An α-Shape Construction from Automatic Extracted Facial Features: Module of Nonlinear Topological Component Analysis

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ABSTRACT
Face Recognition is rapidly changing and challenging area from last few decades. It has number of intra-subject variations. Aging is one of the major issues among all intra-subject variations of face recognition. So, Age Invariant Face Recognition is one of the very challenging areas as age cause variations on face. The various approaches related to age invariant face recognition and nonlinear dimensionality reduction was studied earlier in detail. In this paper, the implementation of first module, of one of the recent approach named Nonlinear Topological Component Analysis on Age Invariant Face Recognition is discussed in detail. In this module the facial features are automatically extracted from facial frontal images. The extracted feature points are placed in latent space which is labeled as α-encoded face. Thus each point in α-encoded face is plotted to form α-shape Tetrahedron.

Keywords
Nonlinear Topological Component Analysis, α-Encoded Face, α-Shape Tetrahedron.

1. INTRODUCTION
Over the last decade, image processing had been drastically evolved. Face Recognition, part of image processing has ample of applications in various fields such as biometrics, pattern recognition, computer vision and so on. Face recognition has many intra-subject variations. These intra-subject variations are related to the variation in the image of face from the dataset used. The variations responsible for the various issues in face recognition are posing, illumination, expression, aging and other occlusions.

Aging is one of the major challenging issues in face recognition. The basic assumption in face recognition is that every individual have different face structure which results different aging effects on each face. The various aging effects are wrinkles, deformation of jaw bones and many more. Age Invariant Face Recognition has the various approaches which work on aging factor.

In this paper, one of the most recent approaches named "Nonlinear Topological Component Analysis" (NTCA) is applied for Face Recognition across aging factor. The nonlinear topological component analysis is the approach used to reduce the dimensionality and capture the topological features. The basic concept of dimensionality reduction is extended in this approach. The detail comparative study of various approaches of face recognition was done. The various dimensionality reduction techniques such as Principal Component Analysis (PCA), Kernel Principal Component Analysis (KPCA), Nonlinear Dimensionality Reduction (NLDR) and many more. One of the recent approaches to age invariant face recognition is Nonlinear Topological Component Analysis [18].In [18], Nonlinear Topological Component Analysis (NTCA), the main objective is to reduce the dimensionality and captures topological features or signatures. The dimensionality reduction is performed to conduct pattern recognition. The methodology used for dimensionality reduction and extracting topological feature works as followed: a) a kernelized radial basis function (KRBF) dimensionality reduction method is integrated, b)the α- shape construction is made for extracting topological features and c) an object identification based on mixture multinomial distribution. The above three steps i.e. the entire NTCA is applied for age invariant face recognition. The different applications fields of the NTCA are Biometrics and Forensic.

The organization of this paper is as follows.The first part contains the summarized introduction to Age Invariant Face Recognition and Nonlinear Topological Component Analysis.A detail overview is given on different techniques used for nonlinear dimensionality reduction in Section II and also the approaches of age invariant face recognition. In section III, the proposed methodology is discussed with each block in detail. The results are shown and discussed in Section IV. Section V concludes the paper and followed by references.

2. RELATED WORK
The Nonlinear Topological Component Analysis is the extended dimensionality reduction technique, which capture the topological features or signatures and perform object identification.

The numerous approaches are applied before on age invariant face recognition among which few approaches are discussed in the paper. In [1], a Global Geometric Framework for Nonlinear Dimensionality Reduction was proposed to solve dimensionality reduction problems. This framework is the combination of Principal Component Analysis (PCA) and Multidimensional Scaling (MDS) and when Isomap fails this combination is used.

In [2], the comparison is made in between Isomap and Locally Linear Embedding (LLE) algorithms on the basis of several synthesis and real datasets. Isomap and LLE are techniques of Nonlinear Dimensionality Reduction. Both this algorithm achieves the better embeddings than PCA. Among Isomap and LLE, Isomap is more reliable and accurate than LLE.

Baback Moghaddam and Ming-Hsuan Yang in [3] had compared the Nonlinear Support Vector Machine results with the traditional classifiers such as Quadratic, Linear, Fisher Linear Discriminant, Nearest Neighbor as well as Radial Basic Function (RBF). This paper provides comprehensive evaluation of all above methods for gender classification from facial images. In [4], Balci and Atalay had focused on the gender estimation on face images by using Principal Component Analysis (PCA) and Multi-Layer Perceptron (MLP) method. The main purpose of the method is to analyze and study the role of Eigenvectors by pruning the MLP classifier connected to the output of PCA.

