New Face Recognition Method Based on Texture Features using Linear Wavelet Transforms

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Abstract: The present paper proposes a novel scheme of face recognition system based on texture features derived from co-occurrence parameters using 1-level linear wavelet decomposition technique. The present method divides the face into four parts. The novelty of the present scheme lies on usage of distance function on texture features for the recognition of facial images. The distance function evaluates the distance between each individual texture feature and eliminates the retrieved facial images in a sequential manner. By this the proposed paper expands the scope of structural face recognition system towards reliable and computationally inexpensive model. The proposed method is implemented on a large facial database collected from FGnet aging database and Google Images. The recognition rates between various linear wavelet transforms and with the original image are compared.

Keywords: *Pose, Illumination, Feature extraction, Orientation, class seperability.*

1. Introduction

Over the past few decades, face recognition has become a popular area of research in pattern recognition and computer vision due to its wide range of commercial and law enforcement applications, such as passports, credit cards, driving licenses, biometric authentication, video surveillance, and information security [1].

Although researchers in psychology, neural sciences and engineering, image processing and computer vision have investigated a number of issues related to face recognition by human beings and machines, it is still difficult to design an automatic system for this task. Until now, a great number of face recognition methods have been developed and one of the most successful techniques is the appearance-based method. In appearance-based methods, a face image is usually considered as a point in the high-dimensional space. Many linear subspace learning methods, such as Eigenface [2], Fisherface [3], LDA/FKT (linear discriminant analysis/Fukunaga–Koontz transform) [4], C-LDA (complete LDA) [5], MMSD (multiple maximum scatter difference) [6], and Laplacianface [7] are typical dimensionality reduction methods to find a low-dimensional feature space.

The algorithm [3] uses LDA to search a set of basis components which maximizes the ratio of between-class scatter to within-class scatter. Due to the `small sample size' problem [8] in face recognition, the within-class scatter matrix is usually singular. Thus, the execution of LDA encounters Computational difficulty. Principle Component analysis(PCA) is often used as a preprocessing step to reduce the dimensionality [3] and LDA is then performed in the low-dimensional PCA subspace where the within-class scatter matrix becomes nonsingular. However, this method may result in the loss of important discriminative information [4]. Many methods [4–6] have been developed to take full advantage of the discriminative information in the face space. Unlike PCA and LDA which attempt to preserve the global Euclidean structure, Laplacianface algorithm [7] that is based on locality preserving projections (LPP) finds a face subspace to preserve the local structure of face manifold. It can be seen that the projection matrices obtained by traditional linear subspace learning methods [2–7] are related to the statistical characteristics of all training samples. The projection axis tries to preserve (e.g. PCA) or discriminate (e.g. LDA) all classes.

Some other techniques developed for face recognition are holistic/template approaches [14, 23, 29, 22], feature based approaches [10], and their combination [17] have also been used to detect faces, but they are computationally very demanding and can not handle large variations in face images. Various approaches to face detection are discussed in [13, 20, 21, 31, 16]. These approaches utilize techniques such as PCA, neural networks, machine learning, information theory, geometric modeling, template matching, Hough transform, motion extraction, and color analysis. The neural network-based [24, 25] and view based [28] approaches requires a large number of face and nonface training examples and are designed primarily to

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locate frontal faces in gray-scale images. The learning-based approach for the detection of frontal faces to profile views. A feature-based approach that uses geometrical facial features with belief networks [32] provides face detection nonfrontal views. Geometrical facial templates and the Hough transform were incorporated to detect gray-scale frontal faces in real time applications [20]. Face detectors based on Markov random fields [19] and Markov random chains [11], make use the spatial arrangement of pixel gray values. A combination of holistic and feature-based approaches [15, 18] is a promising approach to face detection as well as face recognition. Motion [12, 13] and skin tone color [13, 9, 27, 30, 14] are useful cues for face detection.

Based on the above literature survey the present paper proposes a new one-level linear wavelet decomposition technique of face recognition based on texture features derived from co-occurrence parameters. To validate the proposed method, 1004 FGnet aging database images and 500 Google facial images are considered for the experimental analysis.

The remainder of the paper is organized as follows: section (2) introduction to wavelets, section (3) focuses on proposed Face Recognition approach, section (4) describes results and discussion and section (5) describes the conclusion.

