Age Estimation using Facial Images: A Survey of the State-of-the-art

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***Abstract* - Age Estimation plays a significant role in manyapplications such as security control, multimedia communication,human computer interaction, and surveillance. Age estimationis a process of determining the age of a person using hisbiometric features. It is a challenging problem to effectively andautomatically estimate ages of human. In this paper, we providean overview of current state-of-the-art of the researchin age estimationfrom facial images. Furthermore, a comparative study and critical analysis of the existing andrecent algorithms is conducted. Hence the research gaps are identified for futurework in age estimation problem.**

Keywords—Age estimation, Feature Extraction, Biometric Features.

I. INTRODUCTION

Age estimation is an important task in facial image classification.

Age estimation is a process of determining the age of a person using his biometric features[1]. The age definition by computer based on persons appearances called age estimation.

The appearance of age is nearly close to the actual age. The aim of age estimation to estimate age closely to appearance as possible. Age classification from facial images has a series problem because the age of human differs based on many aspects which may be internal or external factors. Internal factors contract age include gender, genetic, etc. on the other hand, the external factors which affect the age include lifestyle, drugs, etc. those factors could make it problematic to frame the human growth pattern[2]. In the automatic age classification, the main aim is to improve a scared algorithm which allows classifying the age based on features extracted from facial images. The accurateness level is on the main challenges of the age classification which is caused by the difficulty of the human aging pattern. So it is not sufficient to classify the human age, but also important to predict it as surely as possible. Another problem related to the age prediction is the age groups range and this limitation is a key factor as different characteristics of aging pattern appear in different groups. Therefore the system got trained to cope with definite range might not be suitable for a various range of age group[2].

The age estimation problem presents extra unique challengesthat contain [11]:

1) Dependence on external factors: Some external factors affect the age estimation process include psychology, health conditions, and lifestyle.

2) Limited interage group variation: Sometimes finding differences in the appearance is challenging task for adjacentage groups, this leads to difficulties in estimating ages. Thisdifficulty is increased when dealing with mature subjects.

3) Data availability: Developing accurate systems for ageestimation needs the availabilities of suitable datasets fortraining and testing. These datasets must consist of manyimages for the same subject covering a wide range of age.

Collecting such datasets necessitates images taken from thepast. The currently available datasets FG-NET and MORPHthat support facial aging experimentation have a limitation thatthe FG-NET database consists of images showing significant non-aging related variation and the MORPH database consistsof for each subject only little samples.

*4) The diversity of aging variation:*Facial wrinkles amountmay differentiate between individuals related to the same agegroup. As a result of that for different groups of subjects,different approaches for age estimation may be needed.

The remaining of this paper is structured as follows. InSection 2, the literature review is introduced. In Section 3age estimation models for facial representation in order toextract useful features are described. And section 4 concludesthe paper.

II.MOTIVATION

There are several known world applications that deal withfacial age estimation directly or indirectly. If we need to labelsomeone with age instead of his identity it is useful to use ageestimation through the automated system.These are some examples of the applications:

1) *Age-based retrieved for image faces*: Depending on basics of age, an indexing in the database of face images can be done.it seems useful in recalling of images based on an age, for example, to discover what percentage of teenagers prefers laptops over desktops[4]

2) *Security Control*: To identify a user's face is the easiest biometric trait to be used in Security Systems. Face recognition is commonly used to secure private systems from unauthorized users. The quality of security provided by face recognition systems is hindered by time which is the only obstacle. This can be reduced by the combination of facial age estimation and face recognition [4]
3) *Forensic Art*: The knowledge of the shape of faces, aging of the human body, psychology, perception is the forensic art. In this art a basic practice is that; changes in face age progression are projected in the photograph by automated systems or artists to include age effects. Forensic artists use age estimation by automated systems to draw face sketch for lost person identification and to find possible suspects [3]
4) *Surveillance*: These days surveillance monitoring is considered as one of the difficult tasks comparing with the easily accessible information. Immature cannot be allowed to enter mature places or use tobacco by using monitoring camera and age estimation. Also, children are forbidden to access adult websites by the same way [3]

