Novel Method of Adult Age Classification Using Linear Wavelet Transforms

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Abstract:
The present paper proposes an innovative technique that classifies adult images with age spans for every ten years based on the topological texture features in the facial skin. The present paper assumes that bone structural changes do not occur after the person is fully grown that is the geometric relationships of primary features do not vary. That is the reason secondary features are identified and exploited. The secondary features that are exploited in the present paper are Topological Texture Features (TTF) on two-level linear wavelet transform of the facial skin. Based on TTF's, the present paper classified the age of an adult, into seven categories i.e in the age groups of 16 to 25, 26 to 35, 36 to 45, 46 to 55, 56 to 65, 66 to 75 and 76 to 85. The proposed method is rotation and pose invariant. The experimental evidence on FG-NET aging database and Google Images clearly indicates the high classification rate of the proposed method. The recognition rates between various linear wavelet transforms are compared.

Keywords
: Topological Texture Features, linear wavelet transforms, facial skin, Rotation invariant, Pose invariant.

1. Introduction

As humans, we are easily able to categorize a person's age group from an image of the person's face and are often able to be quite precise in this estimation. This ability has not been pursued in the computer vision community. In order to begin researching the issues involved in this process, this paper addresses the task of age classification of adult facial image into age groups of 16 to 25, 26 to 35, 36 to 45, 46 to 55, 56 to 65, 66 to 75 and 76 to 85.

Any progress in the research community's understanding of the remarkable ability that human's have with regard to facial image analysis will go a long way toward the broader goals of face-recognition and facial-expression recognition. Very little research work has been reported on the aspects of age information in images of human faces. However, it is appropriate to review research on facial image analysis. Nagamine, Uemerra, and Masuda [4] have developed methods to match features in range images of faces. These images might be produced by, for instance, a binocular system. Using color images of light-skinned faces, Novak [5] uses skin tones to find the face, lip-pinks to find the lips, and bluegreens to find the eyes. In an attempt at recognizing facial expressions, Matsuno, Lee, and Tsuji [3] use potential nets, which undergo structural deformations at features such as the eyebrows, nose, and mouth. Based on the pattern of deformations, classification is achieved. Working in the other paradigm, Turk and Pentland [7] convert an N×N image of a face into a single vector of size N2 by concatenating scan lines. They computed the eigenvectors of the covariance matrix of the set of face images. Only a few of the eigen values are significant, thus characterizing the low dimensional "face-space." A face can be represented in this new space by a few weights. Recognition is considered successful when an image's weights fall within some neighborhood of a set of weights already stored in a database. This method is sensitive to scale, viewing angle, lighting changes, and background noise. Similar work in this paradigm has been reported by Kirby and Sirovich [2]. As another embodiment of this approach, O'Toole, Abdi, Deffenbacher, and Bartlett [6] used auto associative memory techniques, and this proved useful in classifying faces by gender and race, and in recognition. This method sets up an auto associative memory of J completely interconnected units, where J is the number of pixels in an image. The connection strengths were stored in a J×J matrix. Eigenvectors were extracted and the first seven eigenvectors were used to differentiate gender and race. For the training sets they used, it was discovered that the difference in coefficients for the eigenvectors is useful for female/male classification and for Caucasian/Japanese classification. For other work that examined the ability to classify gender using neural networks[1].

There are four publicly available databases that comprise of age separated face image samples namely, the MORPH Database [19], the FG-NET Aging Database [9], the FERET Database [8] and Google database [22]. The MORPH database is the result of an effort to collect a database comprised of longitudinal images of subjects with accompanied physical attribute data (e.g., age at acquisition, weight, height, and ethnicity). It is organized in two albums: MORPH Album 1, which comprises of 1690 digitized images of 515 individuals under the age range [15, 68], and MORPH Album 2 that comprises of 15204 images of nearly 4000 individuals. The FG-NET (Face and Gesture Recognition Research Network) aging database comprises

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of 1002 images of 82 subjects in the age range of [0, 69] years. Besides, for any face image, the database provides 68 landmark features manually identified. In addition, some meta information (image size, age, gender, spectacles, hat, mustache, beard, horizontal pose and vertical pose) is also available and there is no control about aspects such as illumination, head pose and facial expressions. The facial aging in the FERET dataset can be divided in three groups: Gallery-set (1196 images), Duplicate I Probe-set (722 images) and Duplicate II Probe-set (234 images).

