

AGE CLASSIFICATION WITH SHAPE PATTERNS DERIVED FROM CENTRAL PIXEL FLOODING MATRIX ON FACIAL IMAGES

P.Chandra Sekhar Reddy¹ and Bhanu Sreekar Reddy Karumuri²

Abstract- Humans can easily categorize persons into different age groups from facial images of people. The Age classification based on computer vision has widespread applications. For automatic age classification, in this paper shape patterns on Central Pixel Flooding Matrix (CPFMM) are used to classify persons with face images into two classes, child and adult. The CPFMM forms a textured image over the facial image by considering neighborhood pixels which have the same intensity as a central pixel. The shape patterns Lower Triangular Matrix Pattern (LTMP), Upper Triangular Matrix Pattern (UTMP) and Tri-Diagonal Matrix Pattern (TDMP) on CPFMM of facial images are calculated and these features are used for age classification. The experimental results on the FG-Net aging database have shown that this method is more efficient compared to other methods for age grouping of facial images.

Keywords: Age classification, Central Pixel Flooding Matrix, LTMP, UTMP, and SSP.

1. INTRODUCTION

Age estimation is an important in computer vision applications like forensic and criminal investigations, the determination of retirement age, military age, access to web services with age criteria, supervision of minors, demographics, commercial adds and so on. The Age estimation with texture feature [1, 2], contour features and texture features separately [3, 4]. An extraction of skin feature for automatic skin aging estimation [5]. Age classification methods are categorized into three categories [6]. They are an anthropometric model [3,7], aging pattern subspace[8], and age regression[9-12] categories. Recently facial emotion algorithms based on spectral features in ECG signals [13], LBP models [14] are developed. Recently various methods for age classification and age grouping are developed by Vijaya Kumar et. al.[15], Jangala Sasi Kiran et. al.[16] and Chandra Sekhar Reddy et. al.[17]. To address this problem, this paper focuses on the grouping of facial images into two classes, child and adult. The present paper considers the CPFMM of the facial image as a texture. So shape pattern based texture classification method is proposed on the CPFMM of facial images. The rest of the paper is organized as follows. In section2, proposed methodology adopted, Experimental results and discussions are given in section3 and conclusion is drawn in section4.

2. METHODOLOGY

In Face recognition and age classification applications facial image is considered as texture. To evaluate micro texture features of the face, this paper uses the shape patterns over central pixel flooding matrix computed on facial images for age classification. The central pixel flooding matrix forms a group of pixels which have the same intensity value as the central pixel over the 3x3 neighborhood. The central pixel flooding, computed on the image gathers textural information. The

¹ Professor, CSE Dept., Gokaraju Rangaraju Institute of Engineering and Technology, Hyd., pchandureddy@yahoo.com

² B.Tech Final year Student, CSE Dept., Gokaraju Rangaraju Institute of Engineering and Technology, Hyd. bhanusreekaredu@gmail.com

set of shape patterns lower triangular matrix pattern, upper triangular matrix pattern and tri-diagonal matrix pattern on this CPFM are computed.

The frequency occurrences of these features are evaluated. The different aged people facial images can have a variation of skin texture or wrinkles, this can be significantly identified with shape patterns. The proposed method for age classification consists of three steps as shown in the block diagram of Fig.1.

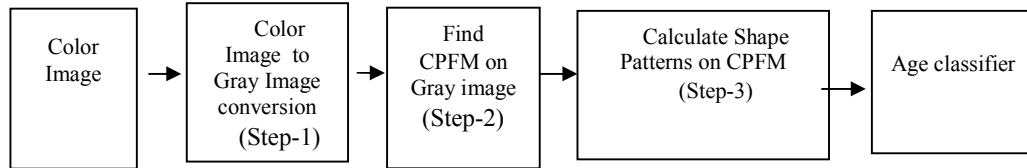


Fig.1: Age classification scheme with Shape patterns on central pixel flooding matrix of images.

A. Color image to Gray Image conversion

The original colour image is converted into a grey level image using RGB color quantization method.

B. Computing Central Pixel Flooding Matrix (CPFM)

The central pixel flooding forms a group of pixels which have the same intensity value as the central pixel over the 3x3 neighborhood. In the 3x3 neighborhood, for all the neighbors which have the same intensity value as the center pixel, then these values are kept unchanged otherwise, it is set to zero. The 3x3 block obtained from this process is called a central pixel flooding. The CPFM is computed over the whole image is described as follows.

(1) Central pixel floodings $I_1(x,y)$, $I_2(x,y)$, $I_3(x,y)$ and $I_4(x,y)$ are computed starting from pixel (1,1), (1,2), (2,1) and (2,2) respectively with 3x3 block from left-to-right and top-to-bottom throughout image $I(m,n)$ with a step-length of three pixels along both horizontal and vertical directions.