III. AGE ESTIMATION MODELS FOR FACIAL

Facial representation has many different models to extractuseful features for age estimation purpose. They are recognizedin [1], [3], [12], [30], and [31] which are:
1. Anthropometric Model Active
2. Aging pattern subspaceModel
3. Aging Manifold
4. Active Appearance Model

A. *Anthropometric model:*

This model measures the sizes and proportions of human faces.
. It consults research associated to the growth anddevelopment of craniofacial. Theory of Craniofacial researchdeals with a mathematical model to describe the head of theperson from birth to adulthood [1]. Farakas [32] provideda facial anthropometry overview. Facial anthropometric isdefined as measures over 57 facial points and landmarksat different ages from infancy to adulthood. Using thesemeasures, computational methods can be developed to makeface characterization at different ages.
Anthropometric model is focused on the human face rations, as shown in Figure 1.
This model is doing well with the people classification inand minors, but it provides bad results in estimating adults' ages.It is suitable foryounger people. It concerns only on geometry of face, noinformation of texture is taken [1].

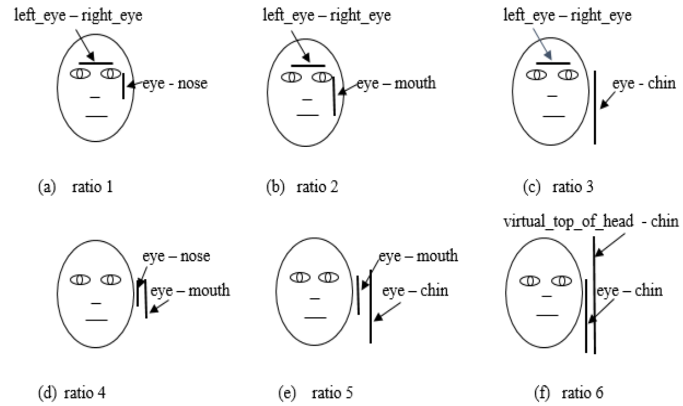

Fig. 1 Ratios on human face [30]

B. *Aging pattern subspace model:*

This model uses a series of facial images instead of usingimages separately to model the process of aging. These imagesare sorted by time. This model is calledAging pattErn Subspaceit (AGES). It involves of two phases. The first phase is thelearning phase, the second phase is the age estimation phase.
In the first phase, the subspace representation is gained usingthe PCA. It differentiates from the standard PCA in that noimages for each aging pattern for each year are founded. Forthat reason, a method of iterative learning is used which is EM
(Expectation-Maximization) to reduce reconstructions error.
This error is the difference between the face reconstructedimages and the available images of the face. In the secondphase, the test image requires to discover a pattern of agingthat suits the test image, and the exact estimated age of aperson for the sample. The importance of the AGES is theuse of images for the human at different ages to get the agingpattern [1][3].

C. *Aging manifold:*

This model learns the age pattern for more than one humanin diverse ages instead of learning it for each human. Morethan one image for each age is used to represent the age. Itis flexible and better than AGES model because a numberof facial images can be used for each person in single ageor age range. It is also easier to gather a greater number offacial images (samples) and construct a bigger database. Amanifold embedding technique is used in this model to learna low-dimensional aging trend of the same age for severalface images. The size of the sample for this model must belarge enough which helps the embedded manifold to get thestatistical sufficiency. [1]

D. *Active Appearance Model:*

Cootes et al. [33] proposes the active appearance model
(AAM) which is a statistical model used for facial imagerepresentation. A set of landmarks that labelled manuallyare used to encode the structure of the face, like facialcontour, mouth, nose, eyes, and so on. Then PCA is

appliedto those landmarks to find the shape representation. To gainthe representation of every new face the AAM models canbe used for new images. The AAM can be applied to diversetasks of face processing and it is a general method for faceencoding [3].

