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An Efficient Approach for Age Invariant Face Recognition using Nonlinear Topological Component Analysis

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ABSTRACT: Face Recognition is a very vast and challenging field. The limited research work has been done in the field of face recognition by considering the aging attribute. The age effect brings certain changes in the face with the progression in age. The mission of proposed methodology is to achieve the age invariant face recognition by using following steps: a) extracting facial features by using Viola Jones algorithm; b) the α-shape is constructed by using the extracted facial features; and c) extracting topological features for face recognition task. The result is evaluated by using two public domain available FGNET and MORPH dataset. From both the dataset certain images are trained to system and test for the face recognition task. The result obtained after the evaluation is 50% for FGNET dataset when 50 subjects are trained to the system and 90% for MORPH dataset when 60 subjects are trained to the system. Experimental results obtained demonstrate the efficiency of the proposed methodology named nonlinear topological component analysis.

KEYWORDS: aging; α-shape construction; topological features; nonlinear topological component analysis

I. INTRODUCTION

Face Recognition has been the centre of attraction from last decades. Face Recognition is a part of image processing domain and have ample of applications in the fields such as Computer Vision, Pattern recognition, Biometrics, and many more. Face Recognition had successfully grabbed the attention of many researches from other domain also. The machine learning and computer graphics communities are also increasingly involved in face recognition.

Face recognition is one of the few biometric methods that possess the merits of high accuracy. Face recognition is the challenging field and have many intra-subject variations. The intra-subject variations are lighting and illumination effects on the human facial images, various occlusions such as sunglass, spectacles, breads or scarf's on face of human facial images, expression, pose, aging and so on. All this variation may became an obstacle for face recognition but among all variations we focused on aging. Aging is one of the most challenging issues in face recognition. Scientifically, along with the physical growth in the human, the facial part also shows some changes. The various aging effects are wrinkles, formation or deformation of jaw bones and many more. Thus, face recognition across age, automatic age estimation from facial images, appearance prediction across aging effects had been the area of growing interest.

From last decade, there was expeditious development of high throughput techniques which generates large and enormous data in image processing domain. While working with the Age Invariant Face Recognition, researchers had been confronted with the problem of large amount of high dimensional data. These enormous data has so many values rather than observation. The Dimensionality reduction techniques are used to analyse the high-dimensional data and to transform it to low-dimensional data. Kernel methods are used to successfully extract features from the feature space which contains the nonlinear information of the input data [27]. One of the recent approaches to Age Invariant Face Recognition is Nonlinear Topological Component Analysis [1]. In this paper, the main focus is on Nonlinear Topological Component Analysis (NTCA) methodology applied for Age Invariant Face Recognition. The NTCA approach is used for dimensionality reduction and to capture the topological features. The main methodology of NTCA

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is as follows: (1) integration of KRBF dimensionality reduction; (2) to build α-shape for each facial image; (3) to extract topological features/ signature and (4) object identification.

II. RELATED WORK

Dimensionality reduction methods are used for the pre-processing in the pattern recognition. Nonlinear Dimensionality reduction (NLDR) methods describe the high dimensional set of points to low dimensional set of points. In [33], the global geometric framework was used to solve the problem of dimensionality reduction. The local metrics are used to understand the geometry of a data set. In [28], pruning scheme was applied, in which MLP (Multi-Layer Perceptron) was used with PCA (Principal Component Analysis) for gender classification from human facial images. The 1-dimensional successive Laplacian Eigenmaps is the robust non-linear dimensionality reduction technique which allows the repeated eigendirections problem [24]. In [23], the kernel Principal Component Analysis (KPCA) was introduced and investigated as novelty detection technique. In other words, KPCA is the nonlinear extension of PCA. While in [16], both the local and global distance information was used by nonlinear dimensionality reduction framework. In [14], the latest development in the areas of dimensionality reduction, manifolds and topological learning was outlined. Nonlinear method is more powerful than linear method. In order to analyze the high-dimensional data, the geometrical and topological methods are applied for machine learning.

