Proposed methods of image recognition depend on the PCA

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Abstract

This paper suggest two method of recognition, these methods depend on the extraction of the feature of the principle component analysis when applied on the wavelet domain(multi-wavelet). First method, an idea of increasing the space of recognition, through calculating the eigenstructure of the diagonal sub-image details at five depths of wavelet transform is introduced. The effective eigen range selected here represent the base for image recognition. In second method, an idea of obtaining invariant wavelet space at all projections is presented. A new recursive from that represents invariant space of representing any image resolutions obtained from wavelet transform is adopted. In this way, all the major problems that effect the image and change its characteristic are solved through calculating invariant eigen range of the recursive resolution forms of all sub-images coefficient. These approaches employed here as multi-wavelet transform identifier with minimum Mahalanobis distance. All method recognition proposed in this paper are applied on different images. Different tables of image recognition resulted in accurate and fast.

Keywords: image recognition, wavelets transform, eignstructure..

1.Introduction

A feature recognition module uses domain specific knowledge to identify feature regions that correspond to defects. This module uses technical data on product features and patterns to identify regions of interest that affect the quality. The knowledge-based system uses rules to determine whether a region is a member of a particular defect class[Yu 03].Three aspects of the image identification approach are:

- The selection of features(principles component analysis(PCA)).
- The choice of a measurement of similarity(Mohalanobis distance)
- A method for creating reference templates.

One can see that the recognition operation for the PCA (using Karhnen-loeve transform(KLT)method) is very effective on the recognition for huge image size, even when this image is suffering from different type image of noise.

The importance of the Wavelet as a multi-resolution technique comes from its decomposition of the image into multilevel of the independent information. This usually can be achieved with changing the scale like a geographical map in which the image has non-redundant information . In this way every image will be transformed in each level of decomposition to a one low information image and three detailed imaged in horizontal ,vertical, and diagonal axis image. Also, the low information image can be decomposed into another four images [Mallat96]. This approach of decomposition process provides us with a number of unrealizable features in the original image, which appear in their levels after the application of the transformation. So the Wavelet can be regarded as the most efficient transform that deals with images, sound, or any other pattern, since it

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provides a powerful time-space(time-frequency) representation [Graps95].

PCA provides means by which to achieve such a transformation where the feature space accounts for as much of the total variation as possible. PCA is well-known technique in multivariate analysis, where the importance of evaluated statistically [Abhijit95].

The goal of PCA is to find and make use of information about the nature of variables in a matrix. Recall those variables are assumed to be contained within matrix columns. The data in the columns of a matrix may or may not all be mutually independent. It may be, for instance, that some columns can be expressed as linear combination, it can be useful to know that the original data matrix can be re-expressed as matrix with a smaller number of mutually uncorrelated columns. Another area of application, filtering out noise from a data matrix, this makes use of the following fact: If the data in the original matrix contain noise that is uncorrelated with each of the matrix variable, this noise can be extracted from the matrix and expressed as one or more separate variables. One of these variables can thus account for purely stochastic noise in the data that are considered to be noise because they are unrelated to the variables of interest. These "noise" variables can be eliminated from a data matrix.

The result will be a new matrix that is an approximation to the original data matrix, but synthesized using the reduced number of variable. PCA will be explained using a geometrical approach. The data in the original data matrix can be viewed as a set of data points in a space similar to the phase space . This space is referred to as the variable space of the data since it is defined by a set of dimensions, each of which corresponds to the data variables.

In order to interpret the above paragraph by representing each matrix in term of its eigenvalues corresponding to eigenvectors; these eigenvalues will specify the relative a mount of variance in the data in term of a set of mutually uncorrelated variables. Hence maximum eigenvalue will represent a maximum variance in the data, while maximum eigenvector will represent the whole characteristic of the maximum variance on data [Edward98]. These eigenvalues may be calculated at some point from converting again matrix into a symmetric covariance or correlation matrix. If such a matrix is already available it can be passed to the PCA directly.

The PCA then reduces the correlation or covariance matrix to tri-diagonal form, using a technique known as Houeholder reduction[Terry79]. Next, the eigenvalues and eigenvectors of the reduced matrix are computed using the QL algorithm(speed algorithm for calculating the eigenstructure for any symmetrical matrix, which specify in appendix B). Using the QL algorithm the covariance or correlation matrix is factored to produce the matrix of eigenvalues D, and the matrix of corresponding eigenvectors[Edward98].