IV. RELATED WORKS IN FACIAL AGE ESTIMATION

In the recent years, many efforts have been devoted to ageestimation study for the human images [1]. A good starting point to explore estimating ages from facial images is the survey paper on Human Age Estimation using Face Images by Petra GRD[1]. Facial aging is divided into two stages in ageestimation, the first one is from birth to adulthood and thesecond is the time from the end of growth of old age, whichmost changes in the first phase while the main changes inthe second one are changes in skin texture because the skinbecomes darker, thinner more leathery and less elastic.

During craniofacial growth the size of the face becomelarger .and during the adult aging the changes of shape stillcontinue, but fewer dramatically due to typical patterns intissue and skin [3]. Facial representation has many models,which are: Anthropometric Model, Active Appearance Model (AAM), Aging Pattern Subspace and Age Manifold. AnthropometricModel consult studies in craniofacial theory, whichuses a mathematical model to define the persons head growthfrom infancy to adulthood. While the active appearance modelis a statistical model for facial image based on the principalcomponent analysis. An aging pattern is declared as a seriesof personal facial images for the same individual. At AgeManifold common pattern or aging, the trend can be studiedformany persons at different ages. The major two phases in the age estimation process are featureextraction and classification. Intensity encoding features,Bio-inspired features, Local Binary Pattern(LBP), Linear Discriminant Analysis (LDA) etc. are the common methods forfeature extraction[4]. Feature extraction is the most significantpart of the age estimation process. A great number of featuresextracted lead to having lower Mean Absolute Error (MAE)for researchers. The classification process contains two phases,training and testing to predict ages. There are three categoriesof facial features which are local features, global featuresand hybrid features. Global features consist of the wholecharacteristics of individual like gender, identity, ethnicity andexpression along with characteristic of aging. Global featuresgive well information about person characteristics such likethe shape and the appearance of the face compared by thewrinkles and skin.

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Local features do better with age groups than the individuals [5].for that reason they classify facial images into age groups.

Local features contain features like hair, wrinkles, skin. Localfeatures do better with age groups than the individuals. For thatreason they classify facial images into age groups. Hybrid featureis a combination of local and global features. They wereproposed using a hierarchical face model through constructinga number of features containing AAM, hair, wrinkles, skin andface configuration features.

There are three methods that can be used to learn theaging function which are: regression, classification, and hybrid [6]. Classification is used when each age label is consideredas one class. Many classifiers can be used such as SVMs, KNNs and artificial neural networks (ANN). We can view ageestimation also as a regression problem because the age labelsare continuous numbers. To learn the aging function several regressors can be used such as a multiple linear regressor andthe quadratic function for regression. Also to know which isbetter using regression or classification we can compare themon multiple datasets empirically and take advantages of both [7].

The formulation of suitable metrics for evaluating the performance of age estimators is a significant aspects of the age estimation problem [34].The Mean Absolute Error (MAE) is the most commonly used error metric between actual and estimated ages of faces in a test set. The use of the cumulative score (CS) also is proposed by Geng et al. [35]. CS presents the percentage of cases in the test set that its age estimation error obtained is less than a threshold. It is considered as a more representative measure relative to the age estimator performance. When the age-group estimation is considered, for performance evaluation purpose a percentage of correct age-group classifications can be used [34].

Recently available datasets that can be used for classificationor age estimation are: MORPH Database, Fg-net AgingDatabase, AI-R Asian Face Database, LHI Face Database,YGA Database, HOIP Face Database, PAL database, WITDB Database, Burt’s Caucasian Face Database, Iranian Face Database, Gallagher’s Web-Collected Database and Ni’s Web-Collected Database [7].

An overview of the method of a new database creation forclassification and age estimation is provided[7].