The proposed work was carried out for age invariant face recognition so, the different techniques for age invariant face recognition was outlined. In [21], 3D aging model technique was proposed with temporal variance for face recognition and age simulation. In [18], the GOP (Gradient oriented Pyramid) was used as discriminative approach and SVM (Support Vector Machine) for classification. In [17], graph matching technique was proposed where the face was represented as a graph which consists of information related to appearance and geometry of face. The BPNN (Back Propagation Neural Networks) was used with combination of PCA for face detection and recognition in [12]. In [11], the proposed framework makes use of periocular region for age invariant face recognition. The WLBP (Walsh-Hadamard Transform Encoded Local Binary Pattern) was used for pre-processing the periocular region. In [10], the discriminative approach was proposed. Scale Invariant Feature Transform (SIFT) and Multi-scale Local Binary Pattern (MLBP) are used as local feature descriptors. In [7], technique for Age Invariant Face Recognition using stable local feature was proposed. In [6], a novel framework, Hidden Factor Analysis (HFA) for age invariant face recognition was proposed. The proposed approach has two hidden factors: a) an identity factor and b) an age factor. They had also developed the Expectation Maximization (EM) algorithm to estimate model parameter from data. In [5], Cross-Age Reference Coding (CARC) technique was proposed. For evaluating face recognition and retrieval across age, a new large dataset of 160,000 facial images of 2000 celebrities from Internet was created. This dataset was named as Cross Age Celebrity Dataset (CACD).

III. PROPOSED METHODOLOGY

The proposed methodology is inspired from the methodology proposed in [1]. The modules used in our methodology are same as methodology in [1], but the algorithms used for feature extraction; the extracted topological features and algorithm used for object identification are different from the algorithms used in [1].

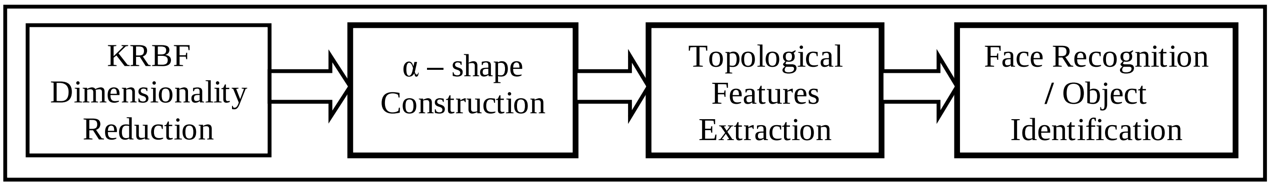

Fig.1: Schematic Diagram of Entire Methodology of NTCA

To understand each block in detail, the explanation of each block is discussed below.

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A. *Kernel Radial Basis Function (KRBF) Dimensionality Reduction:*

The basic idea behind using kernel function is to map the original data space to target space by the nonlinear transformation functions. Principal Component Analysis (PCA) only extracts the features from the input space. Thus, to extract the features from input space along with the nonlinear information within input data kernel function is used. The Gaussian kernel function is commonly used and it is an example of Radial Basic Function (RBF). Thus, the combination is named as Kernel Radial Basic Function (KRBF). In our work, KRBF is used as an extended dimensionality reduction technique. The KRBF Dimensionality Reduction is carried out by following the three steps mentioned below [27] [1]:

Step 1: The original data set is mapped to a Hilbert Space using quadratic function.
Step 2: The obtained dataset in step 1 was mapped to a set spanned by KRBF.
Step 3: The dataset obtained in step 2 was projected linearly on a latent space.

B. *α – Shape Construction:*

An α –shape is the concrete geometric structure formed by the particular set of points. The points set are used to create the α-shapes at the different level of resolution which is an efficient way to represent α shape. The ball of radius$\sqrt{\alpha}$ is inserted around each point and a simplicial complex is built. This simplicial complex represents the intersection among these balls and simplicial space formed is defined as "α-Shape". The construction of α shape is based on the notions of balls, also known as generalized disk. For the given set of points and a specific α value, the α-shape is constructed using the following scheme.

