

A Robust Age Estimation Technique Using Artificial Intelligence

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ABSTRACT: Human age is a fundamental individual trademark, can be finishing up by means of alternate patterns rising from the facial appearance. Machine based age estimation through faces have emerge as exceptionally frequent field seeing that of their explosively rising real-styles functions such as safety manipulate and surveillance tracking, cosmetology, entertainment, forensic art, biometrics, electronic customer relation-ship management. Age estimation is the essential obligation of facial pictures class. It could be depicted as determination of somebody's age or age bunch from facial pictures. This paper offers a top level perspective of recent research in facial age estimation along with an outline of earlier research in this field matter. The age estimation trouble is challenging. The key trouble is that particular individual's age truly distinctive. The aging technique will not only depend on the simplest characteristic gene but in addition many other factors are included such as health, environment, climate conditions and way of life. We constructed a real-time age perdition system that predict age of real face images and also design a new age estimation system using the DCT technique for extraction on large dataset. This novel approach reduces the age estimation errors enormously over all previous methods. An experiment on three dataset such as FACES dataset, Images of Groups dataset and FG-NET aging dataset shows the success of proposed system for human aging estimation.

KEYWORDS: Age estimation, feature extraction, facial aging, DCT (discrete cosine transformation), feature selection, Viola-Jones algorithm.

I. INTRODUCTION

A human face comprises plentiful data regarding personal characteristics together with the identification, gender, age, expressions and so no[1]. In the most recent years, with the expanding utilization of face recognition and video observation frameworks, research on the numerical examination of human faces including face recognition, facial expressions, gender classification, face detection has pulled concentration in the grouping of pattern recognition and computer vision[2]. Age estimation by means of numerical analysis of the face photograph has numerous expertise functions such as the improvement in smart human machine interfaces, enhancing the security and assurance of minors in different and various areas . The age characteristics could also be utilized in the face verification and enhancing the tools utilized in police investigations. Most commonly, automatic age estimation via computer or machine is valuable in purposes where the target is to investigate an age of a person without identifying him[3].

Age estimation from facial pictures is characteristically a challenging mission because of its multi-class nature on account that the age label may be regarded as a single category. From the viewpoint of learning, this issue is much more intricate than gender classification and face detection. Certainly, the binary classifier cannot be specifically connected to the issue of the age estimation. Additionally, the vital trouble is that a specific people age really different .the aging method will depend not only on the simplest characteristic gene but in addition numerous outer factors are involved such as way of life, health, climate conditions and environment. From toddlers birth to adulthood most of the alterations are due to change in craniofacial growth as shown in fig 1. The size of face on a regular basis enlarges for the duration of growth [3]. From adulthood to the seniority, most obvious alterations on this level are changes in pores and skin texture. Additionally, a wrinkle, beneath chin and under eye lower bags are seems. Shape changes proceeds, but less drastically. Likewise, the age of male and female are different[4].

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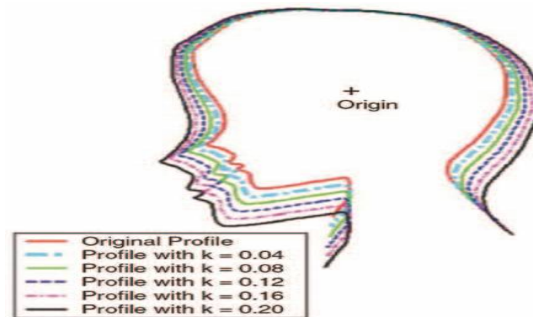


Fig 1. Alterations due to change in craniofacial growth

Assessing age from facial pictures utilizes the system of image processing and machine learning. More often that, all automatic image supported age estimation framework are made out of two modules. First, a set of attributes extracted from face image and the second module presents an estimate of the age settled on this set of attributes. It is clear that the general execution of the framework relies upon these two modules shown in fig 2.

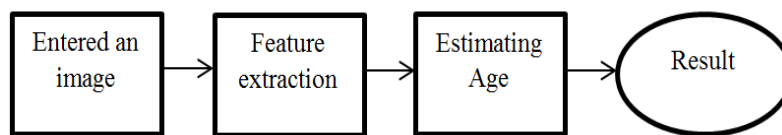


Fig 2. Age estimation framework

II. RELATED WORK

Age estimation is an urgent errand in facial picture class. The point of age estimation is to routinely mark a facial picture with genuine age (year) or age bunch (12 month range). A facial age estimation machine incorporate two key modules:

- 1) The way in which facial photo is represented and
- 2) Learn how to estimate its age notably based on the representation[5].

