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A Comprehensive Study on Facial Aging

A. Deepa*, **and T. Sasipraba****

Abstract: The focus of this paper is study on facial age estimation. A human face when analyzed provides various details such as age, gender, ethnicity, expression etc. Among all these aspects facial age is more difficult because though there are common signs of aging, it differs from person to person and also it is not a single domain aspect. Aging requires concentration on various regards such as geometric dimension, texture analysis, wrinkle analysis and concentration on all the facial regions. The collection of a large database is also vital. In this paper the aspects to be considered for each age group is discussed.

Keywords: SVM, SVD, AAM, MAE

1. INTRODUCTION

Today the Smart era is fully computerized. Gestures, facial recognitions are all unavoidable and have become essential. Artificial intelligence involves gesture identification and face recognition. On considering face recognition, facial age estimation is an interesting and equally challenging research. Estimation of age is required in many areas such as security control, surveillance monitoring, biometrics, age based indexing facial database, human-computer interaction etc. E-commerce and e-trading use age group criteria for better selling of products and product recommendation. Eg. Google, Amazon, Netflix.

Human aging is considered to be a process which is inevitable. In facial age identification various regards exists. The actual age of the subject, the age that is identified from the appearance of the subject and the age that is predicted by the algorithms and procedures. The challenge is that the age estimation should produce the result which is almost the actual age. The visual appearance extracts the required information so as to provide the needy features for the algorithms to the computer system to give out the actual age. The appearance of the face is very much influenced by the age of the person. Some of the factors are uncontrollable and are influenced by the personal characteristics, stress, lifestyle and also hereditary characteristics. For instance wrinkle effect may be less in some people due to here ditary, lifestyle or make up effect. Wrinkle effect can be increased in case of the image of smokers.

Age estimation involves two approaches-one generative and non-generative approach. Generative approach uses a computational model to estimate the age and uses specific recognition algorithms to facial recognition. In non-generative approaches various age invariant features are used for the recognition of the face. In all methods the accuracy can be improve only when the image is properly normalized.

2. MOTIVATION

There are so many age estimation models which produce estimation of age. The age which is produced is fairly accurate. The considerations are age group, race, gender where the accuracy depends on the own kind of the estimator's specifications. Age-based access control -prevention of minors to access some internet pages, age-specific human-computer interaction–such as adjusting text size for different age groups, Age-

* Sathyabama University, Chennai, India

** Sathyabama University, Chennai, India

based indexing of face images–photo albums, Age-invariant person identification, detecting child-pornography, law enforcement, multi clue identification, fingerprint /face age estimation.

3. OVERVIEW OF RELATED WORK

Aging is studied and analysed in various images. All the authors have analyzed the image and have classified the age under certain age groups. The major steps in age estimation involve preprocessing, feature extraction, classification and age estimation. Preprocessing is the process of removing tilt, extracting bulb area, extracting only facial texture, and resizing.

Feature extraction involves various methods such as PCA, Local Binary Patterns, Local Features, AAM, Gabor Filters, Learning Manifolds, Gaussian Process Modeling, Fusion Models and Subspace Analysis. AAM has produced more than 70% accuracy in most of the age groups. The Table.1 discusses the factors considered and the methodology used in various papers. The accuracy rate and MAE obtained are also shown. In classification, SVM, SVD, K-nearest neighborhood and Shortest Distance are the common methods. Robust regression for classification. Neural networks and also shortest distance method have produced better classification.

The various approaches used are subspace based approach, Model based approach, Machine learning approach and Image feature driven approach. The various age models are Local Appearance-based Face Recognition, Feature Selection and Feature Normalization, Face Registration by Minimizing the Closest Classification Distance, Discrete Cosine Transform-based Local Facial Appearance Representation, Generic Face Recognition Algorithms Eigen faces, Fisher faces, and Bayesian face recognition.