Step 1: Each point X_u in the embedded set is assigned a vertex u.

Step 2: An edge is created between two vertices u and v whenever there exists a generalized disk of radius $\sqrt{\alpha}$ containing the entire set of points and which has the property that X_u and X_v lies on its boundary.

There are different types of signatures assigned to α-shapes, which one can capture in the form of topological features or signature [9] [1].

C. *Topological Features Extraction:*

Topological features can be extracted from the α-shape. The extracted features or signature are used for classification or regression task. A α-shape is assigned with many different types of signatures, which can be extracted. The metric properties such as volume, area and length, the combinatorial properties such as number of tetrahedral, triangles, edges and vertices and topological properties such as number of voids, gaps, peak valley, independent tunnels and components [13] [1]. To extract the topological feature, consider the set of points say (x_1, x_2, x_3,...x_n) plotted in α-shape (polyhedron). The extracted topological features α shape are peak, valley and gap. The procedure used to extract the topological features is:

Step 1: If $x_1 < x_2 > x_3$, then x_2 is extracted as peak.
Step 2: If $x_1 > x_2 < x_3$, then x_2 is extracted as valley.
Step 3: If $x_1 = x_2 = x_3$, then x_2 is extracted as gap.

Finally, topological signatures, inherent to the α-shape characterizing the input object to classify, are extracted and stored into a set. Thus, attempt was done to restate the classification problem with respect to the signatures.

D. *Object Identification / Face Recognition:*

There are many algorithms used for the classification, among this several algorithm, k-Nearest Neighbour algorithm is simple and powerful recognition algorithm. The k-NN is a supervised machine learning algorithm and used for classification or regression task. The k-NN finds a group of k objects in the training set that are closest to the test sample, and bases the assignment [8]. To understand the working of k-NN algorithm, first train the system with some samples, say (x, f(x)). Suppose a query instance x_q is given to be classified, then

Step 1: Let x1, x2 ..., xk denotes the k instances from the training samples that are nearest to x_q.
Step 2: Return the class that represents the maximum of the k instance [37].

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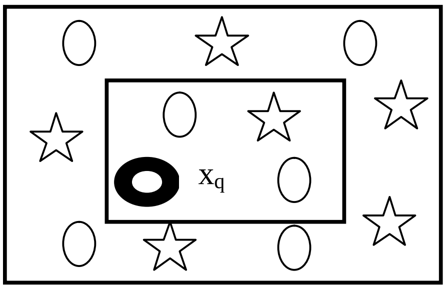

Fig. 2: Diagrammatic view of kNN algorithm where k = 3

In the Fig. 2, there are two samples indicated by star shape and circle shape in the set. The black filled doughnut shape labelled as xq is the query instance. To find the nearest neighbour of the query instance, x_q, we considered k=3. If k=3 then, in this case the query instance x_q will be classified as a circle since two of its nearest neighbour are classified as circle.

IV. IMPLEMENTATION

For propose of implementation, the 64 bit Operating System with 4GB RAM and Intel (R) Core(TM) i3 Processor, installed with MATLAB R2013b is required. The key requirement for the successful implementation of proposed methodology is the age variant dataset having human facial images. To conduct the experiment, FGNET and MORPH Datasets are used. The details of subjects used for experiment from the datasets are discussed in detail in Table 1.

Table 1: Statistics of public domain facial aging databases used for experiment

Dataset	Subjects	Subjects Gender		Age Group			Total images	Images per subject	Age Range
		Male	Female	0-19	20-49	50 & above			
MOPRH	60	51	11	-	238	60	298	~4or 5	25~59
FGNET	50	29	21	400	190	15	605	~12	00~ 69

The proposed method is applied for evaluating age invariant face recognition. The main aim is to find the age invariant face recognition, so the facial images from the well known public domain available datasets are used. The available MORPH (Album-2) and FGNET datasets are having both the RGB (colour) and Gray scale images with different resolution. The images are divided as set of gallery images and set of query images. The set of gallery images are trained to the system. The images in the query set are not trained to the system.