2. Introduction to Wavelets

The wavelet transform is a multi-resolution technique, which can be implemented as a pyramid or tree structure and is similar to sub-band decomposition[33,34].There are various wavelet transforms like Haar, Daubechies(Db6), Coiflet (Cf6), Symlet (Sym8) and etc. They differ with each other in the formation and reconstruction. The wavelet transform divides the original image into four subbands and they are denoted by LL(low-low), LH(low-high), HL(high-low) and HH(high-high) frequency subbands. The HH subimage represents diagonal details (high frequencies in both directions – the corners), HL gives horizontal high frequencies (vertical edges), LH gives vertical high frequencies (horizontal edges), and the image LL corresponds to the lowest frequencies. At the subsequent scale of analysis, the image LL undergoes the decomposition using the same filters, having always the lowest frequency component located in the upper left corner of the image. Each stage of the analysis produces next 4 subimages whose size is reduced twice when compared to the previous scale. i.e. for level ‘n’ we get a total of ‘4+(n-1)*3’ subbands. The size of the wavelet representation is the same as the size of the original.

The Haar wavelet is the first known wavelet and was proposed in 1909 by Alfred Haar. Haar used these functions to give an example of a countable orthonormal system for the space of square-integrable functions on the real line. The Haar wavelet's scaling function coefficients are h{k}={0.5, 0.5}and wavelet function coefficients are g{k}={0.5, -0.5}. The Daubechies wavelets [34] are a family of orthogonal wavelets defining a discrete wavelet transform and characterized by a maximal number of vanishing moments for some given support. With each wavelet type of this class, there is a scaling function which generates an orthogonal multiresolution analysis.

3. Proposed Methodology

To overcome the complexity of using texture features on entire image the proposed method divides the face into four parts of different size. These parts are decomposed with linear one-level wavelet decomposition technique i.e Haar, Db6, Cf6, and Sym8 and It crops the top left $1/4^{th}$ portion of the decomposed parts, and evaluates the texture features of each cropped part separately. The proposed method can be applied on any facial images irrespective of the size and age. The four parts are forehead, right cheek, left cheek and chin portions and with a size of 32×32, 16×16, 16×16 and 16×16 respectively. The texture features are derived from co-occurrence parameters. They are given in the following equations.

Angular Second Moment (ASM) $= \sum_{a,b} P^2_{\phi,d}(a,b)$ (1)

Entropy (ET) $= \sum_{a,b} P_{\phi,d}(a,b) \log_2 P_{\phi,d}(a,b)$ (2)

Maximum probability (MP) = $\underset{a,b}{Max}(P_{\phi,d}(a,b))$ (3)

Inverse Difference (ID) = $\sum_{a,b} \frac{P_{\phi,d}(a,b)}{1+|a-b|}$ (4)

Inverse Difference Moment (IDM) $\sum_{a,b;a\neq b} \frac{P_{\phi,d}(a,b)}{1+|a-b|^2}$ (5)

Mean (M) $= \sum_{a,b} a * P_{\phi,d}(a,b)$ (6)

where $P_{\phi,d}(a, b)$ – is the frequency of occurrences of two pixels, with gray-levels a, b appearing in the window separated by a distance ‘d’ in direction ‘ϕ’.

The texture features are evaluated for each cropped part individually in all orientations. The average value of each texture feature is taken as final value. The algorithm for the proposed scheme is given in Algorithm 1.

Algorithm 1: Preparing one-level linear wavelet compressed face recognition database

Begin

Step1: Read the input face color/gray scale image

Step2: If the input image is colored one, convert it to gray scale image

Step3: Crop the four parts from the gray scale face image i.e forehead, right cheek, left cheek and chin parts.

Step4: Perform one-level linear wavelet decomposition of all four cropped parts

Step5: Crop one fourth part (Top left corner part) from all the four wavelet decomposed parts.

Step 6: calculate all six statistical parameters from one fourth cropped forehead part from the corresponding co-occurrence matrix in all four orientations and sum and average each statistical parameter separately.

Step7: Repeat step 6 for one fourth cropped parts of right cheek, left cheek and chin.

Step8: perform sum of individual statistical parameters of all four cropped parts.

Step9: store these values in the face database.

Step10: Repeat Step 1 to 9 for all the face images for which we want to store in the face database.

End

The face recognition is carried out by the novel distance scheme. This scheme first evaluates the distance between texture feature one i.e ASM of sample image and database image. Based on this distance it picks up the first ten images, that are close to sample image. The same process is repeated for texture features 2, 3, 4, 5 and 6 by selecting 7, 5, 3, 2 and 1 images respectively from the database. The final image is the output image.