There are numerous strategies have been exploited for face picture representation. Know and Lobo[6] proposed an Anthropometric model. This model construct absolutely with respect to the craniofacial change idea and facial skin wrinkle assessment. The progressions of face shape that are identified with development are measured to sort a face into one of the age group. This model probably worthwhile for younger, but is not reasonable for adults. At that point Lanitis et al.[7]proposed an active appearance model. AAMs manage all ages. It truly works in a way that thinks about not only the geometry of human face, as well as its texture also. In this way the age of somebody can be assessed more adequately. As opposed to the use of each face picture independently aging pattern subspace model uses a progression of facial aging framework. This thought was created by Geng et al. [8]that is called AGingpattErn Subspace (AGES). In the spot of taking in the novel aging design for all individuals, Fu and Huang [9] found a typical aging sample for some people through manifold learning. Chen et al.[10]examined another summed up multi-ethnic face age estimation strategy and utilizations the least angle regression (LAR)[11] for feature extraction. Later, Guo et al.[12]Investigated the biologically inspired features (BIF) for human age estimation from face pictures and utilized new operator STD for evaluating age. Guo and Mu [2] used kernel partial least square (KPLS) regression to at the same time decrease feature dimensionality and learn the aging features for age estimation. Shan[13] purposed Adaboost to pick up information about local discriminative features and connected support vector machine (SVM) classifier to examine age. Yang et al.[14]enlisted a rankboost technique for feature selection that takes age estimation as a ranking hassle.

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III. THE PROPOSED ROBUST AGE ESTIMATION ALGORITHM

The determination of this work is to evaluating the human age exactly on big datasets and performing the age estimation project on single picture. The most essential strides in age estimation are distinguishing the face in a picture, removing the components or extracted the features and estimating the age of the face. The local elements and global components are joined together to accomplish a more exact model. The global components included are AAM, face edge, distance and proportion. The local features included are wrinkles and composition.

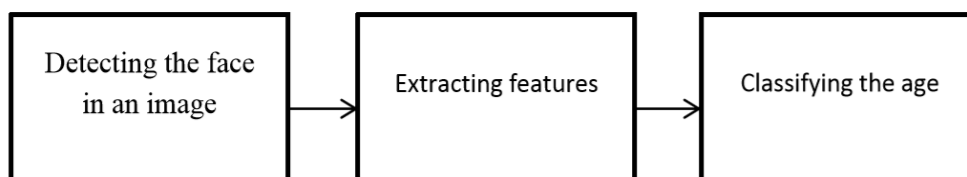


Fig 3. Major steps involved in age estimation technique.

Determination of Tool for Feature Extraction

The various approaches utilized for facial feature extraction are Principle Component Analysis (PCA), Local binary patterns (LBP), Histograms of Oriented Gradients (HOG) and Discrete Cosine Transform (DCT). Here, we are investigating the execution of the two techniques specifically, PCA and DCT. Examine the framework by first training the set for particular no. of pictures and after that examining the execution for the two techniques by computing the error in these two strategies. This work indicated and tested the PCA and DCT transformation methods. In our proposed work we utilize DCT procedure for feature extraction.

PCA is a procedure which includes a technique which numerically transforms number of presumably related parameters into littler number of parameters whose qualities don't change called principal components. DCT is an invertible linear become which states a finite sequence of information facets as a sum of cosine features. Transformation of common signal to frequency area and vice versa is possible via DCT and inverse DCT. 2d-DCT defeats the difficulties such as brightening points, face occlusions, hues and pose. DCT is broadly utilized as a feature extraction and compression technique in different applications because of its properties, for example, decorrelation, vitality compaction, detachability and orthogonality. DCT strategy represents regional areas of a picture. It retrieves facial facets from more than a few frequency bands i.e minimal, medium and highest frequency bands. It is data independent model and practice of consultant set of training information set is just not required. DCT gives frequency information which can be used in taking charges in facial appearance[15]. In comparison with different input unbiased transforms, DCT has the advantages of packing probably the most valuable information into the fewest coefficients, introducing simplest a small error within the reconstructed picture. Moreover, DCT algorithms are typically more efficient than different transforms. In specified, the DCT turn into presents countless advantages over PCA, including producing great quality pictures at compatible compression ratios and the ability to participate in in real time situations as a result of its computational efficiency. Also, unlike the PCA turn into, which determines the most consultant eigenvectors dependently on the set of photographs, the DCT foundation is independent of the set of images.

