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An Active Age Estimation of Facial image using Anthropometric Model and Fast ICA

Santhosh Kumar[1,*], S. Ranjitha[2] and H. N. Suresh[2]

[1] *East West Institute of Technology, Bangalore, Karnataka, India 560004*
[2] *Bangalore Institute of Technology, Bengaluru, Karnataka, India 560004*

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Abstract

In this paper, an efficient feature extraction method based on the Kande-Lucas-Tomasi (KLT) using fast independent component analysis (Fast ICA) & Anthropometric Model as the distance measure is proposed. Each face is extracted facial organs are marked for Anthropometric Model (AM) distance measure. The KLT facial coefficients of low & high frequency in different scales & various angles are obtained. The coefficients are utilized as a feature vector for further processing. Considering the extracted face image & adopt the Fast-ICA algorithm based on entropy to extract the face feature information. Finally, according to the Anthropometric distance to classify face feature & Artificial Neural network (ANN) used to estimate age for all kinds of facial databases. Experiments are done by using the YALE & FERET databases. An experimental outcome shows that the recognition rate Mean Absolute Error (MAE) of the proposed algorithm is acceptable & very promising, & confirm the success of the proposed face feature extraction approach.

Keywords: Kande-Lucas-Tomasi (KLT), Fast ICA, Artificial Neural network (ANN), Anthropometric Model (AM)

1. Introduction

Face images incorporate many information including age, emotional state & identity which are important to make face to face communication & to improve the interaction between humans & machines or computers. Predicting age by using face plays a vital role in multimedia communication & security surveillance. So, estimation of facial age is very important in many applications, for example, security control & surveillance monitoring video surveillance, face detection, face animation, demographics, & control on minors [1], [2]. Age estimation can be widely employed in determining the age of migrant in situations which there are no documents that can determine the age, for web pages that allow access only for persons above a certain age. The person's age is simply estimated by using our experience invariably in ordinary life. The interest in age estimation has incomparably expanded & the problem arises when age estimation needs to be automated. An important point in age estimation is detection & extraction of facial features [3]. Identifying the fundamental feature, for example, eye, nose & mouth is important for many face detection methods. In many facial images detection of facial feature points act as an essential part. In the procedure of automated age estimation, the most vital portions are the internal portions of the face & the area around the eye. A number of methodologies have been implemented to estimate accurate age, but convolution added by assets like inter-personal variation, personal changes & disparity of acquisition conditions have made the task challenging & troublesome. The distinctive features of the face image are extracted & as compared with the images of the database to yield exceptional advancement in facial image age estimation [4], [5].

Histogram of Oriented Gradients (HOG) & Local Binary Pattern (LBP) used to determine feature vector by separating face into small regions to extract features. A person's aging & gender difference appear on the face pigmented spot, the wrinkle, sagging skin, shape, color of skin, & so on. These several features were used for age & gender estimation using a neural network [6], [7]. The facial features were extracted & utilized as inputs to learn neural networks. The network has lowest estimation error & be able to be taken into consideration as a good technique to model accurate age [8]. Most famous face recognition algorithms, for example, Principal Component Analysis (PCA), Independent Component Analysis (ICA), Linear Discriminant Analysis (LDA) & Elastic Bunch Graph Matching (EBGM) have countered few limitations [9], [10]. The accurate age detection is frequently preserved as a classification problem. However, this can be articulated as a regression problem. KNN-regression classifier combines the classification & regression methods to enhance the accuracy of the age estimation system [11], [12]. A craniofacial growth model describes the evolution connected to shape variations detected in human faces all through the formative years. Anthropometric facts gathered base on facial growth describe method of growth factors characterized for facial landmarks utilized as a part of anthropometric studies. The main parameter is distance between two eye center point. This distance is used as a measurement tool to find the centers points of other facial feature regions. Combinations of diverse image processing approaches are employed within the localized regions to find out the facial feature points [15].

An automated face image age detection technique is

E-mail address: santhoshphd2015@gmail.com
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generally composed of three parts, such as, face detection, feature extraction & age estimation. The reason behind the face detection is to localize the face in an image. It is somewhat challenging to detect the face in images because the identified results are highly reliant on numerous conditions, for example, environment, movement, lighting, orientation & facial expressions. These numerous aspects may lead to changes in color, luminance, shadows & contours of images. For these type of complications, we perform normalization along with filtering before feature extraction. Calculating feature extraction has different kind of procedures to make an estimation of an age. A method is proposed using two major algorithms to get facial features using KLT Algorithm & calculating facial geometric points based on Anthropometric Model. After feature selection, dimension reduction process is done for fast computation using Fast ICA this fastens total computation time of our proposed methodology. At last, ANN classifier is utilized to estimate age in testing modules.