The works in this area involve methods based on age prototypes [20], statistical models [13, 10], support vector machines (SVM) and distance-based techniques [12]. They can work on usual two-dimensional face images or 3D scans of faces [18, 21]. Moreover, age estimation methods can be also used as the basis for age-progression algorithms [11]. Besides, geometric aspects may be considered in order to improve/validate age progression techniques [15, 17, 16, 14]. The Google database [22] consists of thousands of randomly chosen facial images.

The present paper proposes a novel wavelet decomposition technique of adult age classification on facial images based on topological texture features derived from individual parts of a facial image. For this the proposed paper is divided into four sections.

The remainder of the paper is organized as follows: Section (2) focuses on proposed adult age classification approach, section (3) describes results and discussion and section (4) describes the conclusion.

2. Proposed Methodology

To classify the adult age group, the present paper identified Topological Texture Features (TTF) based on topological changes in the facial skin. The present paper observed the fact that the facial skin of a person tends to more changes with growing age. These rapid topological changes in the skin are exploited by TTF's. The TTF's are derived from the patterns formed by Bezier, Koch and Elliptic curves and U, V, I, T and Z patterns on the facial skin. The patterns are measured on a 5 x 5 mask, because most of the curve properties do not fit in to 3 x 3 mask.

The other important feature of the present method is out of these TTF's Bezier curve estimates, the rapid changes in the skin at a higher rate, which is the reason an exhaustive number of Bezier curves with different control points are estimated on each 5 x 5 mask. To make the present method as rotational and pose invariant the frequency of each TTF is measured with 0, 45, 90, 180 and 270 degrees. The TTF's of Bezier curves with orientation of 00, and 900 on a 5 x 5 mask are shown in Figure 1 and 2 respectively. The other curve and Alphabetic patterns are shown in Figure 3.

These TTF's are most prominently visible on forehead, below the right eye, below the left eye and chin parts. For this, the proposed method divides face into four parts, forehead, below the right eye, below the left eye and chin parts a cropped size of 64×32, 32×32, 32×32 and 32×32 respectively. Then each part of the facial image is converted into 2-level wavelet image. The linear wavelet transforms considered in the present study are Haar, Db6, Cf6 and Sym8.

The proposed scheme is given in Algorithm 1. In the proposed method the sample images are grouped into the age groups of 16 to 25, 26 to 35, 36 to 45, 46 to 55, 56 to 65, 66 to 75 and 76 to 85. For classification of adult age groups into seven categories the grey level images of each group are converted into binary by taking care of noise factor. Then frequency of occurrence of each TTF on 2-level LL-Sub band image is computed. From this Global Topological Texture Features (GTTF) on each part is evaluated. The GTTF is the sum of all TTF's count on each part of the facial image. Average value of all GTTF count of each part of the facial image on each group is calculated, and is placed in Topological Skin Aging Database (TSAD).

Algorithm 1: Computation of Frequency of occurrences of TTF's and GTTF's on four parts of a Facial Image using two-level wavelet transform.

Begin

Step 1: Read the Input Images (Im_1-------Im_n) and convert them to gray scale.

Step 2: Crop the forehead, below right eye, below left eye and chin parts of sizes 64×32, 32×32, 32×32 and 32×32 respectively for a gray scale image Im_i. and crop two level LL –band linear wavelet facial parts of images IM_1 ……………..IM_n

Step 3: Conversion of gray scale image in to binary by removing noise.

