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Age Classification using Facial Image Features in DCT Domain

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Abstract-Age estimation or age based classification can be achieved using different facial features both in spatial and transform domain. In this paper, transform domain features are used to classify facial images into appropriate age group. This paper provide technique which is helpful in classifying images efficiently using only transform domain features. This algorithm can be used in real time environment for different purposes in human computer interaction. Initially DCT cheeks' energy are used as a threshold parameter to classify images into two broader age based categories. These two main categories are further subdivided into 6 age based sub categories based on Left Cheek wrinkle energy (E-I), cheeks wrinkle energy (E-II) and forehead wrinkle energy (E-III) energy.

Keywords: Wrinkle Analysis, Age Classification, HCI, Discrete Cosine Transform

1. INTRODUCTION

Age estimation, or more precisely facial age estimation, is the task of determining a person's age based on biometric characteristics. Although age estimation can be accomplished using different biometric traits, in this paper we will focus only on facial age estimation that relies only on transform domain facial features such as wrinkle energy.

Human's faces contain various information including gender, ethnicity and age. It is a challenging problem for the existing computer vision system to effectively estimate human ages. Estimating human age via facial image analysis has lots of potential real-world applications, such as human computer interaction and multimedia communication.

Visual aspects of the human face changes considerably with growing age, which include skin texture deformation, bone growth, over all facial shape etc. (Lanitis, 2009, Rhodes, 2009). Performance of face recognition, in age progression, are less effective if it doesn't take account these facial age related changes.

Age estimation have been contemplated with some genuine applications in past reviews, for example, cosmetology, surveillance observing and biometric (Fu *et al.,* 2010, Choi *et al.,* 2011; Choi *et al.,* 2010). Age estimation is additionally utilized as a part of face recognition invariant to age movement (Zhang *et al.,* 2011, Mahalingam and Kambhamettu, 2011). Age estimation system can in like way be used to confine kids from securing liquor and tobacco from vending machines. It can be used to cutoff adolescents from getting to grown-up substance on various web pages plus it can also adjust the contents presented to a user based on her age. Age estimation methods utilizing facial pictures are fall into two principle classifications.

Firstly, age based classification is done utilizing standard classifiers after some particular facial features are assigned to an age class. Secondly, aging progression based modeling are used in age estimation methodologies. Here some of the basic work in the field of humane age estimation are discussed.

One of the first endeavors to create automatic facial age estimation algorithm was accounted for by Kwon andLobo. They use two main types of features: Geometrical ratios calculated based on the distance andthe size of certain facial characteristics andan estimation of the amount of wrinkles detected by deformable contours (snakes) in facial areas where wrinkles are usually encountered. They classify faces into three main categories i.e. seniors, adults and babies based on facial features (Khan *et al.,* 2015; Kwon *et al.,* 1999).

Sirovich and Kirby used PCA to represent facial images. They stated that facial image could be reconstructed as a weighted sum of small group of images that depict a facial premise Eigen pictures, and a mean picture of the face. Skin surface analysis methodologies transformed Skin's visual subtle elements, captured either in scanned or standard digital images, into mathematical and logical space (Sirovich and Kirby, 1987, Kirby and Sirovich, 1990). Facial isosceles triangle joining eye-eye and mouth, was used by Chiunhsiun Lin and Kuo-Chin Fan. Due to the uniqueness of this triangle for different people, it can be used in face recognition and age based classification (Lin and Fan, 2001).

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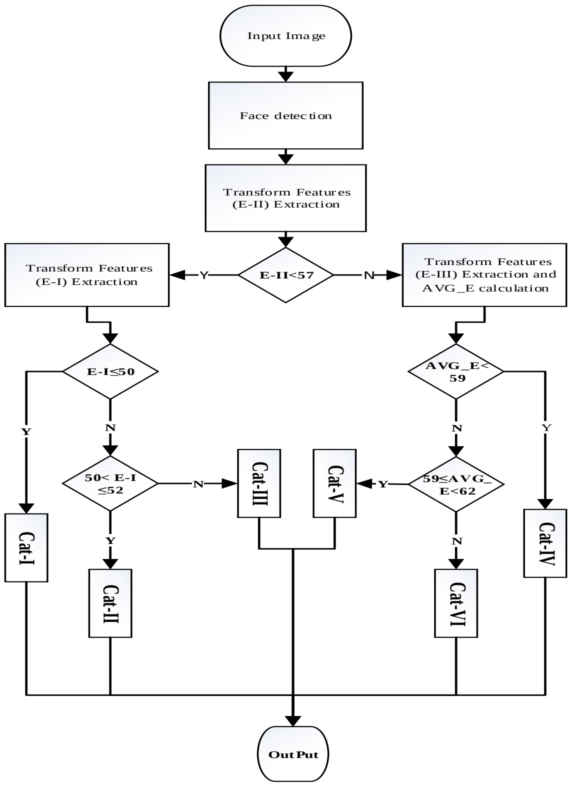