General framework of proposed work

Broad investigations are led on the FACES dataset, Images of Groups dataset, and the FG-NET dataset to demonstrate the force of proposed calculation, in the examination of existing age estimation calculations. Firstly, pick one dataset out of these three datasets. At that point, load dataset and assess PLO and DCT classification.

Algorithm level design: The steps for calculating accuracy in age estimation are explained below and shown in fig 4.3.

Step 1: Start the process of age estimation system.

Step 2: Load matfile. and Choose one dataset out of three datasets (FACES dataset, FG-NET dataset, images of group).

Step 3: Get the information of total number of images and Load the dataset.

Step 4: Read all the images that are positioned in the selecting dataset.

Step 5: Facial features are extracted by using discrete cosine transformation (DCT).

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Step 6: Split the data into train and test dataset. A training set is a set of data used to determine hypothetically predictive relationships. A test set is a set of data used to assess the strength and utility of a predictive relationship.

Step 7: Train with PLO classifier.

Step 8: Test with PLO classifier. Firstly, investigate the system by first training the set for specific no. of images then, investigate the test data and calculating the error in both data.

Process of estimating age on single image

This work is an age model variant of visual facial model of a specific age or race. Creating age models has been utilized to characterize salient features of a specific age. Firstly, every picture is gone to the framework to pre-process the picture with the goal that they can be the database. After that the frontal face landmarks are distinguished of each picture like face, mouth, nose by utilizing viola-jones algorithm and afterward, extracted the features point such as Haar-like elements, geometric elements and wrinkle features. After extracting the features, training dataset is made by utilizing them, which is then gone to the classifier to train it. After that, test dataset is gone to classifier which then predict the human age.

1. Input Image: To identify the age and race preferone face image.
2. Converting of RGB image into the Grayscale: Grayscale transformation is the main task of image pre-processing that includes the transformation of color or RGB image to grayscale image .Fuzzy Histogram Equalization is applied, fuzzy statistics used in digital images for their representation and processing in the fuzzy area which allows the system to handle the approximation of gray level values in a better way for better presentation.
3. Face Detection and Face Normalization: The following stride in the age estimation framework is to recognize the frontal face in an input image. Identify the face within an image is considered as face detection system in our method based on the concept of Viola-Jones algorithm. After face detection face normalization process is applied on facial image
4. Feature Extraction:Subsequently, Geometric features and wrinkles features (detected by the canny edge detection algorithm) have been for the extraction of features. The method based on features uses all the information contained in an image and uses that data as a set of features for detecting the image.
5. Classify the age and race: After, the feature extraction the age and race can be predicted.



Fig 4 Results on single image

IV. EXPERIMENTAL RESULTS

Presently in nowadays, the systems administration or online networking are the main parts of the assets. Internet searcher, for example, Yahoo, Bing, and Google and so forth can identify more assets as indicated by the need. Moreover, clients on long range interpersonal communication locales are mostly the youths. For this reason, in the proposed model, dataset of facial pictures have been gathered from web utilizing web search engine and in addition self-construct database of facial images is used. For this work, it has been documented that dataset is huge, so a random division of dataset for training and testing determination ensures the accurate estimation. For an example, division can be 60% data as training set and residual data as testing set. For implementing the proposed technique, we investigate the performance of the proposed technique on three public accessible datasets that are FACES dataset, Images of Group dataset, FG-NET dataset Evaluate those methods on the basis of Mean Absolute Error (MAE). The MAE is utilized in most of the papers. MAE is described as the average absolute errors among predicted and real or actual age. The algorithm becomes more accurate when the MAE value is lowest.

