International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 02 Issue: 08 | Nov-2015 www.irjet.net p-ISSN: 2395-0072

Support Vector Machines for Face Recognition

Navin Prakash[1], Dr.Yashpal Singh[2]

[1]Research Scholar, IFTM University, Moradabad, UP, INDIA
[2] Associate Professor, Deptt. Of CS&E, B.I.E.T.-Jhansi, UP, INDIA

****

Abstract— The computer vision has become an emerging domain for machine learning ways. In the last decade, face recognition are developed for the image area to achieve correct and speedy performance. Now the face recognition technology (FRT) is in much advanced stage because research in this area is conducting continuously. The main reason of popularity is that it is using in many fields like identity authentication, access control and etc. Support vector machine (SVM) learning is a recent technology that gives a decent broad view performance this paper given the most recent algorithms developed for face recognition and tries to give an idea of the state of the art of face recognition technology. And mention some advantages and disadvantages of the Support Vector Machines and their resolution.

Keywords: *Face Recognition, Person Identification, Combined classifiers, Support vector Machines classifiers.*

1. INTRODUCTION

Face recognition is a significant research problem in many fields and disciplines. Biometric recognition refers to the use of unique physiological (fingerprint, face, retina, hand geometry, iris etc.) and behavioral (voice, gait, signature etc.) characteristics, called biometrics. A reliable identification system is a significant component in several applications that contribute their services specifically to genuine users. Depending on the application situation, a biometric system may operate in two modes either in verification mode or identification mode. In verification or authentication, the user claims an identity and the system verifies whether the claim is genuine. In Identification, the user's input is compared with the patterns of all the persons enrolled in the database and the identity of the person whose pattern has the highest amount of similarity with the user's input is output by the biometric system. So, Matching is 1: *N* in an identification system. Using something we know and hold are two easy identification/verification solutions widely used today. Using something we know only requires a good memory, but sometimes can easily be guessed. An item we hold can be stolen and later on can be used or copied. Biometrics is the only thing which doesn't need to be remembered or carried out. A face recognition system meets various problems in the recognition process. The main objectives is to design robust face recognition system that tackle following challenges as Great face acknowledgment calculations and suitable reprocessing of the pictures can adjust for compensate and slight varieties in introduction, scale and enlightenment. At long last, advances that oblige different people to utilize the same gear to catch their organic qualities possibly open the client to the transmission of germs and impurities from different clients. In any case, face acknowledgment is absolutely non-nosy and not convey any such health dangers.

2. LITERATURE REVIEW

Numerous face recognition algorithms are available along with their modifications, have been developed during the past few decades. Zaho et al. [1] divide face recognition algorithm into three main categories: feature-based , holistic and hybrid approach [2-4].The holistic based methods uses predefined standard face patterns whereas feature based methods focus on extracted features such as distance between eyes, skin color [5, 6], eye socket depth etc. and hybrid which use representations of local face parts .

2.1 Holistic Methods

In holistic-based approach, identify faces using global representations, i.e., descriptions based on the entire image rather than on local features of the face. An overview of some of the methods in these categories follows [1]. Examples are Eigenfaces [7], fisher faces, probabilistic Eigenface etc. These techniques help to lower the dimensions of the dataset. Principal Component Analysis (PCA), Linear Discriminate Analysis (LDA), and Independent Component Analysis (ICA) [8, 9] are the most widely used holistic methods. Holistic scheme further subdivided into two categories.

2.1.1Statistical based

In the least difficult form of the holistic approaches, the picture is represented to as a 2D array of intensity qualities and recognition is performed by direct correlation comparisons between the input face and all the other faces in the database. Despite the fact that this methodology has been appeared to work [10] under constrained circumstances (i.e., equal with illumination, scale, posture, and so on.), it is computationally exceptionally costly and experiences the typical weaknesses of clear relationship based methodologies, for example, face orientation, size, variable lighting conditions, background clutter, and noise [11]. The real prevention to the immediate coordinating routines' acknowledgment execution is that they endeavor to perform classification in a space of high dimensionality [11]. To counter this scourge of dimensionality, a few different plans have been suggested that utilize measurable Dimensionality decrease systems to get and hold the most significant component measurements before performing recognition.

A few of these are mentioned below. The PCA technique was produced in 1991 [Turk and Pentland, 1991].PCA is one of the well-known systems utilized for feature extraction and data representation. It reduces the picture's dimensionality, as well as holds a varieties' portion in the picture information and gives a minimal representation of a face picture. The key thought of the PCA strategy is to change the face pictures into a small set of characteristics feature images, called eigenfaces, which are the principal parts of the initial training set of the face images. PCA yields projection directions that augment the aggregate disseminate over all classes, i.e., overall face pictures. In acknowledgment transform, a test picture is anticipated into the lower-dimension face space spread over by the eigenfaces and afterward Classified either by statistical theory or a classifier. The policy was had a go at using a database of 2,500 pictures of 16 people under all blends of 3 head presentations, 3 head sizes or scales, and 3 lighting conditions and diverse resolutions. Recognition rates of 96%, 85%, and 64% were represented lighting, presentation and scale variety. In spite of the way that the procedure has every one of the reserves of being really solid to lighting mixed bags, its execution taints with scale changes.

PCA seems to function admirably when a solitary picture of every individual is accessible, however when different pictures per individual are available, then Belhumeur et al. [12] contend that by picking the projection which maximizes total scatter, PCA holds undesirable varieties because of lighting and outward appearance. As expressed by Moses et al. [13], "the dissimilarities between the images of the same face because of illumination and lighting direction are quite often bigger than picture varieties because of an adjustment in face personality" Therefore, they propose utilizing Fisher's Linear Discriminant Analysis [14], which augments the proportion of the between-class scatter and the inside of class scatter and is in this manner purportedly preferred for order over PCA. Leading different tests on 330 pictures of 5 individuals (66 of every), they report that their technique, called Fisherfaces, which utilizes subspace projection preceding LDA projection (to keep the inside of class scatter matrix from getting to be degenerate), is better simultaneously handling of varieties in lighting and expression.

Moghaddam et al. [15] propose an option methodology which uses difference pictures, where a distinction picture for two face pictures is characterized as the marked signed arithmetic difference in the intensity values of the corresponding pixels in those pictures. Two classes of difference pictures are characterized: intrapersonal, which comprises of difference pictures starting from two pictures of the same individual, and extrapersonal, which comprises of difference pictures got from two pictures of diverse individuals. It is expected that both these classes begin from discrete Gaussian distributions inside of the space of all conceivable difference pictures.

For a computationally more practical methodology, Moghaddam and Pentland [16] likewise propose overlooking the extrapersonal class data and ascertaining the closeness construct just with respect to the intrapersonal class data. In the subsequent maximum likelihood (ML) classifier.

Various minor departure from and augmentations to the standard eigenfaces and the Fisherfaces methodologies have been recommended following their presentation.