2. Proposed a New Recognition Method for Noisy and Rotated Color Images

In order to apply PCA on color image at different scale of it (Multi-Resolution Analysis (MRA)), adopting the idea of calculating the eignvalues at each scale of this color image. In this case one can represent any scale of this color image with its eigenstructure (orthogonal image details). Thus, the PCA feature (eignvalues) will represent the features of the orthogonal wavelet. One can propose here a new method of recognition to the rotated and noisy patterns that is dependent on the PCA for the eigenvalues structure of the wavelet transform(WT). In this new algorithm(see algorithm 1), four main step must be evaluated:

Algorithm 1;
Input: Color imge.
Output Recognized image.

1. Applying discrete multi wavelet transform(DMWT) to the 2-Dim input color image of 3-Dim object under test in order to obtain three bound of local details information, these three bound are vertical, horizontal, and diagonal bonds respectively (Mallat algorithm).

2.Obtaining the covariance matrix form of diagonal image information (diagonal details)(1)

A- if the image under test is different from the reference image(2) . The proposed method here suggest to take the maximum variance in the eigenvalues range for representation this image only(3).

B- if the image under test represent noisy version of reference image, the proposed method here suggests to develop Akaike algorithm in order to find the principle component eignvalues that represent this image under test (4)[Ali94][Akaike83].

*3.Return to step (1)and apply MRA(5) theory on a given approximated image at that depth then calculating point 2,3 respectively. This operation of decomposition will be stopped until the approximations image size is equal to (8*8).*

(1) which the main diagonal represent the variance among the diagonal image information relatively. Variance values will represent the whole diagonal image information in a small number of the eigenvalues. In such a way the computational burden and the estimation errors are reduced [Ali94].

(2) if the image under test represent rotated oriented version from reference image.

(3) Maximum variance in the eigenvalues is different from one image to another, this is returned to the different eignstructures calculated for different images.

(4) The principle operation of the developed Akaike algorithm is dependent on the same idea proposed in (A). we can say that because the noise signals component are small corresponding to big image signals thus. The noise signals components are un correlated with these big signals but, the noise signals component are correlated with small signals in the image[Starck98]. According to above, we can say that the eigenvalues in the covariance matrix may be partitioned in to signal and noise sub spaces. thus, we need here to accurate and reliable method to select the maximum range of the eigenvalues that represent the original image[Ali94].

(5) Multiresolution analysis

2.1 Developed Akaike (AIC) algorithm

A new simple and computationally efficient method for determining the number of signals in the random process or to find principles component eigenvalues. One can apply AIC algorithm on each covariance from of the diagonal image as follow (see algorithm2)[Ali94]:

Algorithm2;
Input: Covariance matrix from of the diagonal image details.
Output: Recognized image.

1. Calculate the eigenstructure for the covariance matrix from of the diagonal image details using standard algorithm QL. putting the eigenvalues obtained in descending order.

2. Maximum likelihood(ML)must be calculated to estimate the selected depth as :

$$ML = abs(\lambda_p - \frac{1}{M}\sum_{i=p+1}^{M}\lambda_i)$$

Where λ p>λ i and M.>p M>p,M size of block

λ p , λ i:eigenvalues and P:pointer of the range of eigenvalues

3. K_1=-1 , K_2=k_3=1 [(1)]

NFAP=p(1+1/M)………………………………….(1)

GFCN(P)=-K_1log(ML)+K_2(NFAP).K_3 ………….(2)

NFAP: represent the number of free adjustable parameter. GFCN: represent the general form criterion development[Ali94].

4. *Calculate the value of (p), which minimize the value of GFC*[(2)].

[(1)]Where K_1,K_2, and K_3: represent constants and their values depend upon the chosen criterion in the table (1).

[(2)] The value of (p) represents the pointer to the range of eigenvalues.