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Experiment on the FACES dataset

This dataset suggested both the age and facial expressions with ground truth labels, which is first acquainted in [5] for reviewing the human age estimation under different facial expression. The proposed method applied on 714 face images. For feature extraction DCT technique is used instead of PCA. Table 1 shows the greatest experimental outcomes of PLO method and proposed method, as well as the corresponding optimum numbers of the selected features that are listed in the brackets of the first column. Table 1 show that the proposed method achieves the best performance.

Table1 MAE comparison of PLO and Proposed method

Method	MAE
PLO (150 dims)	8.16
Proposed(150 dims)	3.04

In directive to observe how the performance is influenced by the number of the selected features, we plot the curves of MAE against the number of the selected features shown in Fig. 5

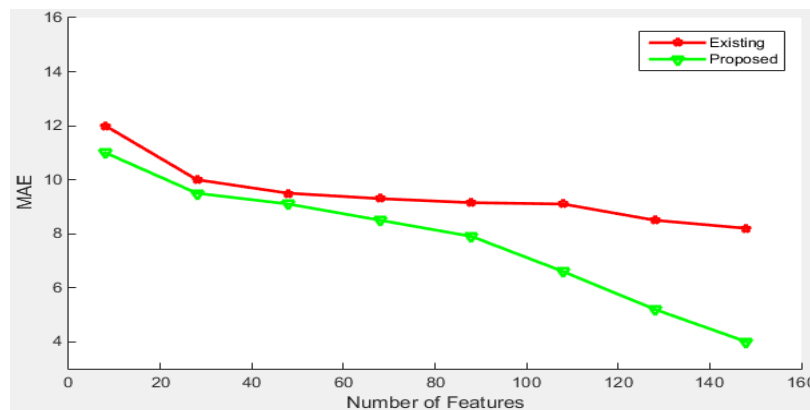


Fig 5 MAE versus number of features on the FACES dataset

We also compare proposed method with some other existing method as shown in table 2. Our proposed method attains the best performance among all the feature selection methods

Table 2 MAE comparison of various feature selection algorithms on FACES dataset

Method	MAE
Adaboost (150 dims)	12.85
Laplacian Score (150 dims)	10.73
FS-ED (150 dims)	10.61
PLO (150 dims)	8.16
Proposed (150 dims)	3.04

Experiment on the Images of Groups dataset

Images of Groups dataset comprises of 28231 faces from 5080 Flickr images, which has been generally used for age range estimation [5]. Seven age groups are measured: 1) 0–2, 2) 3–7, 3) 8–12, 4) 13–19, 5) 20–36, 6) 37–65 and 7) 66+,

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roughly equivalent to different life stages, which are separately labelled as 1,2,...,7. Each face image is normalized to 61×49 pixels based on eye centre. The facial images are downloaded from internet; the quality of many of them is tremendously low. We thus pick out 1910 high quality images used for the experiments. For feature extraction DCT technique is used as a replacement for of PCA. Table 3 shows the greatest experimental consequences of PLO method and proposed method, as well as the equivalent ideal numbers of the selected features that are recorded in the brackets of the first column.

Table 3 MAE comparison of PLO and Proposed method

Method	MAE
PLO (150 dims)	0.864
Proposed(150 dims)	0.333

Fig 6 shows how the performance is influenced by the number of the selected features; we plot the curves of MAE against the number of the selected features.

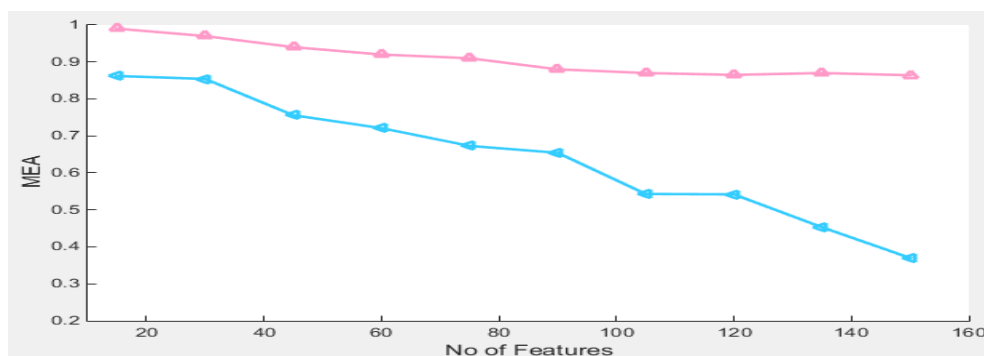


Fig 6 MAE versus number of features on the Images of Groups dataset

We also relate proposed method with some other present method as shown in table 4. Our proposed method achieves the best presentation amongst all the feature selection methods.