Fig. 1. Proposed Algorithm flowchart

Face angle (angle between right eyeball, mouth point, and left eyeball) and its use in age based classification are discussed by (Jana *et al.*, 2012). Based on face angle, facial images are classified into 5 age based classes which include Child, young, adult, middle aged and old. People with 17 year age or below are grouped in child class, those having age from 18 to 25 years are classified into young , 26 to 35 year old as adult ,36 to 45 as middle aged while above 45 as old.

2. PROPOSED ALGORITHM

To classify facial images into appropriate age based category, we used transform domain facial features, extracted from input facial image. We use frontal images of seize 400x400 pixels. In our proposed work, first face of the input image in detected, and then DCT based cheeks' wrinkle energy (E-II) is extracted. Now E-II is used as threshold value. If the E-II value is less than or equal to the threshold value, the dct based left cheek energy is extracted and the image is classified into C1 main category where it is further classified into one of three sub categories i.e. Cat1, Cat2 or Cat3 based on E-I. For E-II value higher than threshold, the image is classified into main category C2, where its forehead area energy is extracted and used in average energy (AVG_E) calculation along with E-II. AVG_E is then used to further classify subject into one of the subcategory i.e. Cat-IV, Cat-V or Cat-VI. This process is shown in **(Fig 1).**

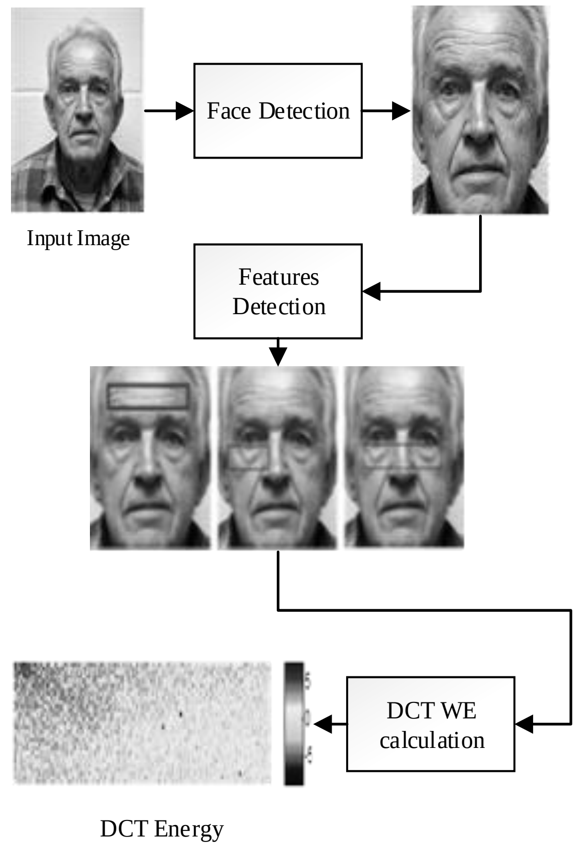


Fig. 2. Transform domain features extraction

Humans with having ages from 1 to 30 are been placed in C1 main category where they are further divided into three sub categories based on their ages. People with having age less than 12 are put in Cat-I, having age from 13 to 20 in Cat-II and from 21 to 30 in Cat-III. C2 main category contains subjects with ages higher than 30. Cat-IV, Cat-V and Cat-VI are C2 sub categories with age range for Cat-IV is 31 to 45, 46 to 60 for Cat-V and60+ for Cat-VI.