Table(1): Table of values assigned to the GFCN to act as AIC or MDL or Developed AIC criteria

Variable	AIC	MDL	Developed AIC
K_1	2	1	-1
K_2	2	0.5	1
K_3	1	LogN	1
NFAP	P(2M-P)+1	P(2M-P)+1	P1(2M-P)+1

2.2 Proposed Matching Algorithm

Suppose the system of matching procedure is containing 100 reference images (10 different color images of part X with 10 different angle for each one). We can measure the distance between any test images and all image in the reference by calculating the vector of invariant feature (PCA feature)for any test image and all image in the reference. One can illustrate the above procedure for measuring the distance between the test image and all image in the reference (see algorithm 3).

Algorithm 3:
Input: Color images;
Output: Recognized image.

*1- Input the group of color images(256*256) to test it.*

2- Input an image of this group with it's Mean

3- For i=0 to 4 do

- *Decompose the image at depth i to get L_o^i,D_1^i,D_2^i,D_3^i*
- *Determine Covariance matrix to D_3^i*

End loop

4- Selection of recognition method

1- For i=0 to 4 do

- *Apply maximum eigenvalues method on the Cov_3^i, matrices to find maximum eigenvalue component from orthogonal details information at each depth of tested image(Algorithm1 2-A).*
- *Apply developed AIC algorithm on the Cov_3^i matrices to find the range of maximum eigenvalues at each depth of tested image(algorithm1 2-B)*

End loop

5- Classification method of the image under test

- *Calculating the Mahalanobis distance between the selected eigenvalues(invariant PCA features calculated at four depth)*
- *detecting the normalization parameter of the selected eigenvalues.*
- $D(\lambda,\lambda^{\Lambda}) = \frac{1}{\max}\sqrt{\sum(\lambda_i,\lambda_i^{\Lambda})^2}$ *……(3)*[(1)]

[(1)] I : indicaters the number of used eigenvalues at five depths.

λ_i : represents the eigenvalues that are selected from tested image.

$\hat{\lambda}_I$: represents the eigenvalues are selected from any reference image

max: represents normalization parameter of the selected eigenvalues.

3. Proposed Recognition Method for High Scale Image

One can propose here new form of represent any image projection in new modified recursive from in order to obtain an invariant wavelet space. In this from, any image resolution will represent it in a same form even when the image is suffering from rotate or shift problem. In this way local PCA Feature obtained from this new domain represent it with small size. In this method we used adaptive recursive forms of details information (horizontal, vertical , and diagonal). The details information must be redistributed according to the normalized grey level values at that scale(the size of this new from equal to the size of detail information). The segmentation procedure here illustrated by diving image into equal small size of block , each block consist of two, four, or eight associated pixels. The image is taken in the shape of matrix(row wise) then each block will be over lapped with next block . This means that if the block size is equal two pixel in the next block etc. In this way the image row of 128 pixels consists of 127 blocks and so on . the generations of the blocks stops to this number of blocks in each row . We can calculate the number of operations as follows:

consider an image with maximum size dimension equals to $MAX_{i,j}$.

Number of operation= MAX_i *(MAX_j -1) …………(4)

Which is equal to the number of blocks.

Thus any block(i.e. two pixels)must be redistributed again in the form of index (meaning that the first pixel value represents row index and the second pixel represents column index).We can interpret this new form as in bellow:

For i=1 to col,
For j-1 to row-1,

rc(image(I,j),image(I,j+1))=rc(image(I,j),image(I,j+1))+1;
end
end

where col, and row represent the maximum dimension size of a given image.

This operation of representation image as a gray distribution matrix is very efficient in the pattern recognition purpose, even when the image is deformed version of the original image, because the relation between each two pixels are different from one image to another. If the block is overlapped with next block in the same row by four or eight pixel this will lead to an increase of the probability of recognition.

This new adaptive segmentation process leads to redistribute low/high information in simple and local locations for calculating different local features. One of the most interested features calculated is the eigenstructure of this small/local form of matrices. After this step we must calculate the local PCA features of the eigenvalues for these new form of approximated and image details matrices.