2. Literature Review

Hu Han et al. [11] have proposed a hierarchical methodology for automated age detection, & gave an analysis of how aging impacts individual facial components. Experimental outcomes on the FG-NET, MORPH Album2, & PCSO databases have demonstrated that eyes & nose are more informative than the other facial components in automatic age detection. Additionally, the paper has been concentrated on the capability of humans to estimate age utilizing information gathered by means of crowdsourcing, & outcomes showed that the cumulative score (CS) in 5-year MAE of the proposed technique is superior compare to the age estimates given by humans.

Sung Eun Choi et al. [12] have proposed another age estimation technique utilizing a hierarchical classifier technique built on both the worldwide & local facial features. The proposed method has three advantages in the following three ways, contrasted with the earlier research work. At First, age estimation correctness has been significantly enhanced by utilizing a combination of the proposed hybrid features & the hierarchical classifier. Second benefit of the proposed technique was the local feature extraction approach which was proposed to increase the efficiency of the hybrid characteristic. Many Gabor filters based on region was used to extract The feature of wrinkle. Every Gabor filter made by utilizing regional direction of wrinkles. After that skin feature was extracted utilizing LBP. It was able to extract the complete textures of skin. At last, they enhanced hierarchical classifier using a support vector machine (SVM) & a support vector regression (SVR). The experimental outcome has shown that the proposed method's performance was better than the other previous techniques when using the BERC, PAL & FG-Net aging databases.

Ion Marques & Manuel Graña [16] have proposed a two component system, presenting Lattice Independent Component Analysis (LICA) for feature extraction & Extreme Learning Machines (ELM) for classification. The initial stage of LICA was to find robust lattice independent components from the data. In next stage, the set of robust lattice independent vector was utilized for linear un-mixing of the data, to get a vector of plenty coefficients. The subsequent abundance values were utilized as features for classification, for face recognition. ELM were perfect & fast-learning advanced classification approaches built on the random generation of the input-to-hidden units' weights followed by the purpose of the linear calculations to get the hidden-to-output weights. LICA-ELM system examined in contrast to feature extraction techniques & classifiers, leave behind them when carried out cross-validation on four large unbalanced face databases.

3. Proposed Methodology

Human face expresses vital cognizable information related to individual qualities. Age is a vital individual attribute straightforwardly inferred by particular patterns emerging from the facial manifestation. Individuals have the capability to define age between 20 & 60 years & envisage aging appearance of the face. An age estimation method, which is to mark a face image automatically with the correct age or the age group of the individual face has been proposed. In this section, we interpret the age estimation procedure by considering the facial features. The proposed method is first formulated by the pre-processing stage where the image obtained is normalized & filtered to reduce the noise followed by the feature extraction process. The features extracted by applying the KLT algorithm is further enumerated by the Anthropometric model to spot the facial genetic points. The dimension is efficiently reduced by the fast independent component analysis that correlates with the ANN classifiers for the precise estimation of the age.

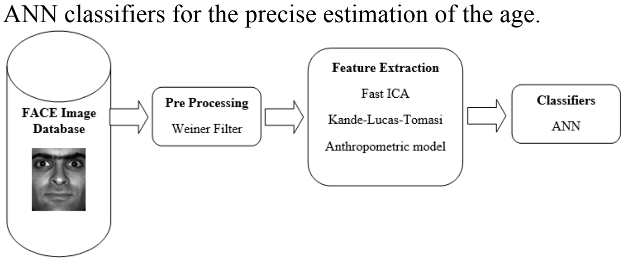

Fig. 1. Block Diagram Facial age estimation

3.1 Facial Image Preprocess Using Image Normalization Using Wiener Filters

It is necessary to detect the face region from any given image. This requires preprocessing of the image under consideration. Preprocessing techniques involve normalization & filtering of the image. It is the primary step in processing, which is necessary to normalize the face images for age estimation because the original images have unessential features including background, clothes, & hair. Normalization is accomplished to extract only the face area from the given image. It is easy to perform normalization based on the eyes by rotation & adjusting the size compared with normalization based on other facial features, thus the face image is normalized on the basis of both eyes. The original image is changed into gray scale image & a filter is used in order to remove the noise. Filters are used to suppress both the high frequency & the low frequency in the image. Filtering is performed to equalize the image, enhance & detect edges in the image.

3.2 Feature Extraction from the Facial Images

The next requisite process in proposed methodology is the feature extraction. It is well known fact that the facial features are changed by aging. Hence it is necessary to extract the facial features to estimate the age of an individual. Feature extraction is a unique embodiment of dimensionality reduction. It is a technique of securing visual content of the images for indexing. Various feature extraction methods have been proposed to accurately select the obligatory constituents from the facial image. The course interpolates extraction of facial features, for example,

- Shape feature
- Texture Feature
- Color Feature.

