWEEN FACE RECOGNITION ALGORITHM-EIGENFACES, FISHERFACES AND ELASTIC BUNCH GRAPH MATCHING", Volume 2, No. 7, July 2011 Journal of Global Research in Computer Science.
24. Mohammed Javed, Bhaskar Gupta, "Performance Comparison of Various Face Detection Techniques" ,International Journal of Scientific Research Engineering & Technology (IJSRET) Volume 2 Issue1 pp 019-0027 April 2013 www.ijsret.org ISSN 2278 – 0882 IJSRET @2013
25. R. A. Fisher, "The Use of Multiple Measurements in Taxonomic Problems", 1996.
26. Belhumeur, V., Hespanda, J., Kiregeman, D., 1997," Eigenfaces vs. fisherfaces: recognition using class specific linear pojection", IEEE Trans. on PAMI, V. 19, pp. 711-720
27. Hong Duan, Ruohe Yan, Kunhui Lin, "Research on Face Recognition Based on PCA", 978-0-7695-3480-0/08 2008 IEEE.
28. Ming-Hsuan Yang, David J. Kriegman and NarendraAhuja, "Detecting Faces in Images: A Survey," IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 24, NO. 1, JANUARY 2012.
29. KIRBY, M. AND SIROVICH, L. 1999. "Application of the Karhunen-Loeve procedure for the characterization of human faces". IEEE Trans. Patt. Anal. Mach. Intell. 12.
30. Li X. and Areibi S.,—"A Hardware/Software codesign approach for Face Recognition", The 16th,International Conference on Microelectronics, Tunisia,2004.
31. Lin-Lin Huang, Akinobu Shimizu, Yoshihiro Hagihara, Hidefumi Kobatake ,"Face detection from cluttered images using a polynomial neural network", Elsevier Science 2010 .
32. U. KreQel, J. SchRurmann, "Pattern classification techniques based on function approximation, in: H.Bunke, P.S.P. Wang (Eds.),
33. Handbook of Character Recognition and Document Image Analysis", World Scienti5c, Singapore, 2000, pp. 49–78.
34. Yue Ming, Qiuqi Ruan, Xiaoli Li, Meiru. Mu, " Efficient Kernel Discriminate Spectral Regression for 3D Face Recognition", Proceedings Of ICSP 2010.
35. R. Bruneli and T. Poggio, "Face recognition: features versus templates," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 15, pp. 1042-1052, 1993. \
36. R.J. Baron, "Mechanism of human facial recognition," Int'l J. Man Machine Studies, vol. 15, pp. 137-178, 2001.
37. Muhammad Sharif, Research Journal of Applied Sciences, Engineering and Technology 4(23): 4979-4990, 2012,ISSN: 2040-7467.

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