The newproposed database ageCFBP can be also used for genderclassification or face recognition. When comparing the Fg-netdatabase with ageCFBP, the results show that the ageCFBPdatabase has more subjects while the Fg-net database has awider age range. An approach is suggested for age estimationwhich uses biometric ratio and wrinkles analysis for facialimages. The methodology is independent of race and colorby using the ratio instead of distance. This shows that it iseasier to predict the lower age group than the older ones. Thisapproach has limitation such as its failure when the foreheador other wrinkle areas are covered with hair [8].

A fast age and gender estimation system for facial images isdeveloped [9]. Principal Component Analysis (PCA) methodand geometric feature based method are used to extract Features.Then a KNN classifier is used for classification phase.The results illustrate that better age estimation and genderclassification.

Various methods for age estimation are investigated. Anda new model is proposed for age estimation using a groupof features that extracted from facial images through manyalgorithms which are active shape model, local binary patterns (LBP) and the histogram of oriented gradients

(HOG) [10]. three age groups are used to estimate ages: child, adult,senior. In classification face K-nearest neighbor (KNN), gradientboosting tree (GBT) and support vector machine (SVM)are used. The FG-NET aging database is used to evaluate theproposed model. The results obtained show that 82% success rate is gained when using the GBT classifier.

Principal Component Analysis (PCA) is used to predict age

[11]. 7 different groups for ages have been divided for facialimages from 10 to 60 years old. The feature extraction is donethrough principal component analysis (PCA) method and thegeometric feature-based method. The results indicate that thesystems performance in age prediction is 92.5%. There is a limitation in predicting ages for people wearing glasses, have disappearance of wrinkles and make modification of eyebrows by makeup.

A biologically inspired features (BIF) has been investigatedto estimate human age from facial images. Gabor filters pyramidhave been used as previously in bio inspired models at allimage points for the S1 units [12]. They found that using pre-learnedprototypes of S2 layer which is then developed to C2did not do well for estimating ages. Gabor filters are used withsmaller sizes. A new operator named STD has been proposedto encode the faces ages. The evaluation is done based on twodatabases YGA which has 8,000 facial images and FG-NETdatabase which is public and available. The results indicatethat their method improve the accuracy of age estimation overthe state-of-the-art methods.

A system for estimating age in groups is proposed [13]. Thesystem is designed for the gray-scale images. They categorizedall images into four groups: babies, young adults, middleaged adults, and old adults. The system process consists ofthree phases which are location then extracting features andfinally classifying ages. They determine the position of noses,mouth, and eyes using region labeling and the operator ofSobel edge based on the gray levels variation and the humanfaces symmetry. Then they obtained three wrinkle features andtwo geometric features from the faces. Finally classification isdone by neural networks. Two classifiers are used, the first oneused the geometric features to decide if the image is belong tobaby. If the facial image didn't belong to baby, then the anotherclassifier use the wrinkle features to categorize the facial imageto one of the other three groups. The experiments is madeon database contains 230 facial images. 115 of the imagesused for training and the other images used for testing. Timeused for classifying image was 0.235 second. The experimentresults show that the accuracy of the system is 81.58

A novel framework for estimating ages is developed basedon the manifold analysis of facial images [14]. They applythe learning methods of manifold to get a sufficient embeddingspace. Also they use a function of multiple linear regression tosolve the low-dimensional manifold data. The results indicatethat the framework was very effective. The experiments wereon a large dataset of images.

A system based on the method of the bio-inspired features (BIF) for age estimation is presented [15].BIF has been combined to the Active Shape Model (ASM).Then fine features from facial images are extracted to make the experiments. The MORPH and FG-NET benchmark databasesare used for evaluation purpose. Their algorithm gives higheraccuracy than other methods. Their future work will be inusing the Active Appearance Model and Gabor functions.

A framework is presented for facial age evaluation centeredon joint of single age evaluators [16].Experimental and mathematical proofs show, if the individual age evaluators are varied in error, and so to advance the outcomesthe ensemble age estimator can be made using the best selected individual age estimators. It is accentuated that despite the neural networksdone to show the experiments, the suggested context is readilyrelevant to any other regressor.