We adopt the KLT algorithm & Anthropometric model for the extraction of the facial geometric points. The dimension reduction is done using the fast independent component analysis.

3.3 Kande-Lucas-Tomasi Feature Tracking Algorithm

It is a feature extraction method which aims at the purpose of negotiating the problem that the traditional image registration methods are generally costly. This procedure exploits the spatial intensity information to direct the search for position that produces the best match & is faster than other techniques for investigating far fewer potential matches. After the pre-processing the following part is to track the components which are needed for estimate the age of the individual. The features in the image are tracked autonomously utilizing the KLT algorithm with translational movement. The algorithm is applied by considering the entire face as the neighboring region & utilizing a single feature at the center of the face.

3.3.1 Computing the Number of Features

KLT feature tracker determines 'm' number of features in the first image, & tracks these features in the impending images. If a feature is forfeited, a substitutive feature is endowed which is tracked from there onwards. The number 'm' varies the accouterment on the efficiency & accuracy of the tracking & detection of objects. If the number 'm' is notably high, the KLT algorithm becomes time consuming & the efficiency & the accuracy of the algorithm is affected. Many wobble features & image noise are also tracked if 'm' is an enormous value. As a contradictory to this, a small value of 'm' eliminates a large number of necessary & strong features affecting the accuracy of the tracking & detection to a large extent. The accuracy & efficiency of the algorithm can be calculated by selecting distinct values of 'm' to estimate the precise number of features to be tracked for better performance & results.

3.3.2 Accuracy can be Calculated by the Number of Correctly Tracked Features

The moderate calculated values provide an estimate to select the value of 'm' between a range of the features of the finest performance in terms of the efficiency & accuracy of code. The large numbers of features not only affect the accuracy by capturing a large number of features comprising salt & pepper noise, but also have a negative impact on the efficiency. The number of features 'm' should preferably be kept between the given range in case of images with low resolution through moderately textured backgrounds.

3.3.3 Matching Tracked Features

The algorithm provides features in the form of matrices: x, y, & values with each having dimensions of m*f with 'm' being the number of features tracked & 'f' being the number of frames. Each element of x & y matrices contains the coordinates or whereabouts of the feature in the image in the appropriate frame. The value matrix reminds about the features which KLT declines to track in the further frame. When the face is locked in the first frame of the image, the algorithm chooses to retain only those features in the computations which exist within the range of the locked area. The 'values' matrix contributes data to decide which of the features are tracked in the future frame & which of the features are disoriented in between. The extensive orientation, small size of the face in the image, & low resolution of the overall image results in an enormous feature loss. The features that are lost are eliminated from the consideration & only the features that match are considered.

KLT feature tracker can track the features from one frame to the next frame. The features are scattered all over the image based on the complete texture of the background, & the total number of objects in the image.

The following equation 1 represents the symmetric definition for the difference between two windows: one in image I & another one in image J.

$$\in = \int\int_w [J(X+\frac{d}{2}) - I(X-\frac{d}{2})]^2 - w(X)dX \tag{1}$$

where x = [x, y] T, the displacement d = [dx, dy]T, & the weighting function w(x) is usually set to the constant 1. Equation (1) is identical to the equation given in (2) except that the current version has been made symmetric with respect to both images by replacing [J(x)−I(x−d)] with [J(x+ d/2)−I(x− d/2)]. Taylor series expansion of J about a point a = [ax, ay] T, truncated to the linear term, is:

$$J(\xi) \approx J(a) + (\xi_x - a_x)\frac{\partial J}{\partial x}(a) + (\xi_y - a_y)\frac{\partial J}{\partial y}(a) \tag{2}$$

where $\xi = [\xi_x, \xi_y]^T$.

Following the derivation in [3], we let x + d/2 = ξ & x = a to get:

$$J(X+\frac{d}{2}) \approx J(X) + \frac{d_x}{2}\frac{\partial J}{\partial x}(X) + \frac{d_y}{2}\frac{\partial J}{\partial y}(X) \tag{4}$$

$$I(X-\frac{d}{2}) \approx I(X) + \frac{d_x}{2}\frac{\partial J}{\partial x}(X) + \frac{d_y}{2}\frac{\partial J}{\partial y}(X) \tag{5}$$

$$\frac{\partial \in}{\partial d} = 2\int\int_w [J(X+\frac{d}{2}) - I(x-\frac{d}{2})] \\ *[\frac{\partial J(X+\frac{d}{2})}{\partial d} - \frac{\partial I(X-\frac{d}{2})}{\partial d}]w(X)dX \tag{6}$$

$$\approx \int\int_w [J(X) - I(X) + g^T d]g(X)w(X)dX, \tag{7}$$

where,

$$g = [\frac{\partial}{\partial x}(\frac{I+J}{2})\frac{\partial}{\partial y}(\frac{I+J}{2})]^T. \tag{8}$$