Let A be the grey scale facial image part and row and col represents the resolution of A.

```
Set the threshold as median value of distinct gray
levels in A.
for i=1:row
    for j=1:col
        if(A(i,j)>threshold)
            binary(i,j)=1;
        else
            binary(i,j)=0;
        end
    end
end
```

Step 4: Initialize the values of frequency of 21 Bezier curves (FBZ_i), Koch curve (FKC), Elliptic Curve (FEC), I pattern (FIP), T pattern (FTP), U pattern (FUP), V pattern (FVP) and Z pattern (FZP) to zero.

```
Step 5: for r=1:row-5
            for c=1:col-5
                  for k=r:r+5
                      for l=c:c+5
                              for m=1:21
                                    if(BZm) ++FBZm end;
                              end
                              if(KC) ++FKC end;
                              if(EC) ++FEC end;
                              if(IP) ++FIP end;
                              if(TP) ++FTC end;
                              if(UP) ++FUP end;
                              if(VP) ++FVP end;
                              if(ZP) ++FZP end;
                      end
                   end
            end
         end
```

Step 6: Repeat step 5 for all four parts.

Step 7: Repeat step 5 and 6 for four orientations i.e. 0^o, 90^o, 180^o and 270^o.

Step 8: Repeat steps 2 to 7 for all images (Im_1-------Im_n).

End

1	1	0	0	0
0	1	0	0	0
0	1	1	0	0
0	0	1	1	0
0	0	0	0	1
CP (1, 2), (2, 1)				

1	1	0	0	0
0	1	0	0	0
0	1	1	0	0
0	0	1	1	0
0	0	0	1	1
CP (1,3), (3,1)				

1	1	0	0	0
0	1	1	0	0
0	0	1	0	0
0	0	1	1	0
0	0	0	1	1
CP (1,4), (4,1)				

1	1	1	0	0
0	0	1	0	0
0	0	1	0	0
0	0	1	0	0
0	0	1	1	1
CP (1,5), (5,1)				

1	0	0	0	0
1	1	1	0	0
0	0	1	0	0
0	0	1	1	0
0	0	0	1	1
CP (2,1), (1,2)				

1	0	0	0	0
0	1	0	0	0
0	0	1	0	0
0	0	0	1	0
0	0	0	0	1
CP (1,1), (1,1)				

1	0	0	0	0
1	1	1	0	0
0	0	1	1	0
0	0	0	1	1
0	0	0	0	1
CP (3,1), (1,3)				

1	0	0	0	0
1	1	0	0	0
0	1	1	1	0
0	0	0	1	1
0	0	0	0	1
CP (3,2), (2,3				

1	1	0	0	0
0	1	1	0	0
0	0	1	1	0
0	0	0	1	0
0	0	0	1	1
CP (3,5), (5,3)				

1	0	0	0	0
0	1	1	0	0
0	0	1	1	0
0	0	0	1	0
0	0	0	1	1
CP (4,5), (5,4)				

1	0	0	0	0
1	0	0	0	0
1	1	1	1	1
0	0	0	0	1
0	0	0	0	1
CP (5,1), (1,5)				

1	0	0	0	0
1	1	0	0	0
0	1	1	0	0
0	0	1	1	1
0	0	0	0	1
CP (5,3), (3,5)				

Figure 1 The TTF's of Bezier curves on a 5 x 5 mask with 00 orientation, CP-denotes control points

0	0	0	0	1
0	0	0	1	0
0	0	1	1	0
1	1	1	0	0
1	0	0	0	0
CP (1, 2), (2, 1)				

0	0	0	0	1
0	0	0	1	1
0	0	1	1	0
1	1	1	0	0
1	0	0	0	0
CP (1,3), (3,1)				

0	0	0	0	1
0	0	0	1	1
0	1	1	1	0
1	1	0	0	0
1	0	0	0	0
CP (1,4), (4,1)				