Some late advances in PCA-based calculations incorporate multi-linear subspace analysis[17], symmetrical PCA [18], two-dimensional PCA [19, 20], eigenbands [21], adaptively weighted subpattern PCA [22], weighted particular PCA [23], Kernel PCA [23,25] and corner to corner PCA [26]. Cases of late LDA-based calculations incorporate Direct LDA [27, 28], Direct-weighted LDA [29], Nullspace LDA [30, 31], Dual-space LDA [32], Pair-wise LDA [33], Regularized Discriminant Analysis [34], Generalized Singular Value Decomposition [35, 36], Direct Fractional-Step LDA [37], Boosting LDA [38],Discriminant Local Feature Analysis [39], Kernel PCA/LDA [40, 41], Kernel Scatter-Difference-based Discriminant Analysis [42], 2DLDA [43, 44], Fourier-LDA [45], Gabor-LDA [46], Block LDA [47], Enhanced FLD [48], Component-based Cascade LDA [49], and incremental LDA [50], to give some examples. Every one of these systems purportedly get preferred recognition results over the baseline methods. One rule drawback of the PCA and LDA frameworks is that these strategies suitably see only the Euclidean structure and disregard to locate the central structure if the face pictures lie on a non-straight submanifold in the pictur space. Since it has been exhibited that face pictures possibly harp on a nonlinear submanifold [51-52].

some nonlinear methods have therefore been proposed to find the nonlinear structure of the manifold, e.g., Isometric Feature Mapping (ISOMAP) [53], Locally Linear Embedding (LLE) [54, 55], Laplacian Eigenmap [56], Locality Preserving Projection (LPP) [57], Embedded Manifold [58], Nearest Manifold Approach [59],Discriminant Manifold Learning [60] and Laplacianfaces [61]. The eigenvectors found by PCA depend just on pairwise connections between the pixels in the picture database. Be that as it may, different strategies exist that can discover basis vectors that rely on upon higher-order relationships among the pixels, and it appears to be sensible to expect that using such methods would yield far better recognition results. Independent component analysis (ICA) [152], a speculation of PCA, is one such system that has been utilized for the face recognition errand. ICA means to locate a independent, as opposed to an uncorrelated, picture decomposition and representation.

Bartlett et al. [63] performed ICA on pictures in the FERET database under two distinct architectures: one regarded the pictures as arbitrary variables and the pixels as results; then again, the second regarded the pixels as the irregular variables and the pictures as results. Both ICA representations beat PCA representations for perceiving appearances crosswise over days and changes in expression.A classifier that joined both ICA representations gave the best performance. Others have additionally tried different things with ICA [64-155] and have reported that this strategy, and varieties of it, seem to perform better then PCA under most circumstances.

Foon et al. [66] have coordinated different wavelet transforms and non-negative matrix factorizations [67] and case to have acquired better verification rates when contrasted with the basic eigenfaces approach. In [68], an intra-class subspace is developed, and the classification depends on the nearest weighted distance between the inquiry face and each intra-class subspace. Test results are exhibited to show that this strategy performs superior to anything some other nearest weighted distance.

A study and comparison of four subspace representations for face acknowledgment, i.e., PCA, ICA, Fisher Discriminant Analysis (FDA), and probabilistic eigenfaces and their "kernalized" versions (if accessible), is exhibited in [69]. An comprehensive review of late advances in subspace investigation for face recognition can be found in [70].

2.1.2. AI Based approaches

2.1.2.1 Neural networks

AI methodologies use tools, for example, neural systems and machine learning strategies to perceive faces. A few cases of strategies having a place with this classification are given .In [71], 50 principal components were separated and an auto-associative neural system was utilized to decrease those parts to five dimensions. A standard multi-layer perceptron was exploited to classify the subsequent representation. In spite of the fact that great results were gotten.

Weng et al. [72] made utilization of a hierarchical neural system which was become consequently and not prepared on the traditional gradient descent method. They reported great results on a database of 10 subjects. Lawrence et al [63] reported a 96.2% acknowledgment rate on the ORL database (a database of 400 pictures of 40 people) utilizing a hybrid neural system arrangement which joins local image sampling a self-organizing map [74, 75] neural system (which gives dimensionality decrease and invariance to little changes in the image sample), and a convolutional neural system (which gives halfway invariance to translation, rotation, scale and deformation). The eigenfaces system [76, 77] delivered 89.5% recognition accuracy on the same information.Supplanting the self-organizing map guide by the Karhunen-Loeve change and the convolutional network by a multi-layer perceptron brought about a recognition rate of 94.7% and 60% individually. Eleyan and Demirel [78] utilized principal components analysis to get feature projection vectors from face pictures which were then arranged utilizing feedforward neural networks. A few tests on the ORL database utilizing different quantities of preparing and testing pictures demonstrated that the execution of this system was superior to the eigenfaces [76, 77].

2.1.2.2 Nearest Neighbor Classifier

one in which a nearest neighbor classifier was utilized for classification. Li and Yin [79] presented a framework in which a face picture is initially deteriorated with a wavelet transform to three levels. The Fisherfaces technique [80] is then connected to each of the three low-frequency sub-images. At that point, the individual classifiers are melded utilizing the RBF neural system. The subsequent framework was tried on pictures of 40 subjects from the FERET database and was appeared to outflank the individual classifiers and the direct Fisherfaces technique.Melin et al. [81] partitioned the face into three regions (the eyes, the mouth, and the nose) and allowed every region to a module of the neural system. A fuzzy Sugeno integral was then used to combine the outputs of the three modules to settle on the last face recognition decision. They tried it on a little database of 20 individuals and reported that the modular network yielded preferable results over a monolithic one. As of late, Zhang et al. [82] proposed a methodology in which a similarity function is found out describing the level of confidence that two pictures have a place with the same individual, like [83]. The facial features are chosen by acquiring Local Binary Pattern (LBP) [84] histograms of the face's subregions picture and the Chi-square distances between the corresponding LBP histograms are picked as the discriminative features.

2.1.2.3 AdaBoost algorithm

The AdaBoost learning algorithm, presented by Freund and Schapire [85], is then connected to choose the most effective LBP features and additionally to get the similarity function as a linear combination of LBP feature-based weak learners. Experimental results on the FERET frontal picture sets have demonstrated that this strategy yields a recognition rate of 97.9 % by using fewer features than a past comparative methodology proposed by Ahonen et al. [86].

A few scientists have additionally utilized the one-against-one methodology [87] for decomposing the multi-class face recognition problem into various binary classification problems. In this technique, one classifier is prepared for every pair of classes, overlooking all the staying ones. The yields of all the double classifiers are then combined to develop the global result. For binary classifiers with probabilistic outputs, pair-wise coupling (PWC) [88] can be utilized to couple these outputs into the set of posterior probabilities.

At that point, the test example is relegated to the class with the maximum posterior probability. One principle burden of PWC is that when a test example does not have a place with both of the classes identified with a binary classifier, then the yield of that classifier is trivial and can harm the global result. In [89], another algorithm called PWC-CC (where CC remains for correcting classifier) is introduced to tackle this issue, PWC-CC performs superior to anything PWC.