4. Results and Discussion

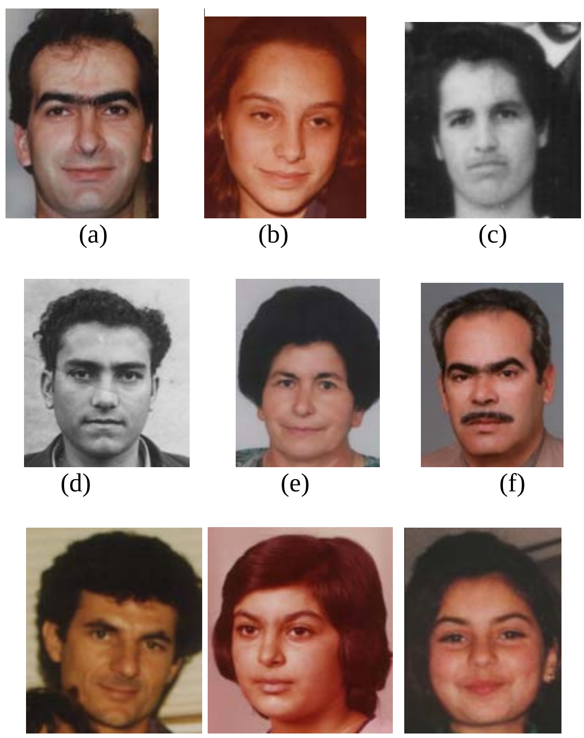
The above texture features are applied on 15 and 12 sample facial images from FGnet aging database and Google Images. The original facial images of FGnet and Google Image databases are shown in Figure 1 and 2 respectively. The facial images of Figure 1 and 2 are named from F-1a to F-1o and F-2a to F-2l respectively. The sample cropped four parts and their Haar wavelet and Db6 wavelet compressed outputs for facial images of Figure 1c and 2b are shown in Figure 3 and 4 respectively.

The texture features are evaluated on each of the facial image as explained in section 3 and listed in Table 1 and 2 with Haar wavelet decomposition for facial images of Figure 1 and 2 respectively and in Table 3 and 4 with Db-6 wavelet decomposition for facial images of Figure 1 and 2 respectively.

For evaluating successful recognition rate of each linear wavelet decomposition technique, each facial image sample is tested ten times. For each type of wavelet, each time the texture features are evaluated. The texture features of each time for the facial images of Figure 1 and 2 are evaluated. The texture features for the facial image of Figure-1d(F-1d) and Figure-2c(F-2c) are listed in tables 5 and 6 respectively. The hit or miss count for each time based on the above novel distance scheme is measured for all test sample images of Figure 1and 2. The hit indicates the successful recognition with a value one and miss indicates an unsuccessful recognition with a value zero. The hit or miss count for each time with all the four wavelets for the facial images of Figure 1d and Figure 2c are listed in table 7 and 8 respectively.

For all four linear wavelet decomposition techniques the average hit ratios are calculated by testing ten times for the entire facial database of Figure 1 and 2 and are listed in Table 9.

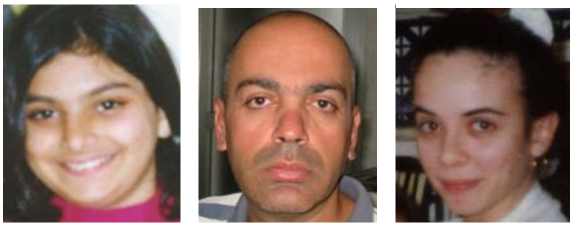
The comparison of hit rates for images F-1d and F-2c are represented in the form of bar graphs in Figure 5 and Figure 6 respectively. The hit rates of four wavelet decomposition techniques for facial images of Figure 1 and 2 are represented in the form of bar graph in Figure 7 and 8 respectively.



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

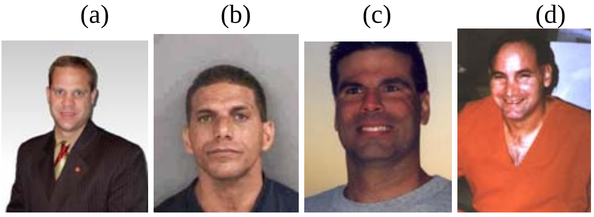


(j) (k) (l)

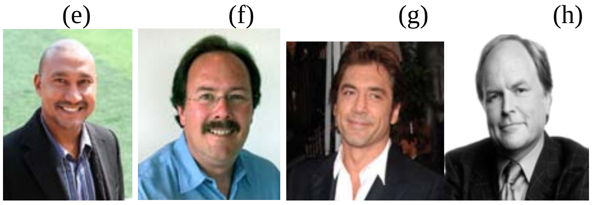
(m) (n) (o)

Figure 1. Samples facial images from FGnet aging database

(a) (b) (c) (d)



(e) (f) (g) (h)



(i) (j) (k) (l)

Figure 2. Samples facial images from Google Images.