0	0	0	0	1
0	0	0	0	1
1	1	1	1	1
1	0	0	0	0
1	0	0	0	0
CP (1,5), (5,1)				

0	0	0	0	1

0	0	0	0	1

0	0	0	1	1

0	0	0	1	1

0	0	0	1	1
0	1	1	1	0
0	1	0	0	0
1	1	0	0	0
CP (2,1), (1,2)				

0	0	0	1	0
0	0	1	0	0
0	1	0	0	0
1	0	0	0	0
CP (1,1), (1,1)				

0	0	1	1	0
0	1	1	0	0
0	1	0	0	0
1	1	0	0	0
CP (3,1), (1,3)				

0	0	1	1	0
0	0	1	0	0
0	1	1	0	0
1	1	0	0	0
CP (3,2), (2,3				

0	0	0	0	1
0	0	1	1	1
0	1	1	0	0
1	1	0	0	0
1	0	0	0	0
CP (3,5), (5,3)				

0	0	0	0	1
0	0	1	1	1
0	1	1	0	0
0	1	0	0	0
1	0	0	0	0
CP (4,5), (5,4)				

0	0	1	1	1
0	0	1	0	0
0	0	1	0	0
0	0	1	0	0
1	1	1	0	0
CP (5,1), (1,5)				

0	0	0	1	1
0	0	0	1	0
0	0	1	1	0
0	1	1	0	0
1	1	0	0	0
CP (5,3), (3,5)				

Figure 2 The TTF's of Bezier curves on a 5 x 5 mask with 900 orientation, CP-denotes control points

1	0	0	0	1
1	0	0	1	1
1	0	0	0	1
1	0	0	0	1
1	1	1	1	1
(a)				

1	0	0	0	1
1	0	0	0	1
1	0	0	0	1
0	1	0	1	0
0	0	1	0	0
(b)				

1	1	1	1	1
0	0	1	0	0
0	0	1	0	0
0	0	1	0	0
1	1	1	1	1
(c)				

1	1	1	1	1
0	0	1	0	0
0	0	1	0	0
0	0	1	0	0
0	0	1	0	0
(d)				

1	1	1	1	1
0	0	0	1	0
0	0	1	0	0
0	1	0	0	0
1	1	1	1	1
(e)				

0	0	0	0	0
0	0	0	0	0
0	0	1	0	0
0	1	0	1	0
1	1	0	1	1
(f)				

0	0	0	0	0
0	0	0	1	1
0	0	1	0	0
0	1	0	0	0
1	0	0	0	0
(g)				

Figure 3 The TTF's on a 5 x 5 mask with 00 orientations (a)U-pattern, (b) V-pattern, (c) I-pattern, (d) T-pattern, (e) Z-pattern, (f) Koch curve, (g) Elliptic curve

3. Results and Discussion

The proposed scheme established a database from the 1002 face images collected from FG-NET database, and 500 face images collected from Google database. The present paper utilized FG-NET, Google database images, because these are random in nature. This will help to indicate the efficiency and reliability of the proposed and also other methods. This leads a total of 1502 sample facial images. The sample facial images of FG-NET aging database and Google images are shown in Figure 4 and 5 respectively.

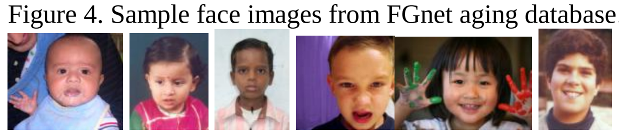
001A08 001A16 001A40 002A12 002A15 002A16

002A36 003A18 003A60 004A19 004A63 005A18

005A40 006A24 006A69 007A01 007A21 007A41

008A06 008A16

Figure 4. Sample face images from FGnet aging database.