2.1.2.4 Hidden Markov models

Stochastic modeling of nonstationary vector time series based on (HMM) has been exceptionally effective for speech applications. In [80] connected this system to human face recognition. Faces were naturally isolated into areas, for example, the eyes, nose, mouth, and so on. Which can be connected with the conditions of a hidden Markov model. Since HMMs require an one-dimensional perception succession and pictures are two-dimensional, the pictures ought to be changed over into either 1D temporal sequences or 1D spatial sequences.

Samaria and Harter [90] utilized an one-dimensional HMM get recognition rate is 87% utilizing ORL database comprising of 400 pictures of 40 people. They later redesigned the one-dimensional HMM to a pseudo two-dimensional HMM [91] and accomplished a best recognition performance of 95% on the same database utilizing a large portion of the pictures for preparing and the other half to test.

Nefian and Hayes III [92] reported a best recognition rate of 98% on the same training and testing sets utilizing implanted HMM [180] face models, and they additionally guaranteed that their system was much quicker than that of Samaria [91] and invariant to the face's size pictures. Some other AI methodologies used for the face recognition undertaking incorporate evolutionary interest [93, 94] and systems [95, 96] taking into account boosting [85, 97]. These plans have supposedly yielded promising results for different troublesome face recognition situations.

2.1.2.5 Support Vector Machine

In [98], a novel PWC-CC (NPWC-CC) system is proposed for the face recognition issue and the consequences of tests on the ORL database are introduced to bolster the case that it outflanks PWC-CC. In [99], the optimal PWC (O-PWC) methodology is acquainted and is appeared with have better recognition rates that the PWC strategy. Feature extraction is finished by utilizing principal components analysis as a part of [188] and by wavelet transform in [99].

In both [98] and [99], Support Vector Machines (SVMs) were utilized as binary classifiers and the SVM yields were mapped to probabilities by utilizing the technique recommended by Platt [100]. It ought to be noticed that Support Vector Machine (SVM) is thought to be a standout amongst the best calculations for pattern classification problems [101]. SVM has been utilized for face recognition by a few different analysts and has been appeared to yield great results [101, 102-106].

As we talked about above Support Vector Machine (SVM) is another classification strategy and has drawn much consideration on this point as of late [107–111]. The theory of SVM depends on structural risk minimization (SRM) [109]. In numerous applications, SVM has been appeared to give higher performance than conventional learning machines [107] and has been presented as capable apparatuses for taking care of classification issues. This technique was initially presented by Vapnik in 1992 and still increases numerous consideration up to this point because of its well speculation (B. Boser, 1992) (Vapnik, 1995) (Mulier, 1998) (Vapnik V. N., 1998) (Wu, 1999) (Byun H., 2003).SVM based detail literature review is given below.

2.2 Feature based and hybrid based

Zaho et al. [3] further divide feature based and hybrid based into three categories given below .hybrid based methods use both the local and holistic features to recognize a face. These methods have the potential to offer better performance than individual holistic methods, since more comprehensive information could be utilized.

Note: From feature extraction point of view holistic and feature template based are equivalent, they used templates to represent detect face or face parts.

a. **Generic based methods:** Generic based methods on generic feature such as edge, lines, curve etc.

b. **Feature template based:** Feature template based method that are used to detect specific facial such as eyes, nostrils, etc.

c. **Structural matching methods:** Structural matching methods that takes into consideration geometry constraints on the feature.

Feature-based methodologies first process the input picture to recognize and extract (and measure) distinctive facial features, for example, the eyes, mouth, nose, and so on., and also other fiducial imprints, and after that figure the geometric relationships among those facial points, consequently reducing the input facial picture to a vector of geometric features. Statistical pattern recognition methods are then utilized to match Faces using these measurements. Early work completed on automated face recognition was basically in view of these strategies. One of the most punctual such endeavors was by Kanade [112], who utilized simple image processing strategies to extract a vector of 16 facial parameters - which were ratios of distances, areas and angles (to make up for the varying size of the photos) - and utilized a simple Euclidean distance measure for matching to accomplish a top performance of 75% on a database of 20 distinct individuals utilizing 2 pictures for each individual (one for reference and one for testing).

Brunelli and Poggio [113], expanding upon Kanade's methodology, computed a vector of 35 geometric features from a database of 47 individuals (4 pictures for each individual) and reported a 90% recognition rate. Be that as it may, they additionally reported 100% recognition rate for the same database utilizing a simple template-matching methodology.

More sophisticated feature extraction systems include deformable templates ([114], [115], [116]), Hough transform methods [117], Reisfeld's symmetry operator [118] and Graf's filtering and morphological operations [119]. Be that as it may, these strategies depend intensely on heuristics, for example, restricting the hunt subspace with geometrical constraints [120].

Besides, a sure resistance must be given to the models since they can never impeccably fit the structures in the picture. On the other hand, the utilization of a vast resistance quality has a tendency to crush the exactness required to perceive people on the model's premise last best-fit parameters and makes these procedures obtuse to the minute variations required for recognition [121]. All the more recently, Cox et al. [122] reported a recognition performance of 95% on a database of 685 pictures (a single picture for every person) utilizing a 30-dimensional element vector got from 35 facial elements.

Then again, the facial elements were manually extracted, so it is sensible to accept that the recognition performance would have been much lower if an automated, and henceforth less exact, feature extraction strategy had been received. When all is said in done, current algorithms for automatic feature extraction don't give a high level of accuracy and require extensive computational limit [123]. Another understood feature-based methodology is the elastic bunch graph matching strategy proposed by Wiskott et al. [124]. This system depends on Dynamic Link Structures [125].

A graph for an individual face is created as takes after: an arrangement of fiducial points on the face are picked. Each fiducial point is a node of a full connected graph, and is named with the Gabor filters' reactions applied to a window around the fiducial point. Every curve is named with the separation between the correspondent fiducial points.

A representative set of such graphs is combined into a stack-like structure. Once the system has a face bunch graph, graphs for new face pictures can then be created consequently by Elastic Bunch Graph Matching. Recognition of another face picture is performed by contrasting its image graph with those of all the known face pictures and picking the one with the most similarity value. Utilizing this architecture, the recognition rate can reach 98% for the first rank and 99% for the initial 10 ranks utilizing an exhibition of 250 people. The system has been improved to permit it to manage different poses [126] however the Recognition performance on countenances of the same orientation continues as before. In spite of the fact that this strategy was among the best-performing ones in the latest FERET assessment [127, 128], it experience the ill effects of the genuine downside of requiring the graph placement for the initial 70 appearances to be done physically before the elastic graph matching turns out to be adequately dependable [129].

Campadelli and Lanzarotti [130] have as of recently tried different things with this system, where they have disposed of the need to do the graph placement manually by utilizing parametric models, in light of the deformable templates proposed in [114], to consequently find fiducial focuses. They claim to have gotten the same performances as the elastic bunch graph utilized in [124]. Other late varieties of this methodology Frameworks for face recognition [126].

