

**Face Recognition Technology Using Fast
Fourier Transform (F.F.T) &
Discriminator Power (Dp)**

**Nada Abdul Karim
AL-Mansour University College**

Keywords: grayscale, Fast Fourier Transform (FFT), Calculate mean value and variance.

الخلاصة

تحويلات فورير السريعة هي طريقة قوية للتحويل لاستخراج خصائص مناسبة لتمييز الوجوه. بعد تطبيق متحويلات فورير السريعة (FFT) على صورة الوجه الكلية بعض المعاملات يتم اختيارها لبناء خصائص معينة. في بعض الحالات، المعاملات ذات التردد الواطئ سوف تهمل لموازنة أو لمعادلة التباين الواضح حيث ان معامل القوة لكل المعاملات هي غير متشابهة او متساوية وبعض هذه المعاملات يمكن تمييزها عن غيرها من المعاملات، حيث يمكننا تحقيق معدل تمييز عالي وصحيح بواسطة استخدام معاملات القوة. في هذا البحث، تم ايجاد معامل القوة للصورة بحيث تؤخذ الصفات المؤثرة في الصورة وتخزن هذه القيم او (الصفات) في قاعدة بيانات عملية اختيار معامل قوة مختلفة (اعلى 50 قيمة) تؤكد من نجاح الطريقة المقترحة، ونستخدم هذه القيم او (الصفات) كاساس للمقارنة مع قيم او (صفات) اخرى جديدة مراد خزنها في قاعدة البيانات.

Abstract

Fast Fourier Transform (F.F.T) is a powerful transform to extract proper features for face recognition. After applying FFT to the entire face images, some of the coefficients are selected to construct feature. In some cases, the low-frequency coefficients are discarded in order to compensate variations. Since the discrimination power of all the coefficients is not the same and some of them are discriminant than other. So we can achieve a higher recognition rate by using discriminant coefficients (DCs). The proposed approach is data-dependent and is able to find discriminator power (Dp) for each image, (the higher 50 value) and store these values in database. The selection of various coefficients confirm the success of the proposed approach. These coefficients are used as a basis for comparison with other attributes store in database.

1-Introduction

As one of the most successful applications of image analysis and understanding, face recognition. Face recognition has recently received significant attention, especially during last few years [1]. Activities in this field come from its applications in different areas such as security and surveillance, commercial and law enforcement. Ability for implementation in real time has intensified the attention to this field. Although research in the field of face recognition is active over 30 years and considerable successes in face recognition system have been achieved, still there are unsolved problem in it. Illumination variation, rotation and facial expression are the basic existing challenges in this area [2]. However, frequency domain analysis methods such as Fast Fourier transform (FFT), have been adopted in face recognition. Frequency domain analysis methods transform the image signals from spatial domain to frequency domain and analyze the features in frequency domain. Only limited low-frequency components which contain high energy are selected to represent the image [3].

In this paper, the high value of discriminator power (Dp) means high discrimination ability of the corresponding coefficient. In other words, it is expected to gain the maximum recognition rate by using the coefficient that has the maximum discriminator coefficients. This method has been tested on a database of facial image and achieves a good performance.

2- Grayscale Image

Grayscale digital images are referred to as monochrome, or one-color, images. They contain brightness information only, no color information. The number of bits used for each pixel determine the number of different brightness levels available. The typical image contains 8 bits/pixel data, which allows us to have 256 (0 – 255) different brightness (gray) levels. This representation provides more than adequate brightness resolution, in term of the human visual system's requirements, and provides a "noise margin" by allowing for approximately twice as many gray levels as required. This noise margin is useful in real-world applications because of the many different types of noise (false information in the signal) inherent in real system. Additionally, the 8-bit representation is typical due to the fact that the byte, which corresponds to 8-bits of data, is the standard small unit in the world of digital computers [4].

3-Fast Fourier Transform (FFT)

The Fourier Transform is an important image processing tool which is used to decompose an image into its sine and cosine components. The output of the transformation represents the image in the Fourier or frequency domain, while the input image is the spatial domain equivalent. In the Fourier domain image, each point represents a particular frequency contained in the spatial domain image [5].