(2) The final central pixel flooding matrix, denoted by $CPF(x,y)$ is computed using equation 1.

$$CPF(x,y) = p \quad (1)$$

Where p is avg (or) avg_g

$avg = (I_1(x,y) + I_2(x,y) + I_3(x,y) + I_4(x,y)) / r$, r is the number of non-zero intensity values.

avg_g = a value which is just greater than avg and equal to one of four intensity values $I_1(x,y)$, $I_2(x,y)$, $I_3(x,y)$ and $I_4(x,y)$ at position (x,y) .

An example of central pixel flooding matrix detection is shown in Fig.2.

| | | |
|---|---|---|
| 8 | 7 | 8 |
| 8 | 8 | 4 |
| 5 | 8 | 9 |

(a) 3x3 block with gray values

| | | |
|---|---|---|
| 8 | 0 | 8 |
| 8 | 8 | 0 |
| 0 | 8 | 0 |

(b) Central pixel flood

| | | | | | | |
|---|---|---|---|---|---|---|
| 5 | 5 | 7 | 9 | 2 | 3 | 8 |
| 4 | 6 | 9 | 1 | 8 | 8 | 8 |
| 3 | 3 | 6 | 1 | 3 | 4 | 4 |
| 8 | 5 | 5 | 3 | 1 | 6 | 4 |
| 5 | 8 | 9 | 5 | 1 | 4 | 4 |
| 4 | 8 | 9 | 9 | 5 | 4 | 6 |
| 8 | 9 | 5 | 3 | 5 | 4 | 4 |

(c) 7x7 Image block

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 6 | 0 | 0 | 8 | 8 | 0 |
| 0 | 0 | 6 | 0 | 0 | 0 | 0 |
| 8 | 0 | 0 | 0 | 1 | 0 | 0 |
| 0 | 8 | 0 | 0 | 1 | 0 | 0 |
| 0 | 8 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |

(d) $I1(x,y)$

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 9 | 0 | 0 | 8 |
| 0 | 0 | 9 | 0 | 8 | 8 | 8 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 1 | 0 | 4 |
| 0 | 0 | 9 | 0 | 1 | 4 | 4 |
| 0 | 0 | 9 | 9 | 0 | 4 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |

(e) $I2(x,y)$

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 3 | 0 | 0 | 3 | 0 | 0 |
| 0 | 0 | 0 | 3 | 0 | 0 | 0 |
| 0 | 8 | 0 | 5 | 0 | 0 | 0 |
| 0 | 8 | 0 | 0 | 5 | 0 | 0 |
| 8 | 0 | 0 | 0 | 5 | 0 | 0 |

(f) $I3(x,y)$

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 6 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 6 | 0 | 0 | 4 | 4 |
| 0 | 0 | 0 | 0 | 0 | 0 | 4 |
| 0 | 0 | 9 | 0 | 0 | 4 | 4 |
| 0 | 0 | 9 | 9 | 0 | 4 | 0 |
| 0 | 0 | 0 | 0 | 0 | 4 | 4 |

(g) $I4(x,y)$

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 9 | 0 | 0 | 8 |
| 0 | 6 | 9 | 0 | 8 | 8 | 0 |
| 3 | 3 | 6 | 0 | 0 | 4 | 4 |
| 8 | 0 | 0 | 3 | 1 | 0 | 4 |
| 0 | 8 | 9 | 5 | 1 | 4 | 4 |
| 0 | 8 | 9 | 9 | 5 | 4 | 0 |
| 8 | 0 | 0 | 0 | 5 | 4 | 4 |

(h) Central pixel flood matrix

Fig.2. Detection of Central pixel flood matrix

C. Evaluation of Shape Patterns

The shape patterns on 3x3 block are defined as follows. In lower triangular matrix pattern, nonzero elements occur on principal diagonal and below this diagonal. In upper triangular matrix pattern, nonzero elements occur on principal diagonal and above this diagonal. In tri diagonal matrix pattern, nonzero elements occur on principal diagonal, below and above this diagonal. These patterns are shown in Fig.3. The frequency occurrences of these shape patterns are computed on CPFM and sum of these shape patterns are computed.

| | | |
|---|---|---|
| N | 0 | 0 |
| N | N | 0 |
| N | N | N |

(a)

| | | |
|---|---|---|
| N | N | N |
| 0 | N | N |
| 0 | 0 | N |

(b)

| | | |
|---|---|---|
| N | N | 0 |
| N | N | N |
| 0 | N | N |

(c)

Fig 3: a) Lower Triangular Matrix Pattern (LTMP) b) Upper Triangular Matrix Pattern (UTMP) c) Tri Diagonal Matrix Pattern(TDMP) , where N is a nonzero element

3. RESULTS AND DISCUSSIONS

The proposed method established a database of the 1002 face images collected from FG-NET database and other 600 images collected from the scanned photographs and sample of these images are shown in Fig.4. In this method, images are classified into two groups as a child (upto 18 years) and adult (above 18 years) based on frequency occurrences of shape patterns. The frequency occurrence of each shape patterns i.e. FLTMP, FUTMP, and FTDMP on CPFM and Sum of Shape Patterns (SSP) are evaluated on facial images and the results for a sample of 20 images is listed out in table1.