1-2 2-1 5-1 5-5 5-6 10-3

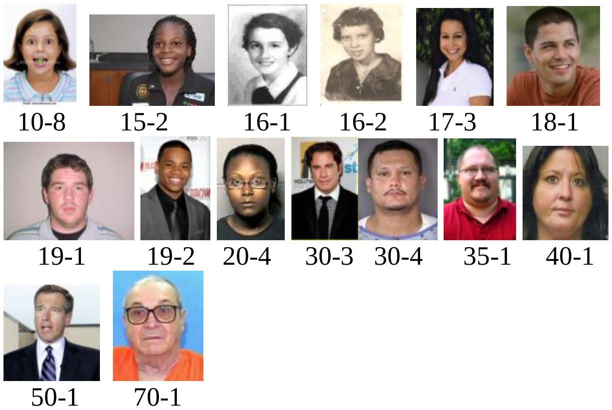


Figure 5. Sample Face images downloaded from Google Images

TSAD's are created on the database images and are listed in Table 1, 2, 3 and 4 for Haar, Db6, Cf6 and Sym8 wavelet transforms respectively. To test the significance, accuracy and reliability of the present adult age classification approach, the present method used test images. For the 2-level LL-sub bands of test images the GTTF's are evaluated. For the classification purpose the novel distance function is used. This scheme first evaluates the distance between GTTF's of foreheads between sample image and TSAD age groups. Based on this distance, it picks up the first 5 age groups, which are close to sample image. The same process is repeated for GTTF's of below the right eye, below the left eye and chin by selecting 3, 2 and 1 age groups respectively from the TSAD. The final out put is the classified age group. The classification results on Haar, Db6, Cf6 and Sym8 are listed in tables 5, 6, 7 and 8 respectively. Based on the above, successful recognition rates on various linear wavelet transforms are compared, and given in the Table 9. All linear wavelet transforms exhibited the same successful age classification rate of adults, and the same is represented in the form of bar graph in Figure 6.

Table 1. Topological Skin Aging Database (TSAD) with 2-level Haar wavelet decomposition

Age group (Years)	GTTF on Fore head (part 1)	GTTF on Below Right Eye (part 2)	GTTF on Below Left Eye (part 3)	GTTF on Chin (part 4)
16-25	505	67	70	98
26-35	713	103	95	105
36-45	886	127	113	123
46-55	995	160	124	154
56-65	1084	209	145	179
66-75	1252	235	175	185
76-85	1454	253	200	225

Table 2. Topological Skin Aging Database (TSAD) with 2-level Db6 wavelet decomposition

Age group (Years)	GTTF on Fore head (part 1)	GTTF on Below Right Eye (part 2)	GTTF on Below Left Eye (part 3)	GTTF on Chin (part 4)
16-25	440	33	55	45
26-35	638	71	83	89
36-45	740	80	105	127
46-55	845	97	112	133
56-65	921	180	132	152
66-75	1050	215	148	158
76-85	1130	242	186	177

Table 3. Topological Skin Aging Database (TSAD) with 2-level Cf6 wavelet decomposition

Age group (Years)	GTTF on Fore head (part 1)	GTTF on Below Right Eye (part 2)	GTTF on Below Left Eye (part 3)	GTTF on Chin (part 4)
16-25	495	71	75	95
26-35	689	101	109	99
36-45	856	124	114	119
46-55	945	163	126	154
56-65	984	212	152	162
66-75	1165	234	178	189
76-85	1254	261	197	219

Table 4. Topological Skin Aging Database (TSAD) with 2-level Sym8 wavelet decomposition

Age group (Years)	GTTF on Fore head (part 1)	GTTF on Below Right Eye (part 2)	GTTF on Below Left Eye (part 3)	GTTF on Chin (part 4)
16-25	476	58	69	96
26-35	718	101	93	102
36-45	889	131	115	119
46-55	967	146	122	149
56-65	1032	199	141	156
66-75	1198	215	167	178
76-85	1278	246	201	215