The Fourier transform has found numerous uses, including vibration analysis in mechanical engineering, circuit analysis in electrical engineering, and here in computer imaging. This transform allows for the decomposition of an image into a weighted sum of two-dimension sinusoidal terms. Assuming an NxN image, the equation for two-dimension Fourier transform is [4]:

$$F(u, v) = \frac{1}{N} \sum_{r=0}^{N-1} \sum_{c=0}^{N-1} I(r, c) e^{-j2\pi \frac{(ur+vc)}{N}} \quad (1)$$

The base of the natural logarithmic function e is about 2.71828; j the imaginary coordinate for complex number, equals $\sqrt{-1}$ the basis functions are sinusoidal in nature, as can be seen by Euler's identity [4]:

$$e^{jx} = \cos x + j \sin x \quad (2)$$

So we can also write the Fourier transform equation as:

$$F(u, v) = \frac{1}{N} \sum_{r=0}^{N-1} \sum_{c=0}^{N-1} I(r, c) \left[\cos\left(\frac{2\pi}{N}(ur + vc)\right) + j \sin\left(\frac{2\pi}{N}(ur + vc)\right) \right] \quad (3)$$

(u,v) is also complex, with the real part corresponding to the cosine terms and the imaginary part corresponding to the sine terms. So a complex spectral component is represented by:

$$F(u,v) = R(u,v) + jI(u,v) \quad \text{—————} \quad (4)$$

Where R(u,v) is the real part and I(u,v) is the imaginary part, then we can define the magnitude and phase of a complex spectral component as [4]:

$$\text{MAGNITUDE} = \sqrt{[R(u,v)]^2 + [I(u,v)]^2} = |F(u,v)| \quad \text{—————} \quad (5)$$

$$\text{PHASE} = \Phi(u,v) = \tan^{-1} \left[\frac{I(u,v)}{R(u,v)} \right] \quad \text{—————} \quad (6)$$

After perform the transform, to get our original image back, the inverse transform is applied. So, the inverse Fourier transform is given by [4]:

$$F^{-1}[F(u,v)] = I(r,c) = \frac{1}{N} \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} F(u,v) e^{j2\pi \frac{(ur+vc)}{N}} \quad \text{—————} \quad (7)$$

The $F^{-1}[\]$ Notation represents the inverse transform. This equation illustrates that the function $I(r,c)$ is represented by a weight sum of the basis functions and that the transform coefficients $F(u,v)$ are weights. With the inverse Fourier transform, the sign on the basis functions exponent is changed from -1 to +1. However, this corresponds only to the phase and not the frequency and magnitude of the basis functions [5].

4- Calculate mean value and variance

The mean is a measure of average gray level in an image and the variance (standard deviation), which is a measure of average contrast [6]. So instead of using the image histogram directly for enhancement. We can use instead some statistical parameters obtainable directly from the histogram. Let r denote a discrete random variable representing discrete gray-levels in the range $[0, L-1]$, and let $p(r_i)$ denote the normalized histogram component corresponding to the i th value of r . $P(r_i)$ as an estimate of the probability of occurrence of gray level r_i . The n th moment of r about its mean is defined as [6]:

$$\mu_n(r) = \sum_{i=0}^{L-1} (r_i - m)^n p(r_i) \quad \text{—————} \quad (8)$$

Where m is the mean value of r (its average gray level):

$$m = \sum_{i=0}^{L-1} r_i p(r_i) \quad \text{-----} \quad (9)$$

It follows from Equation (8) and (9) that $\mu_0 = 1$ and $\mu_1 = 0$. The second moment is given by [6]:

$$\mu_2(r) = \sum_{i=0}^{L-1} (r_i - m)^2 p(r_i) \quad \text{-----} \quad (10)$$

This expression is considered as the variance of r , which is denoted conventionally by $\sigma^2(r)$. The standard deviation is defined simply as the square root of the variance [6].

The global mean and variance are measured over an entire image and are useful primarily for gross adjustments of overall intensity and contrast. A much more powerful use of these two measures is in local enhancement, where the local mean and variance are used as the basis for making changes that depend on characteristics in a predefined region about each pixel in the image [7].