Table 4 MAE comparison of various feature selection algorithms on Images of Groups dataset

Method	MAE
Laplacian Score (150 dims)	0.926
Rankboost (150 dims)	0.911
PLO (150 dims)	0.864
Proposed (150 dims)	0.333

Experiment on the FG-NET dataset

The FG-NET aging dataset encompasses 1002 face images with large dissimilarities in pose, expression and lighting, which is a standard dataset for reviewing age estimation. There are 82 subjects in total with the age ranges from 0 to 69 years old [5]. Table 5 shows the ultimate experimental significances of PLO method and proposed method, as well as the comparable finest numbers of the selected features that are documented in the brackets of the first column.

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Table 5 MAE comparison of PLO and Proposed method

Method	MAE
PLO (150 dims)	1.306
Proposed(150 dims)	0.945

In order to inspect how the performance is influenced by the number of the selected features, we plot the curves of MAE against the number of the selected features shown in Fig.7 the proposed method outperforms then the existing method.

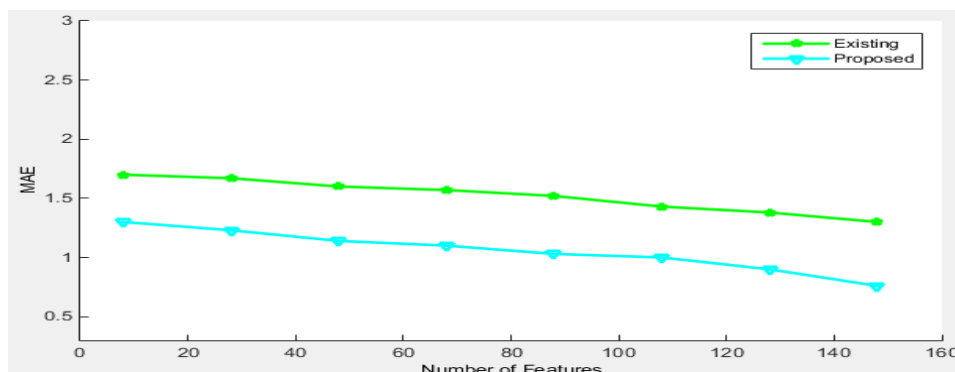


Fig 7 MAE versus number of features on the FG-NET dataset

We also relate proposed method with some other existent method as shown in table 6. Our proposed method accomplishes the best performance amongst all the feature selection methods.

Table 6 MAE comparison of various feature selection algorithms on FG-NET dataset

Method	MAE
Adaboost (150 dims)	1.652
Laplacian Score (150 dims)	1.654
Rankboost(150 dims)	1.400
LAR (150 dims)	1.429
PLO (150 dims)	1.306
Proposed (150 dims)	0.945

V. CONCLUSION

In this work, we examined the developing region of artificial intelligence technique combination with the image processing that is age estimation. Age estimation procedure works with multiple classifiers. So, the intention of our work is to decrease Mean Absolute error (MAE) and enhancing the age estimation framework in most ideal way. We introduced a DCT technique for feature extraction. In DCT, the proportions between facial landmarks and the wrinkles on the face are determined. The information about the relations between facial feature points and the wrinkles are extracted with the DCT features of the face that may support for predicting the human age from facial photograph. In

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the case of human age estimation we required to preserve minute features because of large data should be processed very fast and having low complexity. Therefore, DCT is great decision for the calculation on the grounds that DCT is extremely effective for square information pictures and don't loss any pertinent information. The power of proposed algorithm is compared to the state-of-arts. It produces results almost 70% efficient then existing technique. We also work on single image. We may effectively build a real time age estimation system that predict the age and race for any real image directly downloaded from web. From the experiments and summons encountered in this research, it has been able to observe some of the certain aspects that could not be accomplished within the extent of this work and therefore these can be suggested for the future work. our proposed work not deal with real time application .so in future make it dynamic age estimation system and for single image in future we can deal with more parameters such as gender, group prediction etc. and achieves higher accuracy.

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