In [5], the PCA is extended nonlinearly as kernel Principal Component (KPCA). KPCA is used for higher novel classification. In [6], the proposed technique is automatic age simulation and creating 3D facial aging model for age invariant face recognition. The model is capable to handle the growth and development both and adult face aging and provide performance.In [7], a thorough analysis on the computational problem of facial aging is outlined. In simple words, with multiple factors such as ethnicity, gender, age group, etc. being identified as factors that affect facial aging effects. In addition, the variations are also due to other factors such as illumination, head pose, facial expressions, occlusions, etc. In [8], the recent development in field of dimensionality reduction, manifolds and topological Learning is outlined. The visualization of data in 2D or 3D spaces, extracting relevant number of features from one original image is possible according to recent advance in dimensionality reduction.

In [9], a graph matching technique is used where graph contain the information about the appearance and geometry of facial feature points. In [10], the Gradient Oriented Pyramid (GOP) technique was discussed. A robust face descriptor was proposed to study face recognition across age within passport photo verification. SVM supports GOP for Face verification in paper.In [11], a discriminative model was proposed for face matching in the presence of age variation. The framework here first represents the face in space invariant feature transform (SIFT) and multi-scale local binary patterns (MLBP) used as local descriptor. In [12], a novel formalism of utilizing periocular region for age invariant face recognition was presented. The Walsh-Hadamard transform Encoded binary Patterns (WLBP) and Unsupervised Discriminant Projection (UDP) was used to build subspace on WLBP featured periocular region.In [13], the local binary pattern (LBP) was computed on various facial regions and especially on feature which is more stable e.g. eyes.In [14], the novel formalism was proposed named Hidden Factor Analysis (HFA). HFA is used to tackle the variation problem caused by aging. In HFA, the basic idea was to decompose facial features into age and identity component for improved face recognition.

3. GENERAL FRAMEWORK

The NTCA approach was applied on Age Invariant Face Recognition, which can be achieved by using steps discussed below: a) extracting facial features by using facial feature extraction method; b) building the enrollee the set X using the probability distribution p(x) of the data manifold; c) constructing 3D polyhedron by using α- shape constructor; and d) extracting topological features such as number of edges or number of vertices, or holes or tunnels in 3D polyhedron for face identification task.

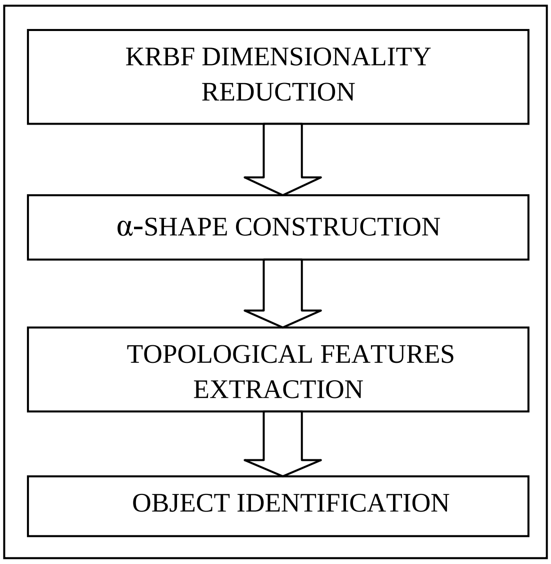


Fig.1: Entire methodology of nonlinear topological component analysis

3.1 Input Image

The preprocessed image was providing as the input image to start the implementation. The facial images from MORPH and FGNET datasets are used for implementation and analysis of result. One of the major objectives is to collect the FGNET and MORPH dataset which consist of facial images of subjects with age variation is under process. In this paper, the images from non-aging ORL datasets and Internet was used.

3.2 KRBF Dimensionality Reduction

When Radial Basis Function (RBF) was applied on kernel space, it is named as Kernel Radial Basis Function (KRBF) [15]. The KRBF performs two steps on the input image which are discussed below:

3.2.1 Mapping Data Space to Latent Space

A nonlinear mapping between the original data set and the latent variable space X was performed by first mapping the data set D of R^D to a subset D_e (e stands for extended) of a high-dimensional Hilbert space H_k using a feature space mapping ϕ. A Hilbert space (H_k) is a real or complex inner product space that is also a complete metric space with respect to the distance function induced by the inner product. Hilbert Space is the dot product of two vectors and produces a (real) inner product number. The best example of Hilbert Space is Euclidean Space. The dimensionality L of the latent space is less than the dimensionality D of the data space and therefore less than the dimensionality H of the Hilbert space. Thus, instead of Hilbert space Latent space is more efficient to be used here [18].