Let (x,y) be the coordinates of a pixel in an image, and let S_{xy} denote a neighbourhood (subimage) of specified size, centered at (x,y) . From Eq.(9) the mean value $m_{S_{xy}}$ of the pixels in S_{xy} can be compared using the expression

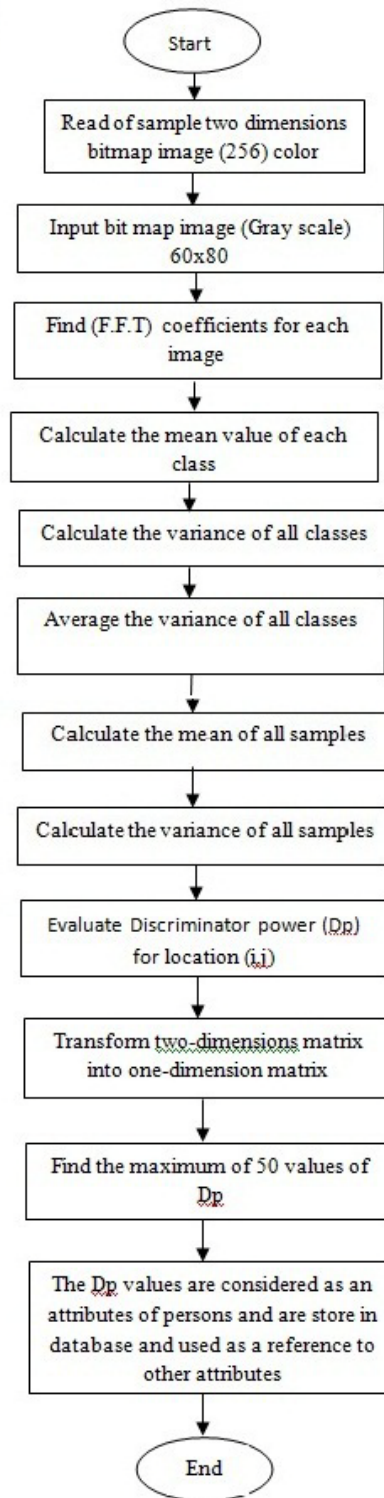
$$m_{S_{xy}} = \sum_{(s,t) \in S_{xy}} r_{s,t} p(r_{s,t}) \quad \text{-----} \quad (11)$$

Where $r_{s,t}$ is the gray level at coordinates (s,t) in the neighbourhood, and $p(r_{s,t})$ is the neighbourhood normalized histogram component corresponding to that value of gray level. Similarly, from Eq.(10), the gray-level variance of the pixels in region S_{xy} is given by:

$$\sigma_{S_{xy}}^2 = \sum_{(s,t) \in S_{xy}} [r_{s,t} - m_{S_{xy}}]^2 p(r_{s,t}) \quad \text{-----} \quad (12)$$

The local mean is a measure of average gray level in neighbourhood S_{xy} , and the variance (or standard deviation) is a measure of contrast in that neighbourhood [6]. An important aspect of image processing using the local mean and variance is the flexibility they afford in developing simple, yet powerful enhancement techniques based on statistical measures that have a close, predictable correspondence with image appearance [8].

6-System Model (the block diagram)

Figure (1): Block diagram for evaluate discriminator power (D_p).

7- The algorithm

Step 1: Read two-dimensions bit map images (256) colors and put these images in two dimensions array. Each value in the matrix represent pixel in the image.

Step 2: read 8 bit Gray scale image.

Step 3: Implement the set matrix, A_{ij} , by choosing the Fast Fourier (FFT) coefficients of the position i and j for all classes and all images:

$$A_{ij} = \begin{bmatrix} x_{ij}(1,1) & x_{ij}(1,2) & \dots & x_{ij}(1,c) \\ x_{ij}(2,1) & x_{ij}(2,2) & \dots & x_{ij}(2,c) \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ x_{ij}(s,1) & x_{ij}(s,2) & \dots & x_{ij}(s,c) \end{bmatrix}_{s \times c}$$

Step 4: Calculate the mean value of each class according to the following:-

$$Mi^c_j = \frac{1}{s} \sum_{s=1}^s A_{ij}(s, c), \quad c = 1, 2, \dots, C \quad \text{-----} \quad (13)$$

Mi^c_j : is the mean value of each class.

Step 5: Calculate variance of each class:

$$Vi^c_j = \sum_{s=1}^s (A_{ij}(s, c) - Mi^c_j)^2, \quad c = 1, 2, \dots, C \quad \text{-----} \quad (14)$$

Vi^c_j : is the variance of each class.