Table 5. Classification results and GTTF's on 2-level Haar wavelet test images

Image name	Part 1	part 2	part 3	part 4	Classified age group	Result
007A18	175	89	6	18	16-25	Success
009A18	432	6	23	315	16-25	Success
009A22	718	6	65	57	16-25	Success
012A18	296	48	80	359	16-25	Success
001A28	104	88	163	77	26-35	Success
001A33	485	45	69	4	26-35	Success
003A35	365	262	0	7	26-35	Success

011A27	603	97	172	2	26-35	Success
012A27	827	4	40	6	26-35	Success
005A35	1260	52	47	5	26-35	Success
006A36	903	94	4	189	36-45	Success
008A41	985	30	3	4	36-45	Success
012A36	519	14	108	0	16-25	Fail
013A41	796	18	56	277	36-45	Success
014A40	1029	10	127	1	36-45	Success
20-1	88	152	344	277	16-25	Success
20-2	66	65	4	96	16-25	Success
20-3	64	96	134	45	16-25	Success
20-4	23	112	69	81	16-25	Success
30-1	55	88	146	190	26-35	Success
30-2	68	47	56	107	26-35	Success
30-3	46	168	128	220	26-35	Success
35-1	26	0	37	100	26-35	Success
40-10	87	73	46	252	36-45	Success
50-3	124	15	166	188	46-55	Success
50-4	121	14	155	172	46-55	Success
60-3	124	15	166	188	56-65	Success
70-1	32	36	160	229	66-75	Success
80-3	88	173	1	60	66-75	Fail
80-4	98	180	20	70	76-85	Success

Table 6. Classification results and GTTF's on 2-level Db6 wavelet test images

Image name	Part 1	part 2	part 3	part 4	Classified age group	Result
007A18	179	88	9	21	16-25	Success
009A18	412	7	14	2145	16-25	Success
009A22	743	8	61	51	16-25	Success
012A18	287	46	67	234	16-25	Success
001A28	112	89	143	72	26-35	Success
001A33	487	42	61	7	26-35	Success
003A35	354	257	8	8	26-35	Success
011A27	612	91	171	4	26-35	Success
012A27	801	8	23	8	26-35	Success
005A35	1198	55	43	6	26-35	Success
006A36	911	91	34	181	36-45	Success
008A41	967	32	6	9	36-45	Success
012A36	498	16	98	6	16-25	Fail
013A41	767	19	51	241	36-45	Success
014A40	1005	11	121	8	36-45	Success
20-1	79	145	301	223	16-25	Success
20-2	62	63	6	89	16-25	Success
20-3	61	93	131	64	16-25	Success
20-4	19	110	63	71	16-25	Success
30-1	57	86	134	167	26-35	Success
30-2	69	44	59	98	26-35	Success
30-3	43	159	121	198	26-35	Success
35-1	29	7	31	92	26-35	Success
40-10	83	71	43	232	36-45	Success
50-3	118	19	161	168	46-55	Success
50-4	117	14	156	152	46-55	Success
60-3	121	15	159	186	56-65	Success
70-1	31	37	167	221	66-75	Success
80-3	83	171	4	56	66-75	Fail
80-4	96	169	20	61	76-85	Success

Table 7. Classification results and GTTF's on 2-level Cf6 wavelet test images

Image name	Part 1	part 2	part 3	part 4	Classified age group	Result
007A18	185	83	8	28	16-25	Success
009A18	415	8	21	278	16-25	Success
009A22	667	9	58	51	16-25	Success
012A18	267	44	76	312	16-25	Success
001A28	114	82	149	71	26-35	Success
001A33	445	49	62	6	26-35	Success
003A35	315	252	5	8	26-35	Success
011A27	567	92	169	6	26-35	Success
012A27	789	5	44	9	26-35	Success
005A35	1162	51	45	6	26-35	Success
006A36	912	91	6	178	36-45	Success
008A41	967	23	5	6	36-45	Success
012A36	511	21	98	8	16-25	Fail
013A41	789	16	48	198	36-45	Success
014A40	1011	9	118	5	36-45	Success
20-1	81	142	312	267	16-25	Success
20-2	61	67	5	86	16-25	Success
20-3	59	92	124	39	16-25	Success
20-4	19	110	66	89	16-25	Success
30-1	51	81	141	180	26-35	Success
30-2	60	39	51	117	26-35	Success
30-3	41	149	122	210	26-35	Success
35-1	22	8	39	98	26-35	Success
40-10	78	71	44	232	36-45	Success
50-3	114	18	161	166	46-55	Success
50-4	112	12	145	165	46-55	Success
60-3	113	19	136	178	56-65	Success
70-1	37	32	150	218	66-75	Success
80-3	82	167	7	59	66-75	Fail
80-4	91	145	21	68	76-85	Success