Replace the Gabor features by a graph matching technique [131] and HOGs (Histograms of Oriented Gradients [132]. Extensive exertion has additionally been committed to recognizing faces from their profiles [133-137] since, for this situation, highlight extraction turns into a to some degree less complex one-dimensional issue [122, 136]. Kaufman and Breeding [135] reported a recognition rate of 90% utilizing face profiles; be that as it may, they utilized a database of just 10 people. Harmon et al. [133] acquired acknowledgment exactness of 96% on a database of 112 people, utilizing a 17-dimensional feature vector to describe face profiles and using a Euclidean distance measure for matching.

All the more as of late, Liposcak and Loncaric [136] reported a 90% accuracy rate on a database of 30 people, utilizing subspace filtering to determine a 21-dimensional feature vector to depict the face profiles and utilizing a Euclidean distance measure to match them.

Geometrical feature matching systems depend on the computation of a set of geometrical features from the photo of a face. The way that face recognition is conceivable even at coarse resolution as low as 8x6 pixels [45] when the single facial features are barely uncovered in point of interest, infers that the general geometrical configuration of the face elements is adequate for recognition. The general configuration can be depicted by a vector representing to the position and size of the main facial features, for example, eyes and eyebrows, nose, mouth, and the state of face diagram.

One of the using so as to spearhead deals with automated face recognition geometrical features was finished by [138] in 1973. Their framework accomplished a top performance of 75% acknowledgment rate on a database of 20 individuals utilizing two pictures for each individual, one as the model and alternate as the test picture.

References [139,140] demonstrated that a face recognition program gave components removed physically could perform recognition evidently with agreeable results. Reference [141] consequently extracted an set of geometrical features from the photo of a face, for example, nose width and length, mouth position, and jaw shape. There were 35 features extracted from a 35-dimensional vector.

The recognition was then performed with a Bayes classifier. They reported a recognition rate of 90% on a database of 47 people. Reference [142] presented a mixture-distance technique method which accomplished 95% recognition rate on a query database of 685 people. Every face was spoken to by 30 manually extracted distances. Reference [143] utilized Gabor wavelet decomposition to identify feature points for every face picture which extraordinarily diminished the stockpiling necessity for the database. Commonly, 35-45 feature points per face were created. The matching process used the data exhibited in a topological graphic representation of the feature points. In the wake of making up for diverse centroid location, two expense values, the topological cost, and similarity cost, were assessed. The recognition accuracy as far as the best match to the right person was 86% and 94% of the correct person's faces was in the main three competitor matches. In the rundown, geometrical feature matching in view of precisely measured distances between components may be most valuable for discovering conceivable matches in an expansive database, for example, a Mug shot collection. On the other hand, it will be reliant on the feature location algorithms. Current automated face feature location algorithms don't give a high level of exactness and require impressive computational time.

3. CONCLUSION

This paper has attempted to review a numerous papers to cover different technologies in face recognition. The current study tells about superior face recognition system. Face recognition is that it can be used in the different fields like identity authentication, access control and etc. Hereafter in this paper we have tried to survey on human face recognition using support vector machine (SVM). SVM is the more effective technique likened to others and SVMs can be successfully trained for face recognition and it is better learning algorithm than the nearest center approach for face recognition. The conclusion is that SVM can be extended in many ways as so, or it can be combined with other classifiers in different ways to achieve better results, but in many situation SVM not achieve better result as SVMs is less sensitive to outliers and noisy samples, an extended technique called Fuzzy SVMs (FSVMs) will be helpful in this scenario. Because a FSVM method assigns different fuzzy membership values for different sample points to reproduce different status in their own classes, while less significant data (such as outliers and noise) are allotted lower membership values.

ACKNOWLEDGEMENT

We would like to thank Dr. Yashpal Singh, Associate Professor, BIET-Jhansi, for his valuable guidance. I also wish to express our gratitude to my family members specially wife Bharti Singh, who render their support during the period of research work.

REFERENCES

[1]W. Zhao, R. Chellappa, P. J. Phillips, and A. Rosenfeld.“Face recognition: A literature survey”, ACM Comput.Surv., 35(4):399-458, 2003.

[2] R. Brunelli and T. Poggio, "Face recognition: features versus templates," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.15, pp.1042-1052, 1993.

[3] M. A. Grudin, "On internal representations in face recognition systems," Pattern Recognition, Vol.33,pp.1161-1177, 2000.

[4] B. Heisele, P. Ho, J. Wu, and T. Poggio, "Face recognition: component-based versus global approaches,"Computer Vision and Image Understanding, Vol.91, pp.6-21, 2003.

[5] Oliver Jesorsky, Klaus J. Kirchberg, and Robert W.Frischholz, “Robust Face Detection Using the Hausdorff Distance”, In Proc. Third International Conference on Audio- and Video-based Biometric Person Authentication,Springer, Lecture Notes in Computer Science, LNCS-2091,pp. 90–95, Halmstad, Sweden, 6–8 June 2001.

[6] J. Terrillon, M. David, and S. Akamatsu. Automatic detection of human faces in natural scene images by use of a skin color model and of invariant moments. In Proc. of the Third International Conference on Automatic Face and Gesture Recognition, pages 112–117, Nara, Japan, 1998.

[7]M. A. Turk and A. P. Pentland. Face recognition using eigen-faces. Computer Vision and Pattern Recognition,1991.Proceedings CVPR '91., IEEE Computer Society Conference on, pages 586-591, 1991.

[8] Onsen Toygar, Adnan Acan, , "Face Recognition Using PCA,LDA and ICA Approaches on Colored Images" , Journal of Electrical & Electronics Engineering, Volume 3 2003

[9]Alaa Eleyan, Hasan Demirel , "PCA and LDA based Neural Networks for Human Face recognition" , Eastern Mediteranian University, Northern Cyprus, Face Recognition, Book edited by: Kresimir Delac and Mislav Grgic, ISBN 978-3-902613-03-5, pp.558, I-Tech, Vienna, Austria, June 2007

[10] R. J. Baron, "Mechanisms of Human Facial Recognition,"International Journal of Man-Machine Studies, Vol.15, pp.137-178, 1981.

[11] R.-J. J. Huang, "Detection Strategies for face recognition using learning and evolution," George Mason University, Fairfax, Virginia, Ph. D. Dissertation 1998.

[12] P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, "Eigenfaces vs. Fisherfaces: Recognition using class specific linear projection," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.19, pp.711-720, 1997.

[13] Y. Moses, Y. Adini, and S. Ullman, "Face recognition: the problem of compensating for changes in illumination direction," in European Conf. Computer Vision, 1994, pp.286-296.

[14] R. A. Fisher, "The use of multiple measures in taxonomic problems," Annals of Eugenics, Vol.7, pp. 179-188, 1936.