To find the displacement d, we set the derivative to zero:

$$\frac{\partial \in}{\partial d} = \iint_w [J[x] - I(X)g^T(X)d]g(X)w(X)dX = 0 \tag{9}$$

Rearranging terms, we get

$$\begin{aligned} &\iint_w [J(X) - I(X)]g(X)w(X)dX = \\ &= -\iint_w g^T(X)dg(X)w(X)dX, \\ &= -[\iint_w g(X)g^T(X)w(X)dX]d. \end{aligned} \tag{10}$$

In other words, we must solve the equation (10)

$$Zd = e \tag{11}$$

where Z is the following 2 × 2 matrix:

$$Z = \iint_w g(X)g^T(X)w(X)dX \tag{12}$$

and e is the following 2 × 1 vector:

$$e = \iint_w [I(X) - J(X)]g(X)w(X)dX \tag{13}$$

KLT delivers a good accuracy & prediction with major errors in detection. There is a miss ratio in the presence of extremely textured background with several objects. For handling this complete problem, the anthropometric model is presented which provides the accurate facial measurements.

3.4 Anthropometric Model for Facial Measurements

Anthropometry is a science of measuring the human body & its diversified sections & is used to classify human body geometry using a series of measurements, proportions & sizes on human body. Data that are obtained from anthropometric measurement informs a range of establishment that depends on knowledge of the dissemination of measurement across human populations. In the proposed model we limit the measurement extraction to the face region. It is based on the geometric ratios of human face.

Face anthropometric studies convey a quantitative explanation of the craniofacial complex by means of measurements taken between key landmarks on human faces across age & are often utilized in characterizing normal & abnormal facial growth. The construction of our face model is inspired by anthropometry studies of human face. Anthropometry data is used to make a good preliminary model, & additionally for keeping in association between parameters in consistent. The measurements taken on human faces are of three types

- Projective measurements
- Angular measurements
- Tangential measurements

These measurements are made in a factually defined way in order to develop favorable statistics from anthropometric measurements. Anthropometric assessment starts with the identification of suitable locations on subject, defined in terms of visible characteristic (skin or bone) on subject. A series of measurements between the landmarks is utilizing carefully stated processes & measuring instruments (for example, levels & measuring tape). Repeated measurements of the same individual (taken with a gap) are highly reliable, & measurements of different individuals can be compared successfully & efficiently. Face anthropometry measurements utilize a set of predetermined landmarks (for example, the outlines, edges of the lips, or the tip of the nose) & the below mentioned different types of measurements

- Distance between two landmarks (for example, the separation of the eyes)
- Distance between two landmarks measured along an axis (such as the vertical height of the nose)
- Distance between two landmarks measured along a surface (such as the upper lip boundary arc length)
- Angle of inclination with respect to an axis (for example, the slope of the nose bridge
- Angle between face locations (such as the angle formed at the tip of the nose)

The core idea of this method is to examine studies in craniofacial development theory. There are two reasons behind the mathematical formulation for age estimation is not reliable:

- The mathematical model cannot identify the humans age effectively when the ages are close to adulthood.
- The head profile is very tough to calculate from face images.

Feature extraction for age estimation methods based on the anthropometry model can deal with young ages considering the human head shape does not change much in its adult period. On the whole, the anthropometry model might be useful for young ages, but is not convenient for adulthood. In application, only frontal faces can be used to measure facial geometries since the ratios of separation span is computed from face images which are sensitive to head pose. Only the facial geometry is considered by the anthropometric model based representations. The age estimation errors don’t differ excessively when the features with minimized dimensions are used. Consequently, we utilize the component analysis method to overcome the computational complexities & errors.

3.5 Dimension Reduction by Fast ICA

ICA is a computational method to separate a multivariate signal into additive subcomponents through assuming the subcomponents are non-Gaussian signals. This signals are statistically free from one another. ICA helps to solve higher order statistics & it identifies the independent source point for components from their linear mixtures. Thus ICA delivers a powerful data presentation by giving independent instead of uncorrelated image decomposition & representation. Generally, estimated independent components achieved by utilizing these algorithms are different to each other. It is very tough to define the energies & the order of the independent components. Earlier several ICA algorithms have already been proposed which differ in their objective functions for statistical independence. For the fast computation & efficient dimension reduction the Fast ICA method is adopted.