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Table 1
Existing Findings as per Literature Survey

Paper	*Factors*	*Methodology*	*Accuracy*	*MAE*
Age estimation from images: challenging problem for audience measurement systems-Vladimir khry aschev, Alexander Ganin, Olgaste-phanova, Anton Labedev, Yaroslavl state university	Genetic, lifestyle expression and environment	i) adaptive feature extraction (LBP) ii) support vector machine classificationDatabase:FG-NET, MORPH	84%	<7
Estimating the age of human face in image processing using mat lab-Aditi Sengupta, Piyas mondel IJECS, 2015	Texture	Preprocessing, thresholding, segmentation, edge detection, median filtering, canny edge detection(optimal edge detection)	80%	NA
A hierarchical framework for facial age estimation-YuyU liang, Xianmai Wang, LiZhang, Zhiliang wang, 2014	appearance features, (fore head, eye corner, face cheek, 68 facial land marks), Wrinkle feature (wrinkle density), shape ratio feature,	ULBP(Uniform local binary pattern), Wrinkle density (WD), LOPO testing strategy	85%	4.97
Age-Invariant Face Recog-nitionUnsang Park, Member, IEEE, Yiying Tong, Member, IEEE, andAnil K. Jain, Fellow, IEEE, 2010	Shape, texture	PCA, AAMDatabase: FG-NET, MORPH, BROWN	50-60%	NA
Face Verification Across Age Progression, Chellappa, Ramanathan, 2006	Texture	Bayesian classification, PCA	50-70%	8.5

Recognition, Feature Selection and Feature Normalization, Face Registration by Minimizing the Closest Classification Distance, Discrete Cosine Transform-based Local Facial Appearance Representation, Generic Face Recognition Algorithms Eigen faces, Fisher faces, and Bayesian face recognition.

The various Databases used are MORPH, FG-NET, and FERET. MORPH Database consists of more than 17000 images of 4000 individuals with in age range 15-68.It includes both male and female images of three different ethnicity. FG-NET (Face and Gesture Recognition Research Network) consists of 1000 images of 82 individuals in age range 0-69 with 68 landmark features. The details such as image size, age, gender, spectacles, etc are included. FERET Database includes image with variations on illumination, pose and facial expressions. It consists more than 2000 images with age separation of 18 months or more. The various works and the age group they have concentrated are listed.

4. AGE PROGRESSION

Most the algorithms provide refined age in specific age group only. This is because, the algorithms concentrates on either texture or shape or geometric dimensions. So the refinement of age is obtained in certain age groups only The age group classification is shown in Table II. Each age group requires concentration in different aspects. For the age group 0 to 10, the cranio facial aspects provide the clear age details. For age group,10-15, and 15-20, the geometric dimensions are to be considered. For age group 20-30, the texture analysis provides more details. For age group 30 and above wrinkle analysis provides clear estimation.

As age increases, the effect of age is more visible in the images as seen in Fig.1. Fig 2 and Fig 3. The signs of aging are shown in Fig 4. The skin loses resilience, and forms wrinkles. Due to wrinkles, skin color and texture changes leading to sagging faces and loss in volume. Natural changes in our skin are accelerated by sun damage, smoking, allergens, toxins, and other extrinsic lifestyle and environmental factors that lead to the development of a variety of changes. The facial bones also recede over time and lose its prominence. These changes may appear in the form of excess skin in the upper eyelids, bags and drooping under the eyes, jowls along the jaw line/lower cheeks, “turkey neck”, drooping or flattened eyebrows, receding chin and flattened cheekbones, dark circles under the eyes, thin lips, hollow temples and other depressions in the skin.

Table 2
Age Groups Considered in Literature Survey

Author /Work	Age Groups
Shan “Learning Local Features for Age Estimation on Real-Life Faces”	0-2 | 3-7 | 8-12 | 20-36 | 37-65 | 66+
Tang, Lu “Age Classification Combining Contour and Texture Feature”	<19 | 19-23 | 24-50 | 50+
Chen, Chang, Ricanek “Face Age Estimation Using Model Selection”	0-9 | 10-19 | 20-29 | …| 80-89 | 90-93 different age groups for different databases
Zhuang, Zhou, Huang, “Face Age Estimation Using Patch-Based Hidden Markov Model Supervectors”	0-9 | 10-19 | 20-29 | …| 60-69 | 70-93
Kwon, Lobo “Age Classification from Facial Images”	baby | adult | senior
Horng, Lee, Chen “Classification of Age Groups Based on Facial Features”	0-2| 3-12 | 13-19 | 20-29 | … | 90-99| 100+
Lanitis, Draganova, Christodoulou “Comparing Different Classifiers for Automatic Age Estimation”	0-10| 11-20 | 21-35 up to 35