[15] B. Moghaddam and A. Pentland, "Probabilistic visual learning for object representation," IEEE Transactions On Pattern Analysis And Machine Intelligence, Vol.19, pp.696-710, 1997.

[16] M. A. O. Vasilescu and D. Terzopoulos, "Multilinear Subspace Analysis of Image Ensembles," in Proc. IEEE Int'l Conf. on Computer Vision and Pattern Recognition, 2003, pp.93-99.

[17] Q. Yang and X. Q. Ding, "Symmetrical Principal Component Analysis and Its Application in Face Recognition," Chinese Journal of Computers, Vol.26, pp.1146–1151, 2003.

[18] J. Yang and D. Zhang, "Two-Dimensional PCA: A New Approach to Appearance-Based Face Representation and Recognition," IEEE Trans. Pattern Analysis and Machine Intelligence, Vol.28, pp.131-m 137, 2004.

[19] J. Meng and W. Zhang, "Volume measure in 2DPCAbased face recognition," Pattern Recognition Letters, Vol.28, pp.1203-1208, 2007.

[20]G. D. C. Cavalcanti and E. C. B. C. Filho, "Eigenbands Fusion for Frontal Face Recognition," in Proceedings of IEEE Internationall Conference on Image Processing, Vol.1, 2003, pp.665–668.

[20] K. R. Tan and S. C. Chen, "Adaptively weighted subpattern PCA for face recognition," Neurocomputing, Vol.64, pp.505-511, 2005.

[21] A. P. Kumar, S. Das, and V. Kamakoti, "Face recognition using weighted modular principle component analysis," in Neural Information Processing, Vol.3316, Lecture Notes In Computer Science: Springer Berlin / Heidelberg, 2004, pp.362-367.

[22] V. D. M. Nhat and S. Lee, "An Improvement on PCA Algorithm for Face Recognition," in Advances in Neural Networks - ISNN 2005, Vol.3498, Lecture Notes in Computer Science. Chongqing: Springer, 2005, pp.1016-1021.

[23] N. Sun, H.-x. Wang, Z.-h. Ji, C.-r. Zou, and L. Zhao, "An efficient algorithm for Kernel two-dimensional principal component analysis," Neural Computing & Applications, Vol.17, pp.59-64, 2008.

[24] D. Zhang, Z.-H. Zhoua, and S. Chen, "Diagonal principal component analysis for face recognition," Pattern Recognition, Vol.39, pp.140-142, 2006.

[25] H. Yu and J. Yang, "A Direct LDA Algorithm for High-dimensional Data with Application to Face Recognition," Pattern Recognition, Vol.34, pp.2067-2070, 2001.

[26] F. Song, D. Zhang, J. Wang, H. Liu, and Q. Tao, "A parameterized direct LDA and its application to face recognition," Neurocomputing, Vol.71, pp.191-196, 2007.

[27] D. Zhou and X. Yang, "Face Recognition Using Direct-Weighted LDA," in 8th Pacific Rim International Conference on Artificial Intelligence. Auckland, New Zealand, 2004, pp.760-768.

[28] L. Chen, H. Liao, M. Ko, L. J., and G. Yu, " A New LDA-based Face Recognition System Which Can Solve the Small Samples Size Problem," Journal of Pattern Recognition, Vol.33, pp.1713–1726, 2000.

[29] W. Liu, Y. Wang, S. Z. Li, and T. Tan, "Null Space Approach of Fisher Discriminant Analysis for Face Recognition," in Biometric Authentication, Vol.3087, Lecture Notes in Computer Science: Springer Berlin / Heidelberg, 2004, pp.32-44.

[30] X. Wang and X. Tang, "Dual-space Linear Discriminant Analysis for Face Recognition," in Proceedings of IEEE International Conference on

Computer Vision and Pattern Recognition, 2004, pp.564–569.

[31] M. Loog, R. P. W. Duin, and R. Haeb-Umbach, "Multiclass Linear Dimension Reduction by Weighted Pairwise Fisher Criteria," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.23, pp.762-766, 2001.

[32] J. H. Friedman, "Regularized Discriminant Analysis," Journal of the American Statistical Association, Vol.84, pp.165-175, 1989.

[33] P. Howland and H. Park, "Generalized Discriminant Analysis Using the Generalized Singular Value Decomposition," IEEE Trans. On Pattern Analysis and Machine Intelligence, Vol.26, pp.995–1006, 2004.

[34] J. P. Ye, R. Janardan, C. H. Park, and H. Park, "An Optimization Criterion for Generalized Discriminant Analysis on Undersampled Problems," IEEE Trans. On Pattern Analysis and Machine Intelligence, Vol.26, pp.982–994, 2004.

[35] J. W. Lu, K. N. Plataniotis, and A. N. Venetsanopoulos, "Face Recognition Using LDA-based Algorithms," IEEE Trans. On Neural Networks, Vol.14, pp.195- 200, 2003.

[36] J. W. Lu, K. N. Plataniotis, and A. N. Venetsanopoulos"Boosting Linear Discriminant Analysis for Face Recognition," in Proceedings of IEEE International Conference on Image Processing, Vol.1, 2003, pp.657-660.

[37] Q. Yang and X. Q. Ding, "Discriminant Local Feature Analysis of Facial Images," in IEEE International Conference on Image Processing, Vol.2, 2003,pp.863-866.

[38] Q. Liu, H. Lu, and S. Ma, "Improving Kernel Fisher Discriminant Analysis for Face Recognition," IEEE Transactions on Circuits and Systems for Video Technology, Vol.14, pp.42-49, 2004.

[39] B. Schölkopf, "Nonlinear Component Analysis as a Kernel Eigenvalue Problem," Neural Computation, Vol.10, pp.1299-1319, 1998.

[40] Q. Liu, X. Tang, H. Lu, and S. Ma, "Kernel Scatter-Difference Based Discriminant Analysis for Face Recognition," in Proc. IEEE International Conference on Pattern Recognition, 2004, pp.419-422.

[41] M. Li and B. Yuan, "2D-LDA: A statistical linear discriminant analysis for image matrix," Pattern Recognition Letters, Vol.26, pp.527-532, 2005.

[42] [134] H. L. Xiong, M. N. S. Swamy, and M. O. Ahmad, "Two-dimensional FLD for face recognition,"Pattern Recognition, Vol.38, pp.1121-1124, 2005.

[43] X. Y. Jing, Y. Y. Tang, and D. Zhang, "A Fourier- LDA approach for image recognition," Pattern Recognition, Vol.38, pp.453-457, 2005.

[44] Y. W. Pang, L. Zhang, M. J. Li, Z. K. Liu, and W. Y.Ma, "A novel Gabor-LDA based face recognition method," in Advances In Multimedia Information Processing - Pcm 2004, Pt 1, Proceedings, vol. 3331, Lecture Notes In Computer Science, 2004, pp.352- 358.