A classified method is suggested for estimating age automaticallyand an investigation of how aging affects single facialmechanisms is offered [17]. Investigational outcomes on the FGNET,MORPH Albums, and PCSO databases display that noseand eyes are more revealing than other facial mechanisms inestimating age automatically. Human observation capacity forestimating age is assessed using gathering obtained data gainedvia the Amazon Mechanical Turk service and paralleled withthe presentation of the suggested automatic age estimation.The presentation of the planned age estimation approach isshown to be better than or equaled to the age estimatesdelivered by individuals on FG-NET and a less subsectionof PCSO database record. We however report a paralleledpresentation to the finest recognized outcome on MORPHAlbum2 and organize so without looking at the benefits ofthe real demographic info delivered with the database, yetthe combination of per-component age estimator showed nobenefits on the MORPH Album2 and PCSO databases. Thefuture work will be done through investigation approaches todevelop our accuracy detecting key point automatically.

Two novel approaches have been presented in this paper[18]. the first one is a simple effective descriptors fusionbased on local appearance and texture. And the second oneis a scheme of deep learning to estimate accurate age. The two approaches under multiple settingsareevaluated and the experiments are done on two big databases, which are FRGC and MORPH. Experiments show better results compared by the previous works.

A system has been implemented to prevent children from accessing the materials or contents of adults in the internetand stop young children from buying cigarette, alcohol, etc. [19].All the images are preprocessed and filtered to get good results. Viola-Jones algorithm is used to extract features.And the KNN classifier is trained and tested through theextracted featuresin the final stage. The results show that the K-NN classifierworks better than other classifiers for the age-group prediction.Their future work will be in creating Indian Aging Databaseand using it.

The methodologies in each phase is analyzed which producebetter results [20]. Discrete Cosine Transform method works better in extracting local and global features for facial images as founded.Extracting global features help in recognizing the age groupclassification. HOG, LBP and DCT Mod2 methods are usedin feature extraction stage. Then a comparison is done againsteach other. Results indicate that DCT method provides betteraccuracy. The key challenge was finding the best featurescombination (angle, distance and ratio).

Age Estimation method named Global and Local feature based Age estiMation (GLAAM) is introduced which relyon local and global features [21]. Active Appearance Models

(AAM) is used to obtain the global features while regional 2DDCT(2- dimensional Discrete Cosine Transform) is used toextract the local features. After that global and local features ofthe images are combined together. The FGNET aging databaseis used in the experiments. Results display that GLAAMworks better than existing methods. GLAAM can be improvedby using Principal Component Regression, as it combines

Regression and PCA in the same stage.

For age feature extraction a new framework is built which isbased on the deep learning model. They use the convolutionalneural network (CNN) to estimate ages [22]. As a comparisonbetween their model and existing models, feature mapsgained from different layers are used for age estimation asan alternative of using a feature gained from the top layer.

Furthermore, for their proposed scheme they incorporate thealgorithm of manifold learning. This significantly increases theperformance. Also the deep learned aging pattern (DLA) isused to evaluate different regression and classification schemesfor age estimation. Their results based on two datasets indicatethat their approach is better than the state-of the-art significantly.

In human age estimation, a novel kernel method to createstatistics of local binary pattern is proposed for facial images[23]. Their main work contributions consist of evaluating a pose correction method by using a simple image flipping, and usingfacial representations to compare two local binary patterns. Thetwo local binary patterns called a novel kernel density estimateand a spatially enhanced histogram. The experiments result incross- and single-database shows that that the kernel densityestimate produces better accuracy in age estimation than thespatially enhanced histogram. The constructed system for ageestimation gives better performance beside the state-of-the-artmethods.

A method for subjective age estimation is proposed [24].They use facial images of people and real age. A rating scalefor the faces is experimented. Subjects are simulated throughit. The image is evaluated as seeing older than the real witha range of response. The experiments results indicate that asubjective age turns to be in negative direction (estimatingfacial image age as younger than the real age). In the futurethey plan to test objective age which is the age defined byothers as it appears to them.