Initially, the Viola Jones Algorithm was applied to each input image, to extract the facial features. While in [1], the facial features are extracted by using Local Binary Pattern (LBP). The Viola Jones algorithm is first object detection algorithm proposed by Paul Viola and Michael Jones in 2001 [31]. The Viola Jones algorithm is efficient in feature selection, computationally fast and high detection rate. Thus total five facial features: left eyes, right eyes, nose, mouth and face are extracted. The extracted features on the face are highlighted by the boxes.

The extracted features will generate the high dimensional feature space, which are nonlinearly transformed to the low dimensional latent space. The Kernel Radial Basis function is used as nonlinear dimensionality reduction technique. The kernel function is directly applied to the original space. The Gaussian kernel function is applied to Radial Basic Function (RBF) neural network to perform nonlinear transformation. The kernel function is applied because it gathers the nonlinear information. Basically the extracted features point space is mapped in latent space and thereby form the cloud of points of extracted features. After the nonlinear mapping of original space to latent space and the probability distribution in latent space, forms cloud of points in the latent space.

The α-shape is a concrete geometric structure represents the particular set of points. The set of points are obtained in the latent space which are latent but abundant in number. These bundles of points are mapped from the latent space in between three axes to form α-shape tetrahedron. The α-shape for gray scale image is visualized as a single diagonal

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line, which is when maximized shows numbers of connection between the vertices. While the α-shape for RGB image forms a tetrahedron, which is a polyhedron. Each and every point in the latent space of dimensionality- L is mapped in the α-shape axes. All the vertices say u and v are connected to each other and form tetrahedron.

The α-shape is created for each and every face. The topological features are extracted for each face is having unique value. The topological features extracted in [1] are the number of components, independent tunnels, voids, triangles, edges and vertices. In our proposed methodology, only three topological features are extracting from the α-shape. The extracted topological features are: peak, valley and gap from the plotted α-shape tetrahedron. Along with extracted topological features, different facial geometric values are calculated by calculating the length and width of various features.

In case of testing, the any query image is provided as input. The k-NN algorithm is used as classifier to find the closest match of query image from the saved values. The k-NN algorithm, classify the difference image from the saved values set. The saved values with minimum difference to query image value is consider as the exact match of the query image, which will be plotted in the GUI along with total matching time and name of matched image. If the subject of query image and matched image is same across age factor, then the age invariant face recognition for that image was performed.

V. RESULT ANALYSIS

The experiment was conducted on two public available datasets: MORPH and FGNET. The experiment is performed on 60 subjects from MORPH Dataset and 50 subjects from FGNET Dataset. The comparative analysis is performed on basis of various parameters.

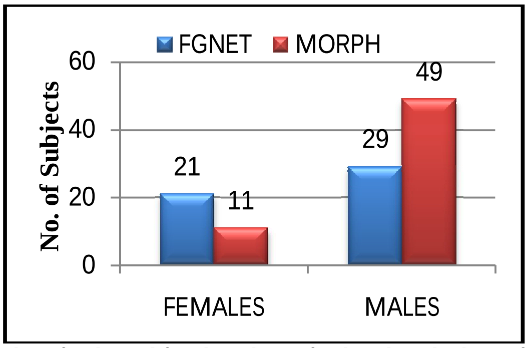

Fig. 3: Analysis of total number of males and females subjects for the selected subjects from the respective datasets

In fig. 3, the plotted graph indicates the total number of males and females in the respective dataset. It is observed that, there are 29 male subjects and 21 female subjects from selected 50 subject of FGNET Dataset. While from the selected 60 subjects of MORPH dataset there are 49 male subjects and only 11 female subjects.