[45] V. D. M. Nhat and S. Lee, "Block LDA for Face Recognition," in Computational Intelligence and Bioinspired Systems, Vol.3512, Lecture Notes in Computer Science: Springer Berlin / Heidelberg,2005, pp.899-905.

[46] D. Zhou and X. Yang, "Face Recognition Using Enhanced Fisher Linear Discriminant Model with Facial Combined Feature," in PRICAI 2004: Trends in Artificial Intelligence, Vol.3157, Lecture Notes in Computer Science: Springer Berlin / Heidelberg,2004, pp.769-777.

[47] W. C. Zhang, S. G. Shan, W. Gao, Y. Z. Chang, and B. Cao, "Component-based cascade linear discriminant analysis for face recognition," in Advances In Biometric Person Authentication, Proceedings, Vol.3338, Lecture Notes In Computer Science, 2004,pp.288-295.

[48] H. Zhao and P. C. Yuen, "Incremental Linear Discriminant Analysis for Face Recognition," IEEE Transactions on Systems, Man & Cybernetics: Part B, Vol.38,pp.210-221, 2008.

[49] Y. Chang, C. Hu, and M. Turk, "Manifold of facial expression," in IEEE International Workshop on Analysis and Modeling of Faces and Gestures, 2003, pp.28-35.

[50] K.-C. Lee, J. Ho, M.-H. Yang, and D. J. Kriegman, "Video-Based Face Recognition Using Probabilistic Appearance Manifolds," Computer Vision and Pattern Recognition, Vol.1, pp.313-320, 2003.

[51]S. T. Roweis and L. K. Saul, "Nonlinear Dimensionality Reduction by Locally Linear Embedding," Science, Vol.290, pp.2323–2326, 2000.

[52] J. Tenenbaum, V. de Silva, and J. Langford, "A global geometric framework for nonlinear dimensionality reduction," Science, Vol.290, pp.2319-2323,2000.

[53] L. K. Saul and S. T. Roweis, "Think Globally, Fit Locally: Unsupervised Learning of Low Dimensional

Manifolds," Journal of Machine Learning Research, Vol.4, pp.119-155, 2003.
[54] M. Belkin and P. Niyogi, "Laplacian eigenmaps and spectral techniques for embedding and clustering,"Advances in Neural Information Processing Systems,Vol.14, pp.585-591, 2001.
[55] X. He, S. C. Yan, Y. X. Hu, and H. J. Zhang,"Learning a Locality Preserving Subspace for Visual Recognition," in Proceedings of 9th IEEE InternationalConference on Computer Vision, Vol. 1,2003, pp.385-392.
[56] S. C. Yan, H. J. Zhang, Y. X. Hu, B. Y. Zhang, and Q.S. Cheng, "Discriminant Analysis on Embedded Manifold," in European Conference on Computer Vision, Vol. LNCS 3021: Springer Berlin / Heidelberg,2004, pp.121-132.
[57]J. Zhang, S. Z. Li, and J. Wang, "Nearest Manifold Approach for Face Recognition," in Proc. IEEE International Conference on Automatic Face and Gesture Recognition, 2004, pp.223-228.
[58] Y. Wu, K. L. Chan, and L. Wang, "Face Recognition based on Discriminative Manifold Learning," in Proc. IEEE Int'l Conf. on Pattern Recognition, Vol.4, 2004, pp.171-174.
[59] X. He, S.-C. Yan, Y. Hu, P. Niyogi, and H.-J. Zhang, "Face Recognition Using Laplacianfaces," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.27, pp.328-340, 2005.
[60] P. Comon, "Independent component analysis—A new concept?" Signal Processing, Vol.36, pp.287-314, 1994.
[61] M. S. Bartlett, J. R. Movellan, and T. J. Sejnowski, "Face recognition by independent component analysis," IEEE Transactions on Neural Networks, Vol.13, pp.1450-1464, 2002.
[62] B. Draper, K. Baek, M. S. Bartlett, and J. R. Beveridge, "Recognizing faces with PCA and ICA,"
Computer Vision and Image Understanding: Special Issue on Face Recognition, Vol.91, pp.115-137, 2003.
[63] K.-C. Kwak and W. Pedrycz, "Face Recognition Using an Enhanced Independent Component Analysis Approach," IEEE Transactions on Neural Networks, Vol.18, pp.530-541, 2007.
[64] N. H. Foon, A. T. B. Jin, and D. N. C. Ling, "Face recognition using wavelet transform and nonnegative matrix factorization," in Ai 2004: Advances In Artificial Intelligence, Proceedings, Vol.3339, Lecture Notes In Artificial Intelligence, 2004, pp.192-202.
[65] D. D. Lee and H. S. Seung, "Learning the Parts of Objects by Non-Negative Matrix Factorization,"Nature, Vol.401, pp.788-791, 1999.
[66] W. Liu, Y. Wang, S. Z. Li, and T. Tan, "Nearest Intra-Class Space Classifier for Face Recognition," in The 17th International Conference on Pattern Recognition (ICPR), Vol.4. Cambridge, UK, 2004, pp.495-498.
[67] J. Li, S. Zhou, and C. Shekhar, "A Comparison of Subspace Analysis for Face Recognition," in Proc. IEEE Int'l Conf. on Acoustics, Speech, and Signal Processing, 2003, pp.121–124.
[68] Q. Yang and X. Tang, "Recent Advances in Subspace Analysis for Face Recognition," SINOBIOMETRICS, pp.275-287, 2004.
[69] D. DeMers and G. W. Cottrell, "Non-linear dimensionality reduction," Advances in Neural Information Processing Systems, Vol.5, pp.580-587, 1993.
[70] J. Weng, N. Ahuja, and T. S. Huang, "Learning recognition and segmentation of 3-D objects from 3- D images," in Proceedings of the International Conference on Computer Vision (ICCV 93). Berlin,Germany, 1993, pp.121-128.
[71] S. Lawrence, C. L. Giles, A. C. Tsoi, and A. D. Back, "Face Recognition: A Convolutional Neural Network Approach," IEEE Transactions on Neural Networks, Special Issue on Neural Networks and Pattern Recognition, pp.1-24, 1997.
[72] T. Kohonen, "The self-organizing map," Proceedings of the IEEE, Vol.78, pp.1464-1480, 1990.
[73] T. Kohonen, Self-organizing maps. Berlin, Germany:Springer-Verlag, 1995.
[74] M. Turk and A. Pentland, "Face Recognition Using Eigenfaces," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 1991,pp.586-591.
[75] M. Turk and A. Pentland, "Eigenfaces For Recognition," Journal Of Cognitive Neuroscience, Vol.3, pp.71-86,1991.
[76] A. Eleyan and H. Demirel, "Face Recognition System Based on PCA and Feedforward Neural Networks," in Computational Intelligence and Bioinspired Systems, Vol.3512, Lecture Notes in Computer Science: Springer Berlin / Heidelberg, 2005, pp.935-942.
[77] B. Li and H. Yin, "Face Recognition Using RBF Neural Networks and Wavelet Transform," in Advances in Neural Networks – ISNN 2005, vol.3497, Lecture Notes in Computer Science: Springer Berlin /Heidelberg, 2005, pp.105-111.