Table 8. Classification results and GTTF's on 2-level Sym8 wavelet test images

Image name	Part 1	part 2	part 3	part 4	Classified age group	Result
007A18	157	92	9	21	16-25	Success
009A18	354	16	31	289	16-25	Success
009A22	672	14	61	67	16-25	Success
012A18	198	39	76	258	16-25	Success
001A28	98	79	153	76	26-35	Success
001A33	385	49	69	9	26-35	Success
003A35	354	241	8	6	26-35	Success
011A27	557	93	172	5	26-35	Success
012A27	765	8	60	7	26-35	Success
005A35	1154	51	37	9	26-35	Success
006A36	876	92	9	169	36-45	Success
008A41	965	31	6	5	36-45	Success

012A36	498	17	118	5	16-25	Fail
013A41	765	16	46	217	36-45	Success
014A40	986	15	123	5	36-45	Success
20-1	98	142	242	247	16-25	Success
20-2	63	61	7	86	16-25	Success
20-3	61	92	138	46	16-25	Success
20-4	28	102	61	85	16-25	Success
30-1	51	86	148	182	26-35	Success
30-2	69	42	58	112	26-35	Success
30-3	48	134	123	212	26-35	Success
35-1	26	8	33	96	26-35	Success
40-10	78	69	48	212	36-45	Success
50-3	114	21	169	156	46-55	Success
50-4	113	16	143	162	46-55	Success
60-3	132	16	156	181	56-65	Success
70-1	29	31	167	212	66-75	Success
80-3	83	164	8	56	66-75	Fail
80-4	96	165	31	67	76-85	Success

Table 9. Comparison of classification rates of 2-level linear wavelets transforms

Image Database	Haar	Db6	Cf6	Sym8
FG-NET Database	93.5	94.1	93.6	94.0
Google Images	90.4	90.8	90.3	90.8

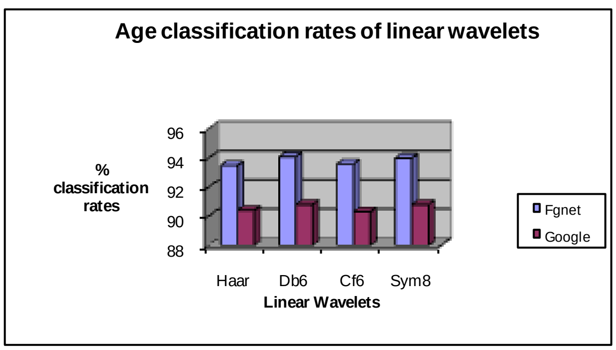


Figure 6. comparison of adult age classification rates of four wavelets for three databases

4. Conclusion

The present paper proposed a new method for age classification of adults in the age groups of 16 to 25, 26 to 35, 36 to 45, 46 to 55, 56 to 65, 66 to 75, and 76 to 85, based on the topological texture features in the facial skin. The significance of the present approach is usage of both curve and other alphabetic patterns on a 5 x 5 mask. The present method is tested for FG-NET aging database and face Images down downloaded from Google Images. The performance of this system is more for the standard face database than images down loaded from Google Images. The performance of this classification system can be further improved by taking more parts of facial image.

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