From the table1 it is observed that FLTMP and FUTMP are dominant patterns and FTDMP patterns are not dominant patterns as these are zero for age varying images. So FLTMP, FUTMP, and SSP can be considered for age classification. The algorithm1 is proposed to classify images into two categories adult and child with shape patterns FLTMP, FUTMP, and SSP.



Fig 4: Sample images from FG-NET Database

Table 1. The frequency of occurrences of LTMP, UTMP, TDMP and SSP

| IMAGE | FLTMP | FUTMP | FTDMP | SSP |
|--------|-------|-------|-------|-------|
| 001A02 | 8357 | 13524 | 0 | 21881 |
| 001A05 | 11584 | 19370 | 0 | 30954 |
| 001A08 | 14996 | 22115 | 0 | 37111 |
| 011A02 | 8477 | 14581 | 0 | 23058 |
| 002A04 | 15932 | 21713 | 0 | 37645 |
| 002A12 | 15442 | 22186 | 0 | 37628 |
| 011A07 | 14697 | 18329 | 0 | 33026 |
| 008A06 | 15583 | 21534 | 0 | 37117 |
| 008A08 | 13820 | 17424 | 0 | 31244 |
| 012A04 | 12590 | 14312 | 0 | 26902 |
| 001A33 | 24295 | 31142 | 0 | 55437 |
| 037A19 | 18161 | 25722 | 0 | 43883 |
| 011A40 | 28104 | 35112 | 0 | 63216 |
| 013A25 | 18843 | 25035 | 0 | 43878 |
| 013A34 | 19014 | 22398 | 0 | 41412 |
| 016A19 | 19440 | 23550 | 0 | 42990 |
| 025A22 | 18326 | 23756 | 0 | 42082 |
| 025A39 | 24053 | 25341 | 0 | 49394 |
| 027A20 | 19362 | 24395 | 0 | 43757 |
| 027A41 | 18019 | 25392 | 0 | 43411 |
| 030A26 | 18128 | 25622 | 0 | 43750 |
| 035A21 | 22049 | 28491 | 0 | 50540 |

Algorithm 1: Age classification using frequency occurrences of LTMP, UTMP, TDMP and SSP patterns on CPFM

Let FLTMP, FUTMP, and FTDMP be frequency occurrences of LTMP, UTMP and TDMP patterns and SSP is the sum of frequency occurrences shape patterns.

Begin

if ((FLTMP < 16000) & (UTMP < 22200)

& (SSP < 38000))

write ("Image is child")

else

write ("Image is adult")

end

The algorithm1 classified the FG-Net facial images into two groups with 98% correct classification rate. The proposed method for age grouping is compared with the existing methods, Age

classification with shape features on lbp based texture by P Chandra Sekhar Reddy et.al.[18]. Child and adulthood classification with geometrical features by Chandra Mohan et.al.[19] and other age classification methods Young H.Kwon et.al.[3] , Tsuneo Kanno et. al.[20] and Wen-Bing Horng Cheng et.al.[4]. The comparison table for proposed and existing methods with the percentage of classification rate is listed in table2. The results indicate that the proposed scheme outperforms with other methods.

Table 2: Comparison of the proposed Shape patterns on CPFM with other methods.

| S.no | Authors | Name of the method | % Classification Rate | Category of age classification |
|------|-----------------------------------|---|-----------------------|--|
| 1 | Proposed method | Shape patterns on -CPFM | 98 | Child and Adulthood |
| 2 | P Chandra Sekhar Reddy et.al.[18] | Shape features on IT-LBP | 95 | Child and Adulthood |
| 4 | Chandra Mohan et.al.[19] | Geometrical features for Child and Adulthood Classification | 94.5 | Child and Adulthood |
| 3 | Young H. Kwon et.al.[3] | Age classification from facial images | 78 | Babies, adults, and Senior adults. |
| 4 | Tsuneo Kanno et al.[20] | Neural networks for Age groups of young male faces. | 80 | young males are classified into age groups 12,15,18 and 22 years |
| 5 | Wen-Bing Horng Cheng et.al. [4] | Facial features for classification into age groups. | 90.52 | Babies, young adults, middle-aged adults, and old adults |

4. CONCLUSION

The present paper evaluated shape patterns on a 3x3 mask using CPFM. This CPFM forms texels from the facial image. The age variation is identified with frequency occurrences of LTMP, UTMP, and SSP patterns. This is a new approach for identifying variation of wrinkles in facial images of age varying people with shape patterns. So classification algorithm uses only these three shape pattern features. The percentage of classification rate is 98% and this is highest classification rate from table2. The proposed method for age classification is easy to implement and also efficient compared to other schemes. The CPFM with new shape patterns and textural properties can be extended in future work.

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