Fast ICA is an adequate & well-known algorithm for ICA, which is based on a fixed-point iteration scheme maximizing non-Gaussian as a measure of statistical independence. The algorithm includes pre-processing, for example, centering, whitening the data. A large number of data points are used in a single step of the algorithm making the computation faster. The image which is an input is centered by computing the mean of each component in the image & subtraction that mean so that each component has zero mean. Whitening the data is the process of linearly transforming the data in which the new components are uncorrelated & the variance is equal to one. This algorithm is based on the reverse entropy to extract the face feature information & according to the distance face feature is classified. This distance value is taken as an input for ANN classifier.

3.6 Estimation of Age Using Classifiers

Age estimation is done by utilizing many different kinds of biometric traits, for instance facial age estimation that depends on biometric features take out from a person's face. Automated age estimation using face aims at utilizing algorithms that allow estimation of age of a person depend on some features derived from their face image. Age is estimated on basis of the classifier output. In proposed system we employ Artificial Neural Networks (ANN) classifier.

3.6.1 ANN Classifier for Facial Age Estimation

A neural network's best feature is its robustness when presented with partly incorrect pattern of input & the endowment to generalize input. This is the reason that motivates its adaptation in this research work. The method utilizes standard back propagation for supervised learning. Several hidden layers can be used & the choice between a logistic or hyperbolic activation function can be made. Learning take place by changing the weights in the node to reduce the dissimilarity among the output node activation & the output. The error is back propagated over the network & weight adjustment is made utilizing a recursive technique. The multilayer perceptron model with error minimization back-propagation learning was applied in this research which is depending on several optimal set of structures & training parameters.

ANN classifiers are inspired by the biological evaluation neural networks used to approximate function that depends on huge quantity of inputs & are usually not known. The ANN is a parallel computational method, containing thoroughly connected adaptive processing components. Adaptive behavior of ANN used to solve extremely nonlinear problems. The ANN has been implemented effectively into several applications which are based on the statistical estimation. Arbitrary function approximation defines classifier capability with the help of learned observed data.

A supervised ANN-based approach is employed for image classification [16]. A multi-layered feed-forward ANN is used to carry out the non-linear classification. This is the foremost wide utilized model & its design consist of one input layer, at the best one hidden layer & & output layer. This algorithm is a promising method for a various circumstance, for example, non-normality, complex feature spaces & multivariate data types, where traditional methods lapse to produce correct results.

ANN is consisting of two phases: training phase & testing phase. All in all, a subset of patterns is initially sampled from the domain into a training subset & testing subset & then exhausted by allocating patterns to both the training subset & the testing subset. In the ANN training phase, the main objective is to find out the element that minimize a specified error for the patterns contained in the subset. This criterion is often defined by the mean squared error function. In general, a training pattern is selected at random from a subset & the error is minimized using the standard or a modified back propagation. In the ANN testing stage the main aim is to define the suitability of the computed components in minimizing a similar error criterion for the patterns contained within the alternative subset. As these patterns are not used to determine the elements, ANN analysis evaluates domain generalization obtained through the trained ANN. In that way building the confidence level of the trained ANN for future estimations. In this phase, ANN depends on the total quantity of training patterns in the previous subset. Generally, several patterns might have to be sampled to approximate complex functions & ANN implementation may become time consuming.

4. Excremental Setup and Simulation Results

All the algorithms are implemented in MATLAB 8.1.0.604 (2013a), wiener filter is used to reduce noise over the image. The single level sub band is used to find the coefficients. To demonstrate the algorithm for images, YALE & FERET databases are employed & resize these images to 256*256. YALE dataset consists of 20 person images; everyone has 4 pictures with different expressions & viewpoint. From this dataset we have selected 10 individuals for experiments. For each individual we have selected 3 images for training, chosen randomly for testing out of 10 face images. To evaluate the efficiently of the proposed method, we have done a number of experimentations utilizing YALE & FERET databases & compare with the experimental results of ICA & Fast ICA algorithms. Table 1 & Table 2 reports the performance result obtained from previous experiments.

The experimental results show that the face recognition rate using new algorithm proposed in this paper is considerably increased compared with traditional ICA algorithm, but we adopted all KLT & Anthropometric Model, the runtime greatly increase. According to the nature of KLT Algorithm, the unique facial points are captured in all kind of circumstances. So, use of low frequency coefficients as identification features, not only contain effective discriminant information, but also reduce the feature space dimension. The Anthropometric Model statistical characteristics depict the face size & local organs size information, effectively, & it is not very sensitive to light change. For this reason, we can select low-frequency or part of high-frequency coefficients for Fast ICA, so we can improve recognition rate & shorten the MAE at the same time.