Step 6: Average the variance of all the classes:

$$Vi^w_j = \frac{1}{C} \sum_{c=1}^C Vi^c_j \quad \text{-----} \quad (15)$$

Vi^w_j : is the average variance of all class.

Step 7: Calculate the mean of all samples:

$$Mij = \frac{1}{s \times c} \sum_{c=1}^c \sum_{s=1}^s A_{ij}(s, c) \quad \text{-----} \quad (16)$$

Mij : is the mean of all sample images.

$s \times c$: is the image dimension (width X height)

Step 8: Calculate the variance of all the samples:

$$Vi^B_j = \sum_{c=1}^C \sum_{s=1}^S (A_{ij}(s, c) - Mij)^2 \quad \text{-----} \quad (17)$$

Vi^B_j : is the variance of all sample images.

Step 9: From Eq.(5) and (7) ,we can estimate the discriminator power for location (i,j) according to the following equation:

$$D(i,j) = \frac{V_{i^B j}}{V_{i^W j}} \quad 1 \leq i \leq m, \quad 1 \leq j \leq n \quad \text{-----} \quad (18)$$

$V_{i^B j}$: is the variance of all sample images.

$V_{i^W j}$: is the average variance of all class.

(m,n) : is the image dimensions.

Step 10: Transform two dimensions matrix into one dimension matrix.

So, to transform two dimensions matrix into one dimension, we should apply the following equation:-

$$\text{Location (Z)} = Y \times \text{width} + X$$

Since, location (Z): mean the location in one dimension array.

X: mean the X-axis.

Y: mean the Y-axis.

Z: mean location in one dimension matrix.

Example: Transform two dimensions matrix to one dimension

		X-axis			
		1	2	3	3
Y-axis	1	(1,1) 1	(1,2) 2	(1,3) 3	(1,4) 4
	2	(2,1) 5	(2,2) 6	(2,3) 7	(2,4) 8
	3	(3,1) 9	(3,2) 10	(3,3) 11	(3,4) 12

Figure (2): show the two dimensions matrix.

From the previous matrix, location (7) is calculated as follows:

$$\text{Location (Z)} = (Y-1) \times \text{width} + X$$

$$\text{Location (7)} = (2-1) \times 4 + 3$$

$$= 1 \times 4 + 3$$

$$= 4 + 3 = 7$$

Location (10) is calculated as follows:

$$\text{Location (Z)} = (Y-1) \times \text{width} + X$$

$$\text{Location (10)} = (3-1) \times 4 + 2$$

$$= 2 \times 4 + 2$$

$$= 8 + 2 = 10$$

and so on.

8 - Experimental Results

In this paper, all computers programming works were done by using C++ language under window. The discriminator power (Dp) of several image tested will be taken as shown in figure (3), (4) and figure (5) apply the previously described methods as in the followings tests:-

For the following figure, the discriminator power (Dp) will shown in table (1)



Figure (3): face (1).

For the following figure, the discriminator power will shown in table (2)



Figure (4): face (2).

For the following figure, the discriminator power will shown in table (3)



Figure (5): face (3).

The discriminator power (Dp) of figure (3) is shown below:

location x	Location y	Discriminator power (Dp)	Location x	Location y	Discriminator power (Dp)
08	49	4.498	57	48	4.449
39	00	4.495	51	46	4.448
23	43	4.495	17	51	4.446
14	16	4.495	70	57	4.446
31	50	4.493	24	51	4.444
61	27	4.493	12	44	4.434
28	22	4.487	01	29	4.433
38	22	4.484	62	42	4.431
15	43	4.484	12	11	4.424
60	38	4.483	48	53	4.423
02	56	4.482	39	59	4.419
73	14	4.482	41	46	4.418
79	19	4.479	49	30	4.418
51	56	4.476	70	56	4.417
63	08	4.476	15	16	4.417
65	33	4.475	79	29	4.416
40	14	4.471	41	00	4.416
38	11	4.466	46	09	4.413
16	55	4.465	02	58	4.410
57	42	4.465	30	40	4.408
55	41	4.455	12	48	4.409
76	20	4.454	22	19	4.404
54	07	4.454	11	08	4.394
14	28	4.452	35	59	4.394
00	12	4.451			

Table (1): show the discriminator power of figure (3)