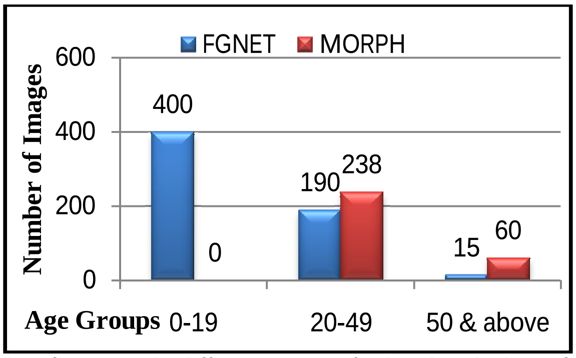

Fig. 4: Analysis of number of images under different age group for the selected subjects from the respective datasets

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The proposed method is for age invariant face recognition, so the datasets are having the images of different age group. The number of images are divided in three age groups: Child (0 to 19); Young adults (20 to 49); and senior adults (50 and above). As shown in the Fig. 4, the FGNET is having maximum child images of age ranging from 0 to 19 and MORPH is having no images in these age range. In the age group of 0~19 for MORPH Dataset there is no image, but for FGNET dataset there are maximum images. The images in the age group of 50 and above in MORPH Dataset as compared to FGNET Dataset.

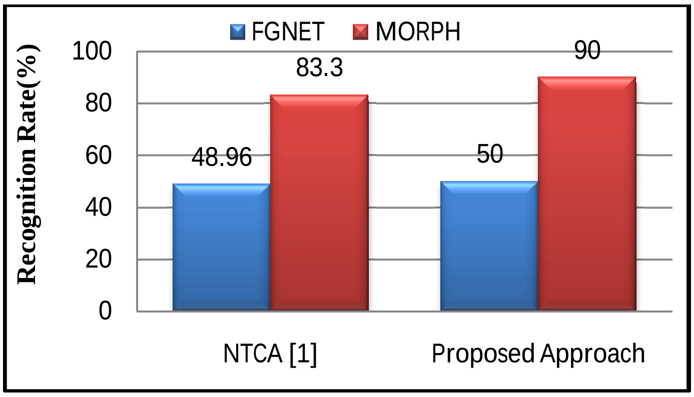

Fig. 5: Comparative result between traditional method and proposed method

In Fig. 5, the recognition rate for the proposed methodology is analyzed for 60 subjects of MORPH Dataset and for 50 subjects of FGNET Dataset. In [1], the MORPH Album-2 recognition rate was 83.33% and each subject is having approximately two images only, while for our proposed method the result for MORPH dataset shows the recognition rate as 90% and there are approximately four to five images for each selected subject. In case of FGNET dataset, the recognition rate for 82 subjects was 48.96% in [1] and for the proposed approach, the recognition rate as 50% for 50 subjects from the dataset.

VI. CONCLUSION AND FUTURE SCOPE

The proposed approach is having same module as Nonlinear Topological Component Analysis [1] but different algorithms or methods are used for the implementation which was applied to age invariant face recognition. The main motivation was to extend the dimensionality reduction and extract the topological features from the constructed α-shape. The facial features were extracted by using the Viola-Jones Algorithm which is of high dimension. These facial features are mapped into latent space. The topological features are extracted from the α-shape, which was constructed from the data in the latent space. The results obtained have demonstrated the potential of the NTCA approach as a whole. The existing NTCA system [1] is having the recognition rate 48.96% for FGNET dataset and 71.30% for MORPH Album-1 and 83.80% for MORPH Album-2. For the proposed methodology, the recognition rate is 50% for FGNET dataset and 90% for MORPH Dataset.

The more classification techniques need to be studied to achieve more accuracy for large datasets. The work can be extended in future for age invariant face recognition by using video clips.