MAE is defined as the mean of absolute error between estimated age & ground age presented in equation 14:

$$MAE = \frac{\sum \left| l_k - l_k^* \right|}{N} \tag{14}$$

ANN is used to classify the age for both male & female face databases. Accuracy level is increased when trained face data is increased.

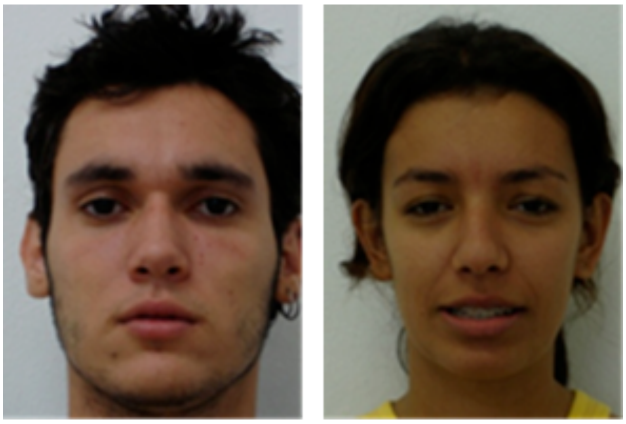

Fig. 1. Real Age 19, Predicted Age 21.2

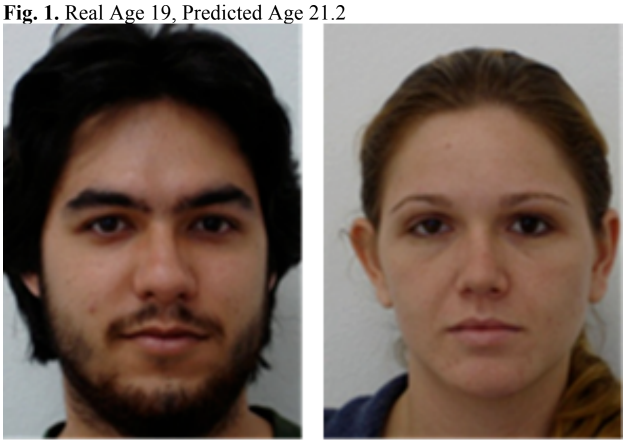

Fig. 2. Real Age 23, Predicted Age 26.6

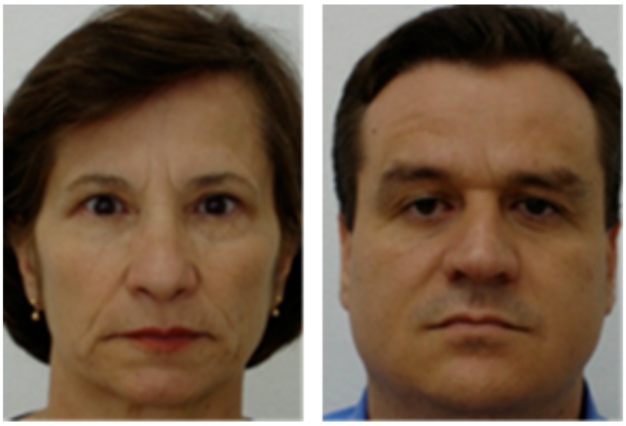

Fig. 3. Real Age 50, Predicted Age 48

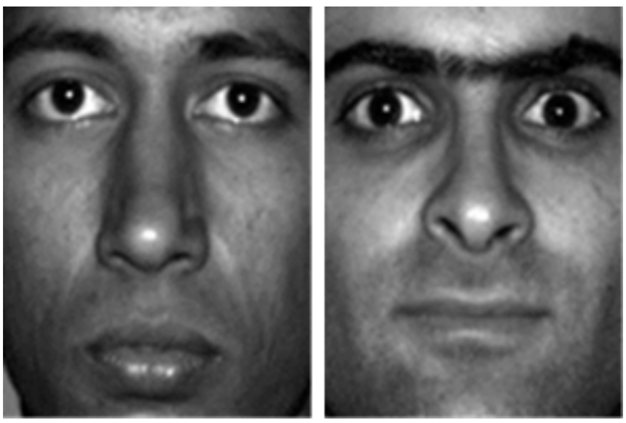

Fig. 4. Real Age 25, Predicted Age 26.12

Figure 2, 3 & 4 shows the FERET database sample image & figure 5 shows YALE database sample images. The MAE between the original & predicted age using PCA & ICA, produce value in the range of 5-7. But, the mean absolute error between the original & predicted age using proposed method Fast ICA, produce value in the range of 2-5. Compare to another methodology PCA, ICA, our proposed method Fast ICA gives better result in MAE.