When the eigenstructure of these details information will be obtained at a selected scale of any image under test, we must return to select the recognition method proposed above(either 3-A or 3-B discussed in the section 2.1). Finally we must classify images using Mahalanobis distance as a classifier. In this case the maximum range selected from the eigenstructure(3-B) will represent image at different scale of it even when image suffering from shift or rotate in direction.We can represent this new approach of image recognition in the following algorithms:

Algorithm Modified form of recursive matrices:
Input : Image(256*256) ,Decompose it using DMWT at Depth$_i$.
Output : eigenvalues range using (2-A or 2-B).
1: for i=0 to 4 do
1.1: Find L_0^i, D_1i, D_2i, D_3i.
1.2: Normalized L_0^i, D_1i, D_2i, D_3i .
1.3: New recursive model $RC_0^i, RC_1i, RC_2i, RC_3i$.
End loop
2: Calculate eignvalues of a given new models.
3: Select: eigenvalues range using (2-A or 2-B).
4: Stop

The final sub-module is the classification by using the Mahalanobis distance. Mahalanobis distance is very useful way of determining the 'similarity' of a set of values from an unknown: sample to a set of values measured from a collection of known: samples. Mahalanobis distance look at not only variations(variance)between the responses at same wavelength, but also at inter–wavelength variations(co-variance). Another advantage of using the Mahalanobis measured for discrimination is that the distance are calculated in unit of standard deviation from the group mean. A classifier is used depend on the Mahalanobis distance measure which is a weighted distance measure. The feature set consist of the features of the decomposed sub images except of the low-low pass sub images of every image. Then to an unknown image, the following classification procedure is in its identification :-

Algorithm Classification;
Input: a group of 5 compressed color image.
Output: logic decision with percentage (accept or reject).
1: go direct to the specific cluster to search it .
2: For all i
2.1: using Mahalonbis distance to compute the similarities measure between the test part image and the part image in reference set(d_i)

- *Calculate the distance measure between the unknown image, and of the i'th image in the reference feature set. The weighted distance measure of Mahalanobis is used. $D(i)=distance(E_1 E_i)$..................(5)*
- *Assign the unknown image to image I if: the decision strategy is based on the assignment of the unknown image to*

$D(i)<D(j)$ for all $i \neq j$ ....(6)

At the end of this Step the unknown image will be given a class label i.
2.2:
$D=(d_1)^2+(d_2)^2+\ldots+(d_i)^2$ ....(7)
3: compare $D^{(1)}$ with normalization factor
if D>= 60 then accept the image then add it into database of products.
if 59>= D> 50 then preprocessing the image again ,goto step 1.
if D<= 40 then reject this part , then add it into defect products.
4: end loop

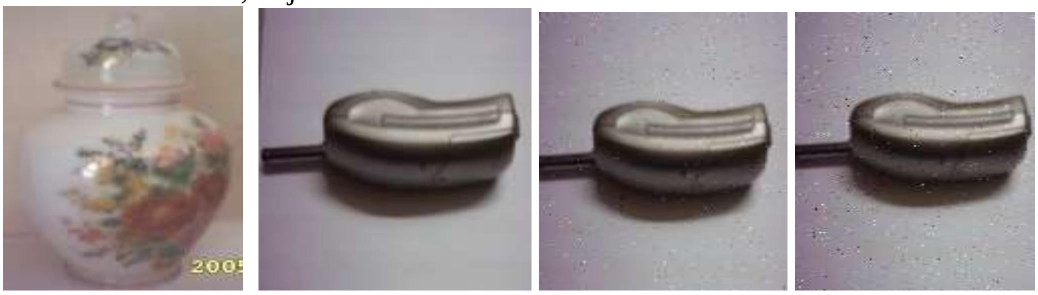
(1)using some previous studies, trails and error method on the minimum distance measurement that obtained from step 2.1 with some weight to adjust the result to detect this value.[shai 2006].

4.Discussion and Conclusion

We can prove that the efficient ability of system for this new proposed methods, when is applied on different selected image examples.

Test one: Consider the system of recognition consists of four images

Object2,Object5 with VAR=0.3,Object5 with VAR=0.5, and Object5 with VAR=0.6, each image will be tested with other for calculating its distance from others See figure(4.12-b) in which the distance of noisy images(Object5 with VAR=0.3,Object5 with VAR=0.5, and Object5 with VAR=0.6) are still in the same class, but the image distance of Object2 , which represents the other class. Finally see table(2), which is classify images in figure(1)



object2 object5(0.3) object5(0.5) object5(0.6)

Figure(1)Application of test One

Table(2): Mahalanobis distance measurement between any tested image with any images in the reference .