[78] P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, "Eigenfaces vs. Fisherfaces: Recognition using class specific linear projection," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.19, pp.711-720, 1997.
[79] P. Melin, C. Felix, and O. Castillo, "Face recognition using modular neural networks and the fuzzy Sugeno integral for response integration," International Journal Of Intelligent Systems, vol.20, pp.275-291, 2005.
[80] G. C. Zhang, X. S. Huang, S. Z. Li, Y. S. Wang, and X. H. Wu, "Boosting local binary pattern (LBP)- based face recognition," in Advances In Biometric Person Authentication, Proceedings, Vol.3338, Lecture Notes In Computer Science, 2004, pp.179-186.

[81] B. Moghaddam, C. Nastar, and A. Pentland, "A Bayesian Similarity Measure for Direct Image Matching," in Proceedings 13th International Conference on Pattern Recognition, 1996, pp.350-358.
[82] T. Ojala, M. Pietikainen, and M. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification width local binary patterns," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.24, pp.971–987, 2002.
[83] Y. Freund and R. E. Schapire, "A decision-theoretic generalization of on-line learning and an application to boosting," Journal of Computer and System Sciences, Vol.55, pp.119-139, 1997.
[84] T. Ahonen, A. Hadid, and M.Pietikainen, "Face recognition with local binary patterns," in Proceedings of the European Conference on Computer Vision, Vol.3021, Lecture Notes in Computer Science. Prague,Czech Republic: Springer, 2004, pp.469-481.
[85] U. Krebel, "Pairwise classification and support vector machines," Advance in Kernel Methods – Support Vector Learning, pp.255-268, 1999.
[86] T. Hastie and R. Tibshirani, "Classification by Pairwise Coupling," The Annals of Statistics, Vol.26, pp.451-471, 1998.
[87] M. Moreira and E. Mayoraz, "Improved Pairwise Coupling Classification with Correcting Classifiers," in Proceedings of the 10th European Conference on Machine Learning, Vol.1398, Lecture Notes In Computer Science. London, UK: Springer-Verlag, 1998, pp.160-171.
[88] Y. Moses, Y. Adini, and S. Ullman, "Face recognition: the problem of compensating for changes in illumination direction," in European Conf. Computer Vision, 1994, pp.286-296.
[89] F. S. Samaria, "Face recognition using Hidden Markov Models," Trinity College, University of Cambridge, Cambridge, UK, Ph. D. Thesis 1994.
[90] A. V. Nefian and M. H. Hayes III, "Face Recognition using an embedded HMM," in IEEE International Conference Audio Video Biometric based Person Authentication, 1999, pp.19-24.
[91] C. Liu and H. Wechsler, "Evolutionary Pursuit and Its Application to Face Recognition," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.22, pp.570-582, 2000.
[92] H.-L. Huang, H.-M. Chen, S.-J. Ho, and S.-Y. Ho, "Advanced Evolutionary Pursuit for Face Recognition," accepted by Journal of VLSI Signal Processing-Systems for Signal, Image, and Video Technology, 2006.
[93] J. Lu, K. N. Plataniotis, A. N. Venetsanopoulos, and S. Z. Li, "Ensemble-based Discriminant Learning with Boosting for Face Recognition," IEEE Transactions on Neural Networks, Vol.17, pp.166-178,2006.
[94] J. Lu and K. N. Plataniotis, "Boosting face recognition on a large-scale database," in Proceedings of IEEE International Conference on Image Processing, Vol.2. Rochester, NY, 2002, pp.109-112.
[95] R. E. Schapire, "The boosting approach to machine learning: An overview," in MSRI Workshop Nonlinear Estimation and Classification, 2002, pp.149-172.
[96] H. Li, F. Qi, and S. Wang, "Face Recognition with Improved Pairwise Coupling Support Vector Machines," in Computational Intelligence and Bioinspired Systems, Vol.3512, Lecture Notes in Computer Science: Springer Berlin / Heidelberg, 2005, pp.927-934.
[97] Z. Li and S. Tang, "Face Recognition Using Improved Pairwise Coupling Support Vector Machines,"in Proc. of Intl. Conf. on Neural InformationProcessing, Vol.2, 2002, pp.876-880.
[98] J. Platt, "Probabilistic Outputs for Support Vector Machines and Comparison to Regularized Likelihood Methods," in Advances in Large Margin Classifiers, A. J. Smola, P. L. Bartlett, B. Sch¨olkopf, and D. Schuurmans, Eds.: MIT Press, 2000, pp.61-74.
[99] H. Q. Li, S. Y. Wang, and F. H. Qi, "Automatic face recognition by support vector machines," in Combinatorial Image Analysis, Proceedings, Vol.3322, Lecture Notes In Computer Science, 2004, pp.716-725.
[100] G. Dai and C. Zhou, "Face Recognition Using Support Vector Machines with the Robust Feature," in Proceedings of IEEE Workshop on Robot and Human Interactive Communication, 2003, pp.49-53.

[101] O. D´eniz, M. Castrill´on, and M. Hern´andez, "Face Recognition Using Independent Component Analysis and Support Vector Machines," Pattern Recognition Letters, Vol.24, pp.2153-2157, 2003.

[102] K. Jonsson, J. Matas, J. Kittler, and Y. P. Li, "Learning Support Vector Machines for Face Verification and Recognition," in Proceedings of IEEE International Conference on Automatic and Gesture Recognition, 2000, pp.208-213.

[103] G. Guo, S. Li, and C. Kapluk, "Face Recognition by Support Vector Machines," in Proceedings of the Fourth IEEE International Conference on Automatic Face and Gesture Recognition. Washington, DC, USA, 2000, pp.196-201.

[104] Y. Liang, W. Gong, Y. Pan, W. Li, and Z. Hu, "Gabor Features-Based Classification Using SVM for Face Recognition," in Advances in Neural Networks – ISNN 2005, Vol.3497, Lecture Notes in Computer Science. Chongqing: Springer, 2005, pp.118-123.

[107] C. Burges, "A tutorial on support vector machines for pattern recognition," Data Mining and Knowledge Discovery, vol. 2, no. 2, 1998.

[108] Xiufeng Jiang Æ Zhang Yi Æ Jian Cheng Lv, Fuzzy SVM with a new fuzzy membership functionNeural Comput & Applic (2006) 15: 268–276 DOI 10.1007/s00521-006-0028-z

[109] C. Cortes and V. N. Vapnik, "Support vector networks," Machine Learning, vol. 20, pp. 273–297, 1995.

[110] V. N. Vapnik, The Nature of Statistical Learning Theory. New York: Springer-Verlag, 1995.

[111] B. Schölkopf, C. Burges, and A. Smola, Advances in Kernel Methods:Support Vector Learning. Cambridge, MA: MIT Press, 1999.