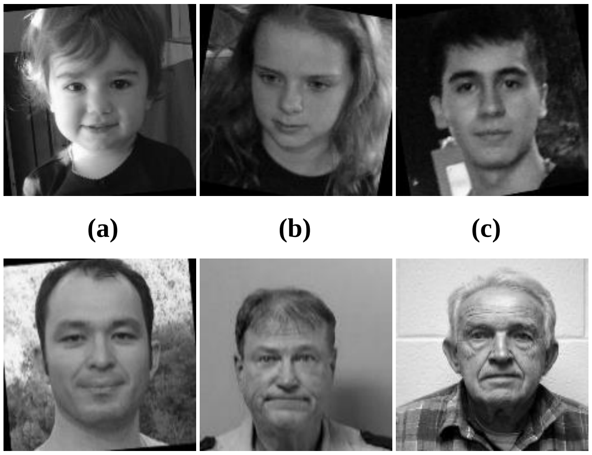
3. TRANSFORM DOMAIN FEATURES EXRACTION

We represent textures information in the form of Discrete Cosine Transform (DCT) energy. To extract transform domain features, we first detect face and then crop cheeks, left cheek alone and forehead area. After cropping these areas, we use DCT-II to find the energy contained, as shown in **(Fig 2).**

Energy contained in left cheek are represented as E-I, in cheeks as E-II and in forehead as E-III. Average energy (AVG_E) is calculated as

AVG_E= (E-II+E-III)/2.

Table 1 shows transform features values for different sample images from different categories



(a) (b) (c)

(d) (e) (f)

Fig. 3. Test images of Six different categories

Table 1. Transform domain features for different facial images

Age Category	E-II	E-I	Average _E
Cat-I	51.60	47.00	X
Cat-II	53.78	50.20	X
Cat-III	54.75	52.50	X
Cat-IV	59.62	---	57.5
Cat-V	61.38	---	61
Cat-VI	67.022	---	68.2

X- Shows don't care condition, which shows the feature doesn't contribute to classification in this category**)**

4. RESULTS ANDANALYSIS

Features are extracted using Matlab. 195 frontal face images of size 400x400 pixels are tested to extract DCT based energy features. Classification is governed by logical combination of these features, which are developed after analyzing the extracted features set. The complete list of these features logical combination decision-making is provided in **(Table 2).**

Table 2. Conditions for age groups

Age Range	Main Category	Sub Category	Condition	
1-12	C1	Cat-I	E-I≤50	E-II<57
13-20	C1	Cat-II	50< E-I ≤52	E-II<57
21-30	C1	Cat-III	52<E-I	E-II<57
31-45	C2	Cat-IV	AVG_E<59	E-II≥57
46-60	C2	Cat-V	59≤AVG_E<62	E-II≥57
60+	C2	Cat-VI	62≤AVG_E	E-II≥57

Subject facial images are classified into two main categories based on E-II threshold value. If the E-II value is less than 57db the image is classified into C1 else to C2. Further in category C1 it is classified into one of the subcategories based on E-I value. It is classified into Cat-I if the E-I value is less than or equal to 50, to Cat-II if greater than 50 and less than or equal to 52 and to Cat-III for all other values.

In C2 it is further classified to Cat-IV, Cat-V or Cat-VI using AVG_E parameter. If the AVG_E value is less than 59db then the image is classified into Cat-IV, for AVG_E value less than 62 or greater than or equal to 59 it is classified into Cat-V, and for all other values to Cat-VI.

Table 3. Age Group Classification using only E-II threshold value

Category	Range In years	Images/ Cat	Correct classified images	Class Correct Percentage
C1	1 - 30	90	85	94
C2	30+	105	102	97
Overall average				95.79

Table 3 shows experimental data when only E-II threshold value are used for classification of images into two main categories. To measure the efficiency of the algorithm, class correct percentage parameter is used. This parameter indicates percentage of images correctly classified.

Fig 5 shows class correct percentage along with number of total input and correctly classified images.