REFERENCES

1. D. Bouchaffra, "Nonlinear Topological Component Analysis: Application to Age Invariant Face Recognition", IEEE Trans. on Neural Networks and Learning systems, 2162-237© July, 2014.
2. Santoshi, Vikas, and Amit Kr. Gautam, "Comparative survey on age invariant face recognition and verification techniques", International Conference on Advances in Engineering & Technology (ICAET), PP 33-37, 2014
3. Uma Shankar Kurmi, Dheeraj Agrawal, R. K. Baghel, "Study of Different Face Recognition Algorithms and Challenges", International Journal of Engineering Research, Volume No.3, Issue No.2, pp : 112-115, 01 Feb. 2014
4. Wangjam Niranjan Singh, Dipankar Medhi, Mrudula S. Nimbarte, "Study on Age Invariant Face Recognition System", International Conference on Advances in Engineering & Technology ,PP 68-73, 2014.

ISSN(Online): 2320-9801
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5. Bor-Chun Chen, Chu-Song Chen, and Winston H. Hsu, “Cross Age Reference Coding for Age Invariant Face Recognition and Retrieval”, ECCV, 2014.
6. Dihong Gong, Zhifeng Li, Dahua Lin, Jianzhuang Liu, and Xiaoou Tang, “Hidden Factor Analysis for Age Invariant Face Recognition”, IEEE International Conference on Computer Vision (ICCV), Pages 2872- 2879, 2013.
7. Jyothi S. Nayak and Indiramma M., “Stable Local feature based Age Invariant Face Recognition”, International Journal on Application or Innovation in Engineering and Management (IJAIEM), vol. 2, Issue: 12, December 2013.
8. Putu Wira Buana, Sesaltina Jannet D.R.M., and I Ketut Gede Darma Putra, “Combination of K-Nearest and K-Means based on term Re-weighting for classify Indonesian News”, International Journal of Computer Applications, Vol. 50- No. 11, July 2012.
9. Bouchaffra, D., “Mapping Dynamic Bayesian Network to α-shapes: Application to Human Face Identification across Ages”, IEEE Trans. On Neural Networks and Learning Systems, Vol. PP, Issue 99, 2012.
10. Zhifeng Li, Unsang Park, and Anil K. Jain, “A Discriminative Model for Age Invariant Face Recognition”, IEEE Transaction on Information Forensics and Security, Vol. 06, Issue: 3, Part: 2, Pages 1028-1037, 2011.
11. Felix Juefei-Xu, Khoa Luu, Marios Savvides, Tien D. Bui, and Ching Y. Suen, “ Investigating Age Invariant Face Recognition based on Periocular Biometrics”, IEEE International Joint Conference on Biometrics (IJCB), Pages 1-7, 2011.
12. M. Kashem, S. Ahemad, Md. N. Akhter, and Md. M. Alam,” Automatically Face Detection and Recognition System based on Principal Component Analysis with Back Propagation Neural Network”, ISSN 2078-5827, Vol. 02, Issue 01, IJCIT, 2011.
13. Bouchaffra D., “Topological Dynamic Bayesian Networks” IEEE Trans., 20th International Conference on patterns Recognition, 2010.
14. Axel Wismuller, Michel Verleysen, Michael Aupetit, and John A. Lee, “Recent Advance in Nonlinear Dimensionality Reduction, Manifold and Topological Learning”, Computational Intelligence and Machine Learning, Bruges, ESANN, April 2010.
15. Bilgin Esme and Bulent Sankur, “Effects of Aging over Facial Features Analysis and Face Recognition”, Bogazici University, March 2010.
16. Guy Rosman, M. M. Bronstein, A. M. Bronstein, and Ron Kimmel, “Nonlinear Dimensionality Reduction by Topologically Constrained Isometric Embedding”, IJCV, February 2010.
17. Gayathri Mahalingam and Chandra Kambhamettu, “Age Invariant Face Recognition using Graph Matching”, IEEE International Conference on Biometrics: Theory Application and Systems (BTAS), Pages 1-7, 2010.