[112] T. Kanade, "Picture Processing System by Computer Complex and Recognition of Human Faces," Kyoto University, Japan, PhD. Thesis 1973

[113] R. Brunelli and T. Poggio, "Face recognition: features versus templates," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.15, pp.1042-1052, 1993.

[114] A. Yuille, D. Cohen, and P. Hallinan, "Feature extraction from faces using deformable templates,"in IEEE Computer Society Conference on Computer Vision and Templates. San Diego, CA, USA, 1989,pp.104-109.

[115] N. Roeder and X. Li, "Experiments in analyzing the accuracy of facial feature detection," Vision Interface '95, pp.8-16, 1995.

[116] C. Colombo, A. D. Bimbo, and S. D. Magistris, "Human-computer interaction based on eye movement tracking," Computer Architectures for Machine Perception, pp.258-263, 1995.

[117] M. Nixon, "Eye spacing measurement for facial recognition," in SPIE Proceedings, 1985, pp.279-285.

[118] D. Reisfeld, "Generalized symmetry transforms: attentional mechanisms and face recognition," Tel-Aviv University, PhD. Thesis, technical report 1994.

[119] H. P. Graf, T. Chen, E. Petajan, and E. Cosatto,"Locating faces and facial parts," in International Workshop on Automatic Face- and Gesture- Recognition, 1995, pp.41-46.

[120] I. Craw, D. Tock, and A. Bennett, "Finding face features," in Second European Conference on Computer Vision, 1992, pp.92-96.

[121] T. Jebara, "3D Pose Estimation and Normalization for Face Recognition," Center for Intelligent Machines, McGill University, Undergraduate Thesis May, 1996.

[122] I. J. Cox, J. Ghosn, and P. N. Yianilos, "Featurebased face recognition using mixture-distance," in Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, 1996, pp.209-216.

[123] S. Lawrence, C. L. Giles, A. C. Tsoi, and A. D. Back, "Face Recognition: A Convolutional Neural Network Approach," IEEE Transactions on Neural Networks, Special Issue on Neural Networks and Pattern Recognition, pp.1-24, 1997.

[124] L. Wiskott, J.-M. Fellous, N. Krüger, and C. von der Malsburg, "Face Recognition by Elastic Bunch Graph Matching," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.19, pp.775- 779, 1997.

[125] M. Lades, J. C. Vorbrüggen, J. Buhmann, J. Lange, C.v. d. Malsburg, R. P. Würtz, and W. Konen, "Distortion invariant object recognition in thedynamic link architecture," IEEE Trans. Computers, Vol.42, pp.300-311, 1993.

[126] L. Wiskott, J. M. Fellous, N. Krüger, and C. von der Malsburg, "Face Recognition by Elastic Bunch Graph Matching," in Intelligent Biometric Techniquesin Fingerprint and Face Recognition, L. C. Jain, U. Halici, I. Hayashi, S. B. Lee, and Jae-Ho, Eds.: CRCPress, 1999, pp.355-396.

[127] P. J. Phillips, P. Rauss, and S. Der, "FERET (FacE REcognition Technology) Recognition Algorithm Development and Test Report," U.S. Army Research Laboratory ARL-TR-995, 1996.

[128] P. J. Phillips, H. Moon, S. A. Rizvi, and P. J. Rauss, "The FERET Evaluation Methodology for Facerecognition Algorithms," in Proceedings, IEEE Conference on Computer Vision and Pattern Recognition, 1997, pp.137-143.

[129] G. Sukthankar, "Face recognition: a critical look at biologically-inspired approaches," Carnegie Mellon University, Pittsburgh, PA, Technical Report: CMURITR- 00-04 2000.

[130] P. Campadelli and R. Lanzarotti, "A Face Recognition System Based on Local Feature Characterization," in Advanced Studies in Biometrics, Vol.3161, Lecture Notes in Computer Science, M. Tistarelli, J. Bigun, and E. Grosso, Eds. Berlin: Springer, 2005, pp.147-152.

[131] H. Shin, S. D. Kim, and H. C. Choi, "Generalized elastic graph matching for face recognition," Pattern Recognition Letters, Vol.28, pp.1077–1082, 2007.

[132] A. Albiol, D. Monzo, A. Martin, J. Sastre, and A. Albiol, "Face recognition using HOG–EBGM," Pattern Recognition Letters, Vol.29, pp.1537-1543,2008.

[133] L. D. Harmon, M. K. Khan, R. LAsch, and P. F. Raming, "Machine Identification of human faces," Pattern Recognition, Vol.13, pp.97-110, 1981.

[134] L. D. Harmon, S. C. Kuo, P. F. Raming, and U.Raudkivi, "Identification of human face profiles by computers," Pattern Recognition, Vol.10, pp.301-312,1978.

[135] G. J. Kaufman and K. J. Breeding, "Automatic recognition of human faces from profile silhouettes," IEEE Transactions On Systems Man And Cybernetics, SMC, Vol.6, pp.113-121, 1976.

[136] Z. Liposcak and S. Loncaric, "A scale-space approach to face recognition from profiles," in Proceedings of the 8th International Conference on Computer Analysis of Images and Patterns, Vol. 1689, Lecture Notes In Computer Science. London, UK: Springer- Verlag, 1999, pp.243-250.

[137] Z. Liposcak and S. Loncaric, "Face recognition from profiles using morphological signature transform," in Proceedings of the 21st Int'l Conference Information Technology Interfaces. Pula, Croatia, 1999, pp.93-98.

[138] Sani, M.M.; Ishak, K.A.; Samad, S.A.; “Evaluation of face recognition system using Support Vector Machine” IEEE Student Conference on Research and Development (SCOReD), 2009 , pp: 139 - 141

[139] A.J. Goldstein, L.D. Harmon, and A.B. Lesk, “Identification of human faces,” Proc. IEEE, vol. 59, pp. 748, 1971.

[140] Y. Kaya and K. Kobayashi, “A basic study on human face recognition,” Frontiers of Pattern Recognition, S. Watanabe, ed., pp. 265, 1972.

[141] R. Bruneli and T. Poggio, “Face recognition: features versus templates,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 15, pp. 1042-1052, 1993.

[142] I.J. Cox, J. Ghosn, and P.N. Yianios, “Feature-Based face recognition using mixture-distance,” Computer Vision and Pattern Recognition, 1996.

[143] Jun Qin; Zhong-Shi He;” A SVM face recognition method based on Gabor-featured key points” Proceedings of International Conference on Machine Learning and Cybernetics, 2005,pp 5144 - 5149 .

BIOGRAPHIES

[1]Navin Prakash is working as an Assistant Professor in Department of Computer science and Engineering, IFTM, University Moradabad. His current research interests include Image Processing, Machine learning.

[2]Dr. Yashpal Singh, has published several papers in various reputed Journals, and International conferences in the field of Image processing and AI and he has vast experience in teaching profession. He is currently working as Associate professor in BIET-Jhansi.