The discriminator power (Dp) of figure (4) is shown below:

Location x	Location y	Discriminator power (Dp)	Location x	Location y	Discriminator power (Dp)
37	49	14.252	01	58	8.079
65	10	12.321	48	44	8.049
77	55	10.575	55	48	8.016
53	46	10.510	41	46	8.014
28	22	10.310	31	28	7.990
20	40	10.031	65	08	7.984
64	57	9.590	68	27	7.914
09	11	9.498	46	03	7.900
36	28	9.066	08	40	7.897
37	35	9.062	58	14	7.872
24	04	8.915	43	24	7.862
25	23	8.850	58	58	7.784
32	50	8.761	27	55	7.779
75	38	8.584	68	06	7.756
32	39	8.526	30	37	7.615
04	36	8.451	66	41	7.712
46	09	8.345	03	30	7.641
53	30	8.333	18	13	7.617
16	06	8.261	10	17	7.607
41	14	8.212	10	25	7.587
79	24	8.212	11	43	7.584
10	05	8.170	76	02	7.563
22	41	8.152	33	52	7.554
51	39	8.138	11	04	7.536
05	07	8.102			

Table (2): show the discriminator power of figure (4).

The discriminator power (Dp) of figure (5) is shown below:

Location x	Location y	Discriminator power (Dp)	Location x	Location y	Discriminator power (Dp)
05	46	33.628	49	36	13.820
29	32	23.200	03	23	13.789
66	54	21.264	45	45	13.640
66	13	19.931	06	07	13.313
28	20	19.291	17	51	13.274
43	24	19.237	21	37	13.262
68	42	18.429	14	33	13.014
03	24	17.524	63	02	12.755
68	27	17.194	77	19	12.646
26	15	17.168	71	39	12.373
05	33	17.008	42	30	12.305
51	39	16.569	36	35	11.976
00	11	16.176	04	17	11.905
75	17	16.130	68	00	11.809
32	39	15.434	06	31	11.737
02	58	14.961	17	22	11.711
09	22	14.948	14	19	11.688
39	23	14.580	16	42	11.504
66	17	14.369	12	48	11.503
42	01	14.355	78	54	11.472
68	13	14.281	73	12	11.430
15	44	14.238	01	29	11.220
43	44	14.230	08	53	11.185
64	18	14.208	02	45	11.174
66	37	14.166			

Table (3): show the discriminator power of figure (5).

9- Conclusions

A summary of some important conclusions is presented as below:

- 1- Take the most effective attributes in the image (maximum 50 values), store these values in database and compare these values with other attributes. This will reduce storage space, quick the search time, decrease computational cost.
- 2- The purpose of several tested images to determine the locations of each attributes in the image to take the final results, hence each image take the same locations.
- 3- In this paper, decrease or increase the attributes in the image according to the nature of person's information. So, we can deduce or combine other statistical rules in mathematical computations.
- 4- Using (FFT) as an excellent tool for face pattern recognition using personal computer. FFT function could be easily applied with less time consuming, and is quite simple in application. So, the parameters obtained for face recognition directly fit to the FFT function.

11-References

- [1] L. Zhao and C. Zou, "Face recognition using common faces method, Pattern Recognition", (2006), Vol. 39, No. 11, pp.2218-2222.
- [2] S.Dabbaghchian, M.P.Ghaemmaghami, "Pattern Recognition", (2010) available at: <http://elsevier.com/locate/pr>.
- [3] E.O., Brigham, (2006), "A New Principle for Fast Fourier Transformation", New York: prentice- Hall.
- [4] Unbaugh, S. E., "Computer Vision and Image Processing: A practical approach using CVIP tools", Prentice-Hall PTR, 1998.
- [5] A. Walker and E. Wolfart, "Fast Fourier Transform", September/27/2010 available at: <http://homepages.inf.ed.ac.uk/rd/HIPR2/fourier.htm>.
- [6] Gonzalez, R.C., and Woods, R.E., "Digital Image Processing", Prentice-Hall. Inc., 2002.
- [7] S. Ben Bernake, "Arithmetic mean", July/23/2010 available at: http://pulse.yahoo.com/y/apps/bv0wM_F30/?yap_intl=us&yap_js=US.
- [8] Darrell, "Standard Deviation & variance", available at: <http://daviamlane.com/hyperstat/A16252>.