3.2.2 Latent Space Probability Distribution

A probability distribution p(t) in which t ∈ D, this will infer a corresponding probability distribution p(x) that generates the set X in the latent space R^L[18].

$$p(x) = p(x|W,\beta) = \frac{1}{M}\sum_{l=1}^{l=M} p(x\,|t_l, W, \beta)$$

3.3 α-Shape Constructor

As described in [17], the notions of ball also called as generalized disk are used for α-Shape construction. α-Shape is a concrete geometric structure which is a 3D or 2D polyhedron. Given a set of points and a specific α value, the α-shape was constructed using the following scheme.

1. Each point X_u in the embedded set is assigned a vertex u.
2. An edge is created between two vertices u and v whenever there exists a generalized disk of radius √α containing the entire set of points and which has the property that X_u and X_v lie on its boundary.

However, the notion of generalized disk is defined as follows.

1. If α > 0 but very large, then the generalized disk is a half- plane (very large radius!).
2. If α > 0 but not large, then the generalized disk is a closed ball of radius √α.
3. If α < 0, the generalized disk is the complement of a closed ball of radius√-α.

3.4 Topological Features

One can extract signatures of α-shapes such as metric properties: (volume, area, and length), combinatorial properties: (number of tetrahedral, number of triangles, number of edges, number of vertices), and topological properties: (number of components, number of independent tunnels, number of voids, and number of gaps). These signatures (or features) characterize a α-shape [16].

3.5 Object Identification

The aging and non-aging database was used for age invariantface recognition. The aging database was used to identify the individuals at different age intervals. The MORPH and FGNET datasets are aging databases used in [18]. The non-aging and agingboth the databaseswas used to analyze the efficiency of NTCA model without and with aging effect. GeorgiaTech Dataset was used as non-aging database in [18].

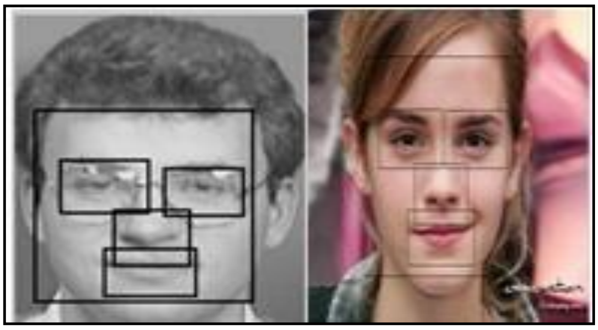
4. RESULTS

The result section in this paper contains the comparison between two different types of images having a difference of color. Among two images one image is Black & White while another one is color (RGB). The partial results of the implementation of Nonlinear Topological Component Analysis on Age invariant face recognition is described below in form of images:

(a) (b)

Fig.2: Original Images provide as input image (a) Gray Image and (b) Color Image

In Fig.2 the original facial image is shown which is provided as input image. These two images are different from each other. In Fig. 2(a), the facial image of man with spectacles is presented, which means that image with occlusion can also be used. Now the features from the given input facial images are extracted. The result of feature extraction is as follows:



(a) (b)

Fig. 3:Boxes in the images represents the extracted facial features(a) Gray Image and (b) Color Image

In above Fig. 3 (a), there are five boxes on each image. These five boxes on each image represent the five extracted facial features. The big box indicates the face part while the left and right box indicates left eye box and right eye box. The middle located box indicates the nose box and lower small box represents the mouth box. These extractions are performed by using Viola Jones Algorithm. The face region is detected and localized by using Viola Jones Algorithm. Now the various features like eyes, mouth and nose is detected from the extracted facial part. This facial part is represented by big box in Fig 3. The features to be extracted from detected face region are facial key components. The highly efficient cascaded structure is used in Viola-Jones object detection method [19]. The Viola-Jones face detection method is extended to detect small-scale facial components with wide shape variations. The cascade structure is inbuilt function in the MATLAB's Toolbox. The Computer vision Toolbox and Image processing Toolbox can be used directly in MATLAB R2007-R2014 for feature extraction.