Procedure for Anthropometric Model & KLT:

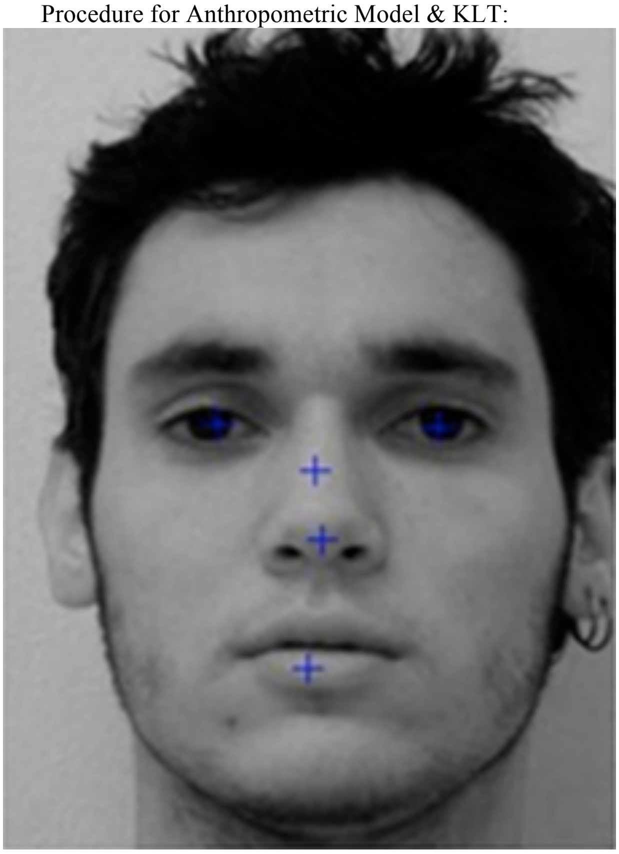

Fig. 5. Anthropometric Model feature extraction

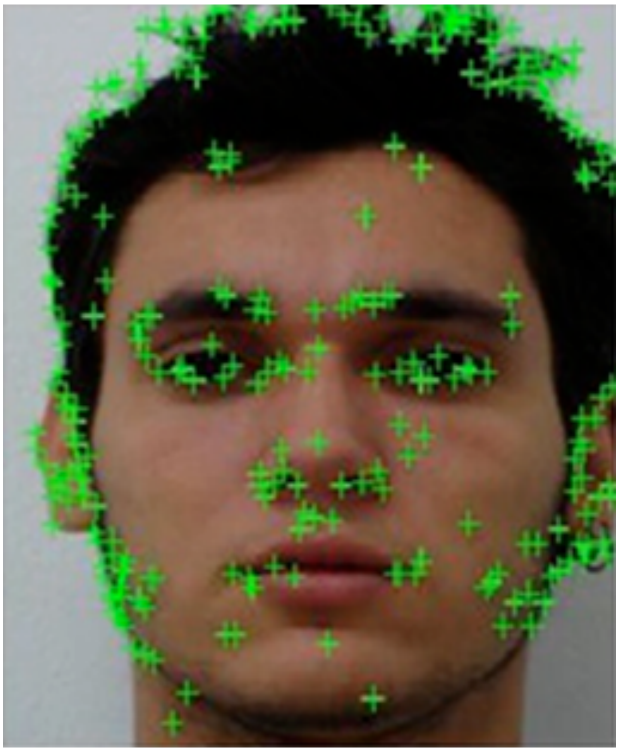

Fig. 6. KLT feature extraction

The Age was estimated based on a number of training &

testing images. Recognition rate & MAE had been increased with the increment in the number of training images. During the experiment, at first we had trained the data based on 2 training images & then we had trained 3 training images. The outcomes of the experiment showed that the proposed method, Fast ICA gave a better MAE with compared to older methods like ICA & PCA in both YALE & FERET database. It had also found out that the recognition rate had increased to 90-95% & MAE has come between 2-5. Additionally, the Anthropometric distance was calculated between marked points. This measurement gives face organ size & symmetric value of face which presented in figure 6. The KLT algorithm provides strong facial points for extracted facial portion which presented in figure 7. Table 1 & table 2 shows Recognition Rate & MAE value between various methodologies.