18. Haibin Ling, Stefano Soatto, Narayanan Ramanathan, and David W. Jacobs, “Face verification across Age Progression using Discriminative Methods”, IEEE Transaction on Information Forensics and Security, Vol. 05 Issue 1, pages 82-91, March 2010.
19. Narayanan Ramanathan, Rama Chellappa, and Soma Biswas, “Computational methods for modelling facial aging: A Survey”, Journal of visual Languages and Computing, Science Direct, 131-144, Elsevier, 2009.
20. L.J.P. van der Maaten, E. O. Postma and H.J. van der Herik, “Dimensionality Reduction: A Comparative Review”, MICC, Maastricht University, Elsevier, 11th January, 2008.
21. Unsang Park, Yiying Tong and Anil K. Jain, “Face Recognition with Temporal Invariance: A 3D Aging Model”, IEEE International Conference on Automatic Face and Gesture Recognition, Pages 1-7, September 2008.
22. Ce Zhan, Wanqing Li, Philips Ogunbona and Farzad Safaei, “Real-time facial feature point extraction”, Pacific-Rim Conference on Multimedia, Pp 88-97, Germany: Springer, 2007
23. Heiko Hoffmann, “Kernel PCA for Novelty Detection”, Elsevier Science Direct, Pattern Recognition, Vol. 40, No. 03, pages 863-874, March 2007.
24. S. Gerber, T. Tasdizen and R. Whitaker, “ Robust Non-Linear Dimensionality Reduction using Successive 1-Dimensional Laplacian Eigenmaps” 24th International Conference on Machine Learning, Corvallis, OR, 2007.
25. Paul Viola and Michael J. Jones, “Robust Real-Time Face Detection”, International Journal of Computer Vision 57(2), 137–154, Kluwer Academic Publishers, 2004.
26. Tapas Kanungo, David M. Mount, Nathan S. Netanyahu, Christine D. Piatko, Ruth Silverman, and Angela Y. Wu, “An Efficient k-Means Clustering Algorithm: Analysis and Implementation”, IEEPE Transactions On Pattern Analysis And Machine Intelligence, Vol. 24, No. 7, Pages 881-892, July 2002.
27. Yuan Wang, Yunde Jia, Changbo Hu, and Matthew Turk, “Face Recognition based on Kernel Radial Basis Function Networks”, 2002.
28. Koray Balci and Volkan Atalay, “PCA for Gender Estimation: Which Eigenvectors Contribute?”, IEEE International Conference on Pattern Recognition, Vol. 03, Pages 363-366, 2002.
29. Paul Viola and Michael Jones, “Robust Real-time Object Detection”, Second International Workshop On Statistical And Computational Theories Of Vision – Modeling, Learning, Computing, And Sampling Vancouver, Canada, July 13, 2001.
30. Baback Moghaddam and Ming- Hsuan Yang, “Learning Gender with Support Faces”, MERL- A Mitsubishi Electric Research Laboratory, TR-2002-12, January 2002.
31. Paul Viola and Michael Jones, “Rapid Object Detection using a Boosted Cascade of Simple Features”, Conference On Computer Vision And Pattern Recognition, 2001
32. Tobias Friedrich, “Nonlinear Dimensionality Reduction- Locally Linear Embedding versus Isomap”, Machine Learning Group, The University of Sheffield, S1 4DP, U.K., 2000.
33. Joshua B. Tenenbaum, Vin de Silva, and John C. Langford, “A Global Geometric Framework for Nonlinear Dimensionality Reduction”, Science, Vol. 290, Pages 2319-2323, 22nd December, 2000.
34. www.faceaginggroup.com: MORPH Dataset Commercial and Non-Commercial White Paper Release.
35. Karl Ricanek Jr and Tamirat Tesafaye, “MORPH: A longitudinal Image Database of Normal Adult Age-progression,” IEEE 7th International Conference on Automatic Face and Gesture Recognition, Southampton, UK, pp 341-345, April 2006.
36. FGNET [Online] : www.eecs.quml.ac.uk/~yf300/FG_NET_data/alldata download.tar.
37. www.dumn.edu/~deoka001/knn.html