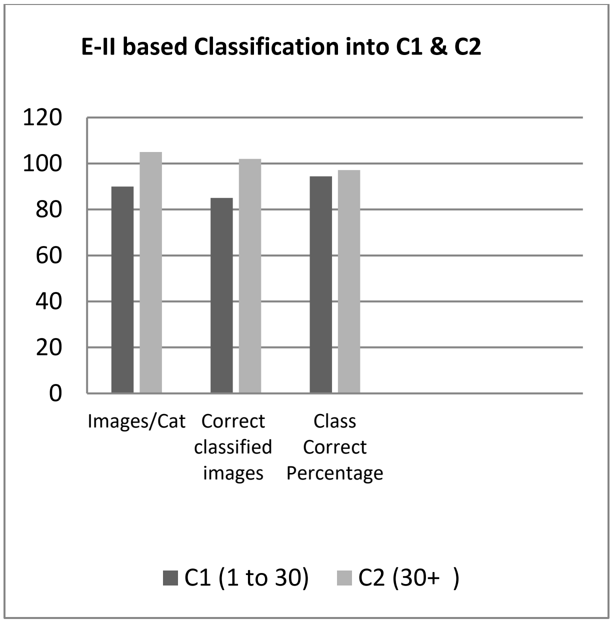


Fig. 4. Bar chart showing class correct percentage for C1 andC2

Table 4 contain experimental data regarding classification into 6 sub categories. All these classification is governed by the logical and mathematical rules shown in Table 2. Class correct percentage for each sub category along with number of total and correctly classified images are shown in Fig 5 as bar chart. Fig 6 shows the efficiency of proposed algorithm for different age based categories and shows the higher effectiveness of this algorithm for high age categories as compared to low age categories.

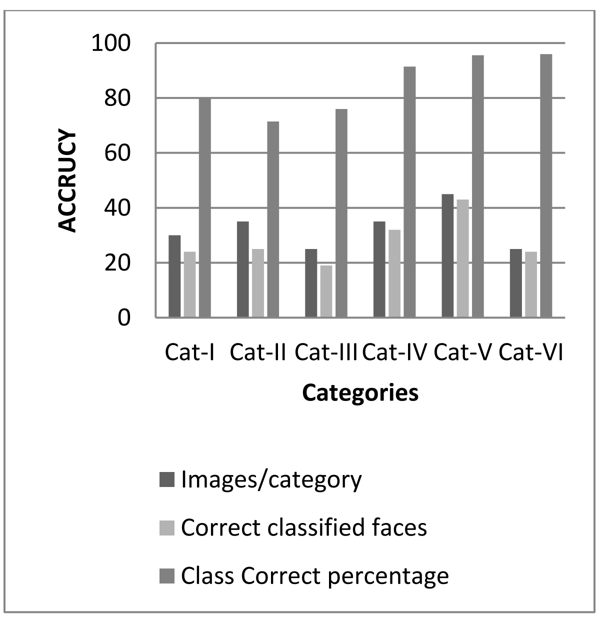


Fig. 5. Bar chart showing class correct percentage

Table 4. Complete Age Group Classification using Table 2

Category	Images/ category	Correct classified faces	Class Correct percentage
Cat-I	30	24	80
Cat-II	35	25	71.43
Cat-III	25	19	76
Cat-IV	35	32	91.43
Cat-V	45	43	95.56
Cat-VI	25	24	96
Over all percentage			83.93

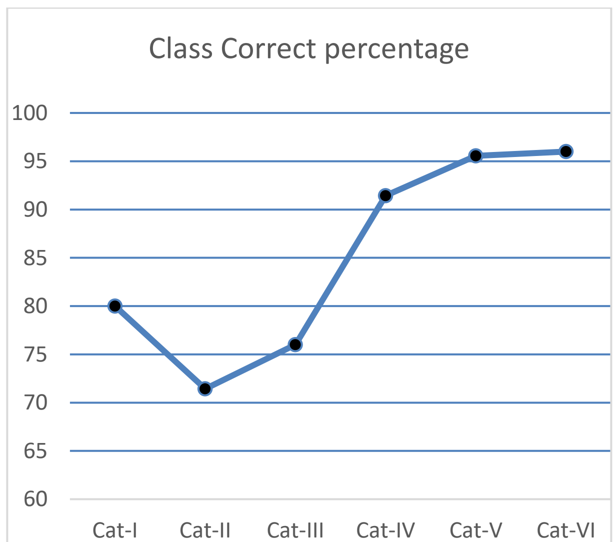


Fig. 6. Algorithm efficiency in term of Classcorrect percentage for each category

5. CONCLUSION

From the analysis, it can state that using multiple transform domain features we can classify images into broader categories. Classification based on these features in high age classes is much more accurate as compared to low age classes. The efficiency normally decreases with the increase in no of age based classes. Higher classes are classified more accurately using energy and features as compared to lower classes because facial texture deformation normally does happened at later stage of life.

In future spatial domains' features can be used along with these transform features to improve the efficiency in lower age classes. The work can be extended from classifying simple images to real time environment.

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