A new method based on divide-and-conquer is proposedfor facial images which named fusion of multiple binary agegroupingestimation systems [25]. Firstly a several binarygroupingsystems are employed to classify age groups. Allimages have been classified to the two predefined groups. Forage estimation purpose they trained two models. The influenceof diverse age grouping systems performance is investigatedfor age estimation error and age grouping accuracy. A sequentially selection algorithm is proposed to find the lastresult of age estimation. They use MORPH2 database in theirexperiments and results indicate that the proposed frameworkachieves satisfying results.

It is shown that such aged shapes can be successfullyremoved from a discriminant subspace knowledge procedureand pictured as separate assorted constructions over thevarious process of inquiry on face pictures, the dimensionalityrepetition of the new picture space can apparently be less withsubspace learning [26]. A manifold lined reversion method,exactly with a quadratic ideal purpose can be simplified by thelittle dimensionality to display the diverse space symbolizingthe discriminative assets. A treating like this has been assessedby wide imitations and matched with the state-of-the-art procedures.

Investigational outcomes on big scope aged databaseprove the value and strength of our future framework.

In [27] accuracy of binary classification has been improvedwhen using the Kwon-Lobo papers features and two novelfeatures. Combining wrinkle analysis enhanced results of 96

A preprocessing stage for all used images is made tostrength their system [28]. This stage includes detection ofnose and eyes. Gabor filter and local binary patterns (LBP) areused to extract features for age estimation. Histograms from

LBP analysis is used for feature classification stage. FG-NETaging database is trained and results of the images trained giveaccuracy of 39.8

An effective system of age estimation is presented for facialimages [29]. The system uses 2D-Gabor filter for featureextraction. Then Multi linear Principle Component Analysis(MPCA) is used to compress the extracted features. Forclassification phase the K-NN classifier assigned the inputimage into one of the age groups. All ages are categorizedinto 10 groups. A large Indian database for facial images hasbeen developed to find the exact age. The database consists of

750 Indian images, their ages between 0 and 74. They triedto gain maximum Indian images at different ages.

V. DISCUSSION

A comparison is presented in table 1 for some of the existing and recent algorithms for age estimation problem. The table displays that theexisting methods either use local features like wrinkles or representfaces with a holistic representation. The table discussesthe techniques and database used in different papers. Classifier,results, Procs and Concs are also shown. As mentioned usingwrinkles to estimate age increases the performance of thesystems, but sometimes these systems fail because it getshigher edge density when there is hair in the forehead, whichthe system perceives as wrinkles [8]. And this provides wrongresults for ages that have been estimated. The FG-Net datasetwhich is public was used by most of the researchers for theexperiment results purposes [17, 20, 21, 22, and 27]. Another database; which isone of the largest Indian facial image dataset is developed; gives 80 percentage as determined as high result, butages are estimated in groups only and also this dataset didnot have large numbers of facial images of people at differentage [29]. Deep learning technique have been introduced andused for the first time for age estimation purpose [22] andthis increases the performance as compared by the state of thearts. The two age estimation algorithms used are classificationand regression. For classification, K-nearest neighborhood andSVM are the common methods. Still there are research gapsto improve accuracy in age estimation.