Figure 1: Age progression

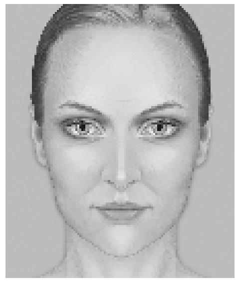

Figure 2: Young age

Figure 3: Old age

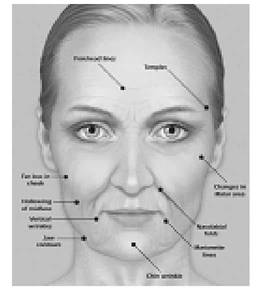

Figure 4: Signs of aging

The more visible aging signs are greater visibility of bony landmarks, lines and wrinkles, prominence of transverse forehead lines, nasolabial folds become more prominent, hollowing of the mid-face (loose skin), changes in the area around the mouth (vertical wrinkles, lip thinning and flattening), development of prejowl depression (marionette lines)

5. AGING IN DIFFERENT AGES

Aging is an unavoidable change. Aging differs from person to person. The way aging occurs can be studied from the following figures

5.1. Baby Face

In baby faces, (Fig 5.) the eyes are bigger in proportion compared to the face. The face is mostly rounded and cheeks appear plumber. The head is also larger in proportion than the face. The eyebrows are short and flat. The nose is relatively small, short and turned up.

5.2. Child face

In this age group, seeing Fig 6, the teeth are variously missing or spaced. The eyebrows are flat than the child brows. The ears appear oversized and nose appears small, short and wide. The cheeks are flatter and less defined. The baby fat is found throughout the face and less distinctive features are seen.

5.3. The Young Adult Face (16 To 25)

In the age of 16 to 25, as in Fig.7, the elasticity of the face gets reduced. The sags are formed in the cheeks and the corners of the lips begin to look frown. The eye region creates sags and drifting in forehead appears. The eyebrows drop downward and become flat. The nose gets lengthens, enlarges and moves the tip down.

Figure 5: Baby face

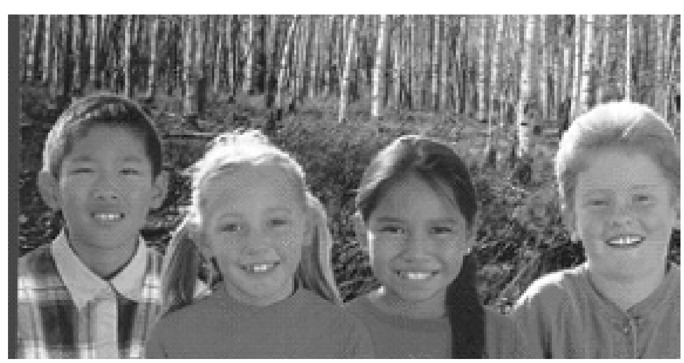

Figure 6: Child face

Figure 7: Young adult face

5.4. Age 30s

In the age group of 30s, the upper eyelids gradually become hooded. Pouches appear in lower eyelids and fine wrinkles begin in the eye region. Trace of frown lines in lower forehead and between eyes begins. Also fine wrinkles appear at outer corners.

5.5. Age 40s

In the age group of 40, the upper and lower eyelids begin to sag and creates deep-set look. The crow's feet get developed. In the forehead region, frown lines deepen, horizontal wrinkles develop. Vertical lines begin to appear and deepen around lips and wrinkling becomes more prominent

5.6. Age 50s

In the age group of 50, pouches appear in the upper cheek area and cheeks sag down and in. Horizontal lines are established and sags appear in the forehead. Vertical lines appear and deepen around the mouth. Wrinkling becomes more prominent. Eyebrows sag, causing eyelids to appear hooded and heavy. Jaw line sags, creating the impression of jowls.

5.7. Age 60s

In the age of 60s, the elasticity of the face reduces. Lines are visible in the forehead. Vertical wrinkling appears around lips. Eyebrows tend to sag and hooded appearance becomes more pronounced. The nose tip gets drooped and neck skin droops turkey neck begins to appear. The eyes appear more deeply set by the age of 60s. Eye sockets widen and become longer. The cheekbones beneath the eyes appear descending.

These are the common effects of aging in almost all human faces. The texture analysis and wrinkle analysis provide more clear age estimation. Combining geometric dimensions and this texture analysis provide good age estimation.

6. CONCLUSION

Facial age estimation is successful when age analysis is done thoroughly. In this paper, we have discussed the process of aging, how age progression differs from person to person. The common factors influencing aging and the way a face gets aging signs are discussed. Instead of concentrating on dimension, texture or wrinkle, all the aspects have to be studied with regard of the age group suspected. When the study of aging is accurate, the estimation algorithm can also provide more refined age.

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