Figure 3. Cropped four parts fore head, left cheek, right cheek and chin respectively of facial image f-1c, and their one-level Haar wavelet compressed output images

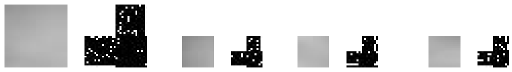


Figure 4. Cropped four parts fore head, left cheek, right cheek and chin respectively of facial image f-2b, and their one-level Db6 wavelet compressed output

Table 1: One-level Haar wavelet decomposed Texture features of sample facial images from FGnet aging database

Image Name	ASM	ENT	MP	ID	IDM	M
F-1a	547	199	15	80	56	2841
F-1b	427	134	11	77	54	3485
F-1c	668	233	17	72	50	4485
F-1d	487	118	10	83	53	5759
F-1e	323	76	11	58	38	4771
F-1f	473	141	12	81	54	5594
F-1g	922	322	20	127	87	7098
F-1h	290	60	10	54	35	4510
F-1i	1010	364	16	135	93	7553
F-1j	312	80	11	58	38	4652
F-1k	579	168	12	93	61	6835
F-1l	675	214	13	96	65	6873
F-1m	509	161	13	77	51	6069
F-1n	498	158	13	75	49	5972
F-1o	799	262	17	124	85	7423

Table 2: One-level Db6 wavelet decomposed Texture features of sample facial images from FGnet aging database

Image Name	ASM	ENT	MP	ID	IDM	M
F-1a	312	28	9	61	33	6092
F-1b	348	38	8	63	33	6893
F-1c	311	34	8	53	27	7013
F-1d	284	26	8	51	27	6503
F-1e	644	120	10	112	63	9947
F-1f	556	114	9	88	47	10749
F-1g	459	60	9	86	50	7895
F-1h	262	15	7	46	24	6668
F-1i	474	57	8	85	46	9142
F-1j	215	17	6	38	20	6079
F-1k	443	39	9	74	39	9923
F-1l	505	66	9	91	52	9852
F-1m	303	30	8	54	29	7414
F-1n	257	26	8	42	20	6742
F-1o	381	29	8	72	37	7917

Table 3: One-level Haar wavelet decomposed Texture features of sample facial images from Google Images

Image Name	ASM	ENT	MP	ID	IDM	M
F-2a	320	55	10	57	33	6373
F-2b	379	77	11	66	38	7154
F-2c	508	147	12	80	50	7973
F-2d	470	123	15	68	44	7349

F-2e	822	238	16	118	76	10004
F-2f	737	227	20	102	66	9088
F-2g	426	71	9	77	45	6556
F-2h	330	52	10	51	28	7757
F-2i	611	132	13	102	62	10994
F-2j	597	115	12	93	50	13516
F-2k	544	135	11	79	45	12458
F-2l	466	78	12	73	41	10977

Table 4: One-level Db6 wavelet decomposed Texture features of sample facial images from Google Images

Image Name	ASM	ENT	MP	ID	ID M	M
F-2a	1345	238	34	60	34	8111
F-2b	855	165	26	61	33	8707
F-2c	3356	360	62	43	25	6445
F-2d	918	211	26	50	33	6295
F-2e	991	205	27	80	47	10203
F-2f	2496	324	53	59	35	7457
F-2g	668	129	21	64	34	8539
F-2h	985	186	27	55	33	10055
F-2i	1129	189	32	77	40	13071
F-2j	1485	236	36	73	39	13664
F-2k	1453	258	35	83	47	14598
F-2l	1222	211	32	58	33	9191

Table 5: Ten times tested Haar wavelet decomposed texture features of facial image sample F-1d

Test Sl.No	ASM	ENT	MP	ID	ID M	M
1	380	91	10	62	38	6353
2	253	50	10	42	25	4904
3	236	42	8	41	25	5008
4	330	81	8	50	29	5889
5	773	246	13	96	60	10336
6	953	312	12	112	72	11692
7	253	36	8	44	26	4913
8	392	102	8	60	35	6476
9	346	84	8	52	29	5979
10	293	69	8	46	26	5462

Table 6: Ten times tested Db6 wavelet decomposed texture features of facial image sample F-2c

Test Sl.No	ASM	ENT	MP	ID	ID M	M
1	3135	341	61	34	20	4445
2	2528	326	53	54	34	6214
3	3340	363	61	54	31	6488
4	3596	369	64	51	30	6324
5	3121	371	59	60	33	7557
6	2880	369	56	62	36	7454
7	2576	338	53	63	38	7326
8	2836	336	55	52	31	6162
9	3443	380	63	60	35	7209
10	2892	336	56	52	31	6275