Table 1. Project selection matrix rules

Database	*Methodology*	*Recognition Rate*	*MAE*
YALE	PCA	85.20	8.25
	ICA	89.00	7.09
	Fast ICA	92.12	6.20
FERET	PCA	83.32	7.38
	ICA	88.30	6.19
	Fast ICA	90.08	4.60

Table 2. Two face Training

Database	*Methodology*	*Recognition Rate*	*MAE*
YALE	PCA	82.42	9.15
	ICA	85.33	8.11
	Fast ICA	89.50	7.65
FERET	PCA	81.56	8.82
	ICA	84.78	7.21
	Fast ICA	88.70	5.20

5. Conclusion

An age estimation algorithm is proposed to predict individual age in different scenarios like lighting, pose, & gender. Here, we used a new feature extraction based on KLT Algorithm & Fast ICA. Our experimental outcomes showed that this new method is very high on recognition rate. MAE reduced significantly because of hybrid feature extraction. Fast ICA gives an optimal feature selection at low computation times compare to other dimension reduction algorithms like PCA, ICA, MPCA. The Fast ICA gives increased recognition rate up to 90-95% with compare to older methods like PCA, ICA. Additionally, using proposed method MAE is reduced up to 30-33% with compare to older methodology. This technique is suitable for real time application for visual surveillance & robotics systems & also can be used for any other classification.

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References

1. C. H. Chu, S. H. Huang, C. K. Yang, C. Y. Tseng, "Design customization of respiratory mask based on 3D face anthropometric data", International Journal of Precision Engineering & Manufacturing, vol. 16, no. 3, pp.487-494, 2015.
2. T. Wu, P. Turaga, R. Chellappa, "Age estimation & face verification across aging using landmarks", IEEE Transactions on Information Forensics & Security, vol. 7, no. 6, pp.1780-1788, 2012.
3. H. H. K. Tin, "Subjective Age Prediction of Face Images Using PCA", International Journal of Information & Electronics Engineering, vol. 2, no. 3, pp.296, 2012.
4. E. Eidinger, R. Enbar, T. Hassner, "Age & gender estimation of unfiltered faces", IEEE Transactions on Information Forensics & Security, vol. 9, no. 12, pp.2170-2179, 2014.
5. A. A. Mohammed, R. Minhas, Q. J. Wu, M. A. Sid-Ahmed, "Human face recognition based on multidimensional PCA & extreme learning machine", Pattern Recognition, vol. 44, no. 10, pp.2588-2597, 2011.
6. X. Luan, B. Fang, L. Liu, W. Yang, J. Qian, "Extracting sparse error of robust PCA for face recognition in the presence of varying illumination & occlusion," Pattern Recognition, vol. 47, no. 2, pp.495-508, 2014.
7. D. Lacko, T. Huysmans, P. M. Parizel, G. De Bruyne, S. Verwulgen, M. M. Van Hulle, J. Sijbers, "Evaluation of an anthropometric shape model of the human scalp", Applied ergonomics, vol. 48, pp.70-85, 2015.
8. W. L. Chao, J. Z. Liu, J. J. Ding, "Facial age estimation based on label-sensitive learning & age-oriented regression", Pattern Recognition, vol. 46, no. 3, pp.628-641, 2013.
9. H. Dibeklioglu, F. Alnajar, A. Ali Salah, T. Gevers, "Combining Facial Dynamics with Appearance for Age Estimation", IEEE Transactions on Image Processing, vol. 24, no. 6, pp.1928-1943, 2015.
10. Z. L. Sun, K. M. Lam, "Depth estimation of face images based on the constrained ICA model", IEEE Transactions on Information Forensics & Security, vol. 6, no. 2, pp.360-370, 2011.
11. H. Han, C. Otto, A. K. Jain, "Age estimation from face images: Human vs. machine performance," In Proceeding(s) of the 2013 International Conference in Biometrics (ICB), pp.1-8, 2013.
12. S. E. Choi, Y. J. Lee, S. J. Lee, K. R. Park, J. Kim, "Age estimation using a hierarchical classifier based on global & local facial features", Pattern Recognition, vol. 44, no. 6, pp.1262-1281, 2011.
13. C. T. Lin, D. L. Li, J. H. Lai, M. F. Han, J. Y. Chang, "Automatic age estimation system for face images", International Journal of Advanced Robotic Systems, vol. 29, 2012.
14. R. Weng, J. Lu, G. Yang, Y. P. Tan, "Multi-feature ordinal ranking for facial age estimation", In Proceeding(s) of the 10th IEEE International Conference & Workshops on Automatic Face & Gesture Recognition (FG), pp.1-6, 2013.
15. X. Geng, C. Yin, Z. H. Zhou, "Facial age estimation by learning from label distributions", IEEE Transactions on Pattern Analysis & Machine Intelligence, vol. 35, no. 10, pp.2401-2412, 2013.
16. I. Marques, M. Graña, "Face recognition with lattice independent component analysis & extreme learning machines", Soft Computing, vol. 16, no. 9, pp.1525-1537, 2012.
17. R. He, B. G. Hu, W. S. Zheng, X. W. Kong, "Robust principal component analysis based on maximum correntropy criterion", IEEE Transactions on Image Processing, vol. 20, no. 6, pp.1485-1494, 2011.