Techniques	Database used	Classifier	Results	Pros	Cons
Canny Edge Detection, Biometric ratios and wrinkle analysis	N/A	K-NN Classifier, Decision Tree, Nave Bayesian Classifier	K-NN shows better recall and precision for middle ages.	Incorporation of wrinkle increases the performance	Getshigher edge der when there is hair in forehead, which the system perceives as wrinkles.
Principal Component Analysis(PCA),Neighborhood Preserving Projections (NPP), Locality Preserving Projections (LPP),Orthogonal LPP and manifold learning	UIUC-IFP Age Database	Regression model, 4nearest neighbors	Compared with PCA and NPP, LPP and OLPP has more stable and unifieddistributions of aging pattern discriminating power against error level and dimension changes.	The first workinvolving themanifold ways of age estimation, the images have high-resolution	-------------------
Holistic BIF features,eye region BIF	The FG-NET, MORPH Album2, and PCSO databases	SVM classifiers	On FG-NET the MAE is 4.7 with a variance of 24.8, while on the PCSO data the MAE is 7.2 with a variance of 32.0	Improve ageEstimation performance by fusing different features for different age groups.	The accuracy varies when using a big sul of PCSO databases. Demographicinform is not considered.
Local Binary Patterns(LBP), Speeded-Up Robust Features(SURF), Histograms ofOriented Gradients(HOG)	MORPH dataset, FRGC dataset	Regression (Canonical Correlation Analysis(CCA) and its derivations)	The early fusion ofHOG, LBP andSURF improves overthe best MAE scorereported resulting in4.25 years compared to the 4.42.	Using a deep analysis of the different parameters for the compared feature detectors	Need larger images for their experiment which is not available
Principle Component Analysis (PCA),Local binary patterns(LBP), Histogramsof Oriented Gradients (HOG)and Discrete CosineTransform (DCT)	The FG-NET database	Neural network, nearest neighbor, KNN,hierarchicalclassifier, AGES,SVM	DCT methodprovides betteraccuracy	feature normalization enhances the contract of images	Challenge lies inidentifying the bestcombination of thefeatures (distance,ratio and angle).
Active AppearanceModels (AAM),2-dimensional DiscreteCosine Transformand PrincipalComponent Analysis	The FG-NET database	Multiple linear regression	Achievesbetter results than earlier methods likeAAS and AGES onthe FG-NETdatabase	Use global and local features of facialimages which obtainbetter performance	Did not use methods do not require normalization such a SIFT and ASIFT.
Deep learningtechniques	MORPH	SVMs, SVR, PLS and	Withmanifold	The first time	-------------------

andmanifold learningalgorithm	dataset, FG-NET database	CCA	learning,the MAE obtainedon MORPH is 4:77.	thatdeep learningisapplied forage estimationproblem	
Manifoldrepresentation, Conformal Embedding Analysis	the UIUC-IFP database	Quadratic regression	CEA shows itssuperiority for most of dimensionalityreduction cases.	CEA increase the performance	The results dependo on regression.
Wrinkle analysis,Feature based onface shape, based onthe relative areas ofeyes to the rest ofthe face.	The FG-NET agingdatabase	SVM regression	binary classificationaccuracy improved (97.84% vs.92.94%AUC). 96 % total accuracy	Wrinkle analysis pushed classification accuracy even higher	Resolution of image not high, whenthere hair in faces this appear aswrinkles which getinaccurate results
2D-Gabor filter,Multi LinearPrinciple ComponentAnalysis (MPCA)	Indian Facial ImageDatabases, GeorgiaTech Database	K-NN Classifier	Near about80% result	Develop one of the largest Indian facialimage database	Estimate age ingrou Did not havelarge numbers offacial im ofpeople at different

TABLE I
A COMPARISON OF SOME OF THE PUBLISHED METHODS FOR AGE ESTIMATION.

VI. CONCLUSION

Age estimation is an important task in facial image classification.It is the process of determining the exact age or agegroup of a person using his biometric features. Many knownworld applications deal with facial age estimation directly orindirectly like: security control, multimedia communication,human computer interaction, and Surveillance.In this paper existent and recent researches in the ageestimation field have been discussed. A lot of researchers madea contribution and still working to optimize this field. All thestate-of-the-art techniques for age estimation are presented.Along with the state-of-the-art techniques, age estimationmodels for facial representation in order to extract useful featuresare described: anthropometric model, active appearancemodel, aging pattern subspace and age manifold.There are several challenges in order to implement a robustsystem for age estimation. We identify the main challengeswhich may motivate novel investigations in the future.

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