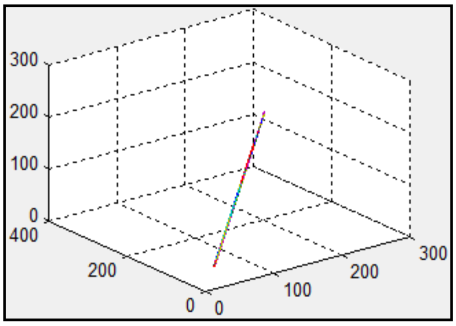
(a) (b)

Fig. 4: α- Encoded Face mapped in the latent space (a) Gray Image and (b) Color Image

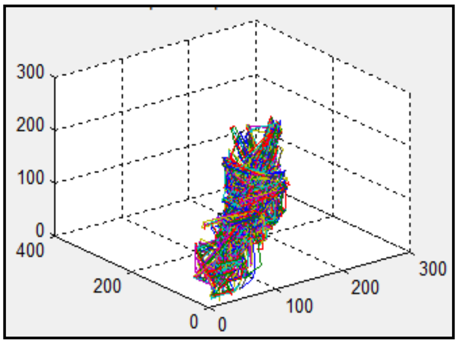
In Fig. 4 (a) and (b), α- Encoded Face is shown. All the points present in the detected face box is located in the latent space. The latent space is the result of dimensionality reduction. The Kernel Radial Basis function is used as nonlinear dimensionality reduction technique. The kernel function is directly applied to the original space. The Gaussian kernel trick is applied to Radial Basic Function (RBF) neural network to perform nonlinear transformation. The kernel trick is applied because it gathers the nonlinear information. Basically the original image space is transformed into latent space. The extracted features points are spaced in latent space and thereby form the cloud of points of extracted features. This cloud of points of extracted features is collectively called as α-Encoded Face. A α-shape is a concrete geometric object that is uniquely defined for a particular set of points. The parameter α controls the desired level of details of the shape.

Dynamic Bayesian networks (DBNs) represent a powerful formalism for encoding probabilistic or causal relationships between random variables. Visible Observation (VO) sequence as a flow of symbols which represents either: 1) temporal data (times series), generated by some causal process or 2) sequential data (such as bio-sequences), where the generating mechanism of this sequence is unknown [17].

Once all feature vectors assigned to local areas of a face image are captured in the frequency domain, they are viewed as VOs (Visible Observations). Five facial regions are considered: forehead (F), right eye (RE), left eye (LE), nose (N) and mouth (M) are latent variables (or hidden states) and the block feature vectors O_i are the observables; all these variables represent vertices of a DBN. The weights in this DBN represent conditional probabilities values between a facial region and a feature vector. These weights are incrementally updated and learned using the training set of facial images of the same individual.



(a)



(b)

Fig.5:α- Shape Tetrahedron (Polyhedron)built for(a) Gray Image and (b) Color Image

All the points of α-Encoded face are then plotted in between three axes representing red, green and blue to form tetrahedron. Tetrahedron is a geometric figure also known as polyhedron Tetrahedron is a polyhedron placed within three axis which are red, green and blue. α- Shape Tetrahedron for black and white image is straight line as it has only the two values black and white as plotted in fig. 5(a). While in fig 5(b) α- Shape tetrahedron can be visualized for second color image is plotted in between three axes. The α-shapes define a hierarchy of shapes from a set of points that allows features multiscale modeling that is very useful in macromolecule structure exploration as well as in facial aging. Thus, α- Shape Constructor is used to construct the polyhedron (Tetrahedron) from the latent space points shown in Fig. 4.The α-Shape construction is the formation of 3D polyhedron by using notion of balls can be defines as an α- shape is a concrete geometric object that is uniquely defined for a particular set of points.

As per the description of α-shape construction in section 3.3, the α-shape can be visualized as the manifold. As shown in the Fig 5, there no such visualization, only all the vertices in the axes are joined to reduce the time and to increase the accuracy of the methodology, NTCA.

5. CONCLUSION

In this paper, the construction of α-Shape for nonlinear topological component analysis techniques was discussed in detail. This Nonlinear Topological Component Analysis technique is applied on Age Invariant Face Recognition. The aging factor is especially chosen as it is more liable for the variations on the face. In future, the topological signature or feature will be extracted from α-Shape tetrahedron. The topological feature will be extracted for each face from α-Shape tetrahedron which will be constructed for each facial image in the data set and stored. These stored signatures will be then compared with the topological signature extracted from the query facial image. Thus the object identification will be performed, which is face recognition when applied on Age Invariant facial image datasets. Instead of multinomial distribution [18], the identification task will be performed by using supervised classifier. The main objective, to increase the efficiency of the proposed technique in [18] is under process. The real time video clips dataset can use in future for application of methodology.

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