Table 7: Recognition sequence (Hit/Miss) for all the four wavelets for the facial image F-1d

Test Sl.No	Haar	Db6	Cf6	Sym8
1	1	1	1	1
2	1	1	1	1
3	1	1	0	1
4	1	1	1	1
5	1	1	1	1
6	0	1	1	1
7	1	1	1	1
8	1	1	1	1
9	1	1	1	1
10	1	1	1	1

Table 8: Recognition sequence (Hit/Miss) for all the four wavelets for the facial image F-2c

Test Sl.No	Haar	Db6	Cf6	Sym8
1	1	1	1	1
2	1	1	1	1
3	1	1	0	1
4	0	1	1	1
5	1	0	1	0
6	0	1	1	1
7	1	1	0	1
8	1	1	1	1
9	1	1	1	1
10	1	1	1	1

Table 9: Average hit ratio of all the facial images of Figure 1 and 2 for each linear wavelet.

Database Name	Haar	Db6	Cf6	Sym8
FG net Database	0.945	0.96	0.95	0.96
Google Images	0.82	0.90	0.87	0.85

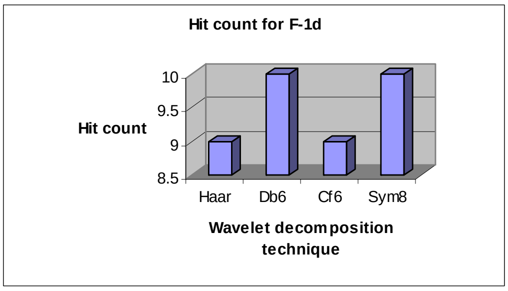


Figure 5. Bar graph of Hits for ten times input of F-1d image with the four wavelet decompositions

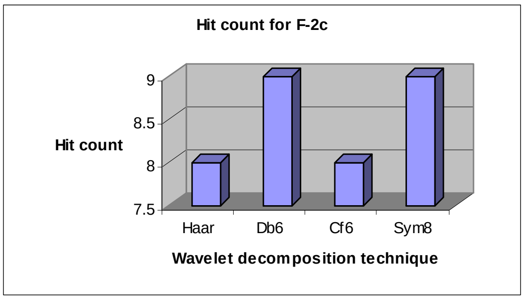


Figure 6. Bar graph of Hits for ten times input of F-2c image with the four wavelet decompositions.

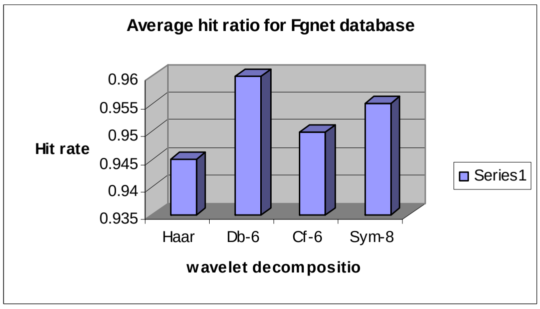


Figure 7. Bar graph of average Hit rates of all images of Figure 1 with the four wavelet decompositions.

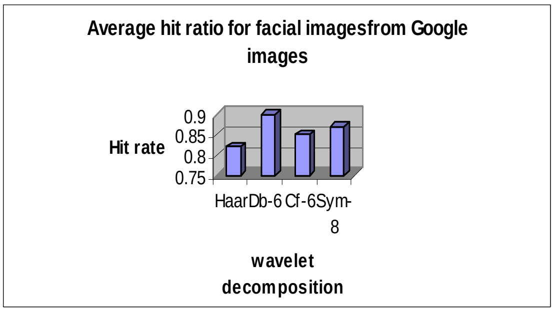


Figure 8. Bar graph of average Hit rates of all images of Figure 2 with the four wavelet decompositions

5. Conclusion

In this paper a novel method for face recognition based one-level linear wavelet decomposed texture features derived from co-occurrence matrices in all orientation. And also the present paper outlined a new distance function scheme that eliminates retrieved facial images step by step. Till now no research work is carried out for face recognition based on this approach. The present method is tested for both FGnet aging database and face Images down loaded from Google Images. Among the four wavelet decomposition techniques that are used, the Db6 is having slightly better performance than Cf6, Sym8, and Haar. On over all basis it is proven that the performance (speed, recognition rate) of the face recognition system is improved by applying one-level linear wavelet decomposition techniques. And also the performance of this system is more for standard face database than images down loaded from Google Images. This variation is due changes in image capturing environment, noise, and variation in properties of the images that are down loaded from Google Images. The performance of this recognition system can be further improved by increasing the number of parts which are extracted from a facial image.

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