Mahalanobias Distance	Object2	Object5(VAR=0.3)	Object5(VAR=0.5)	Object5(VAR=0.6)
Object2	0.0000	0.3638	0.3677	0.3638
Object5(VAR=0.3)	0.3638	0.0000	0.0061	0.0000
Object5(VAR=0.5)	0.3677	0.0061	0.0000	0.0061
Object5(VAR=0.6)	0.3638	0.000	0.0061	0.0000

Test Two:

We consider the system of recognition consists of four images Object45^{O},Object35^{O},Object225^{O} and Object315^{O}), each image will be tested with other for calculating its distance from others. See figure(2) and its classifier table(3) related to it, which is classify different versions of the rotated object to the same class of the original object image.

object45 object35 object225 object315

Figure(2)Application of test two

Table(3): Mahalanobis distance measurement between any tested image and any image in the reference

Mahalanobias Distance	Object45^{O}	Object35^{O}	Object225^{O}	Object315^{O}
Object45^{O}	0.00000	0.000111	0.000115	0.000218
Object35^{O}	0.000111	0.00000	0.000218	0.000331
Object225^{O}	0.000115	0.000228	0.00000	0.000103
Object315^{O}	0.000218	0.000331	0.000103	0.00000

object256 object35 object 215 object110

Figure(3)Application of test Three

Table(4): Mahalanobis distance measurement between any tested image and any image in the reference .

Mahalanobias Distance	Object256	Object35^{O}	Object215^{O}	Object110^{O}
Object256	0.00000	0.000463	0.000311	0.000625
Object35^{O}	0.000463	0.00000	0.0001485	0.000156
Object215^{O}	0.000311	0.000148	0.00000	0.000303
Object110^{O}	0.0002625	0.000156	0.000303	0.00000

Test Three: We consider the system of recognition consists of four images Object256, Object35^{O},Object215^{O} and Object110^{O}), each image will be tested with other for calculating its distance from others. See figure(3) and its classifier table(4) related to it, which classified different versions of the rotated Object to the same class of the original Object image.

Table(5) represents the distance calculated according to the proposed method mentioned in(2.1). We proved here that dramatic results obtained when two classes of images are tested. The first class represents here Object image with different oriented in direction and Object1 , which represents second class. This table is explained the Mahalanobis minimum distance measurements between any tested image(object256, object35, object215, and objct1) with all images in the reference. Using here four depths with four resolutions of each depth. The value of the distance is either zero or 0.5, this means that there are two classes of images. See table (6), which proved the result.

Table(5): Mahalanobis distance measurement between any tested image and any image in the reference .

Mahalanobias Distance	Object256 ^{O}	Object35^{O}	Object215^{O}	Object1
Object256 ^{O}	0.00000	0.0005	0.0003	0.501
Object35^{O}	0.0005	0.00000	0.0002	0.493
Object215^{O}	0.0003	0.0002	0.00000	0.488
Object1	0.501	0.493	0.488	0.00000

Table(6): The eigen structure computed for 4 images under test

Sub_image resolution	Maximum eigenvalue Object256 *1Exp3	Maximum eigenvalue Object_35^{O} *1Exp3	Maximum eigenvalue Object_215^{O} *1Exp3	Maximum eigenvalue Object1 *1Exp3
L_0^0	3.7482	3.7672	3.7511	136.4439
L_0^1	0.8331	0.8311	0.8431	17.8231
L_0^2	0.1600391	0.1610	0.1620	5.0388
L_0^3	0.0220	0.0230	0.0230	1.7337
L_0^4	0.0034	0.0035	0.0032	0.0062
D_1^0	4.4825	4.4892	4.4865	814.3925
D_1^1	0.8836	0.8856	0.8987	87.3747
D_1^2	0.1632	0.1631	0.1622	9.7597
D_1^3	0.0230	0.0240	0.0250	1.6964
D_1^4	0.00321	0.00340	0.00320	0.0065
D_2^0	4.7061	4.9684	4.6757	481.2705
D_2^1	0.8828	0.8799	0.8767	59.7198
D_2^2	0.1622	0.1642	0.1641	8.0308
D_2^3	0.0230	0.0240	0.0230	1.8869
D_2^4	0.0032	0.0035	0.00311	0.0059
D_3^0	6.3929	6.4015	6.453	532.0222
D_3^1	0.9888	0.9885	0.9677	87.7625
D_3^2	0.1709	0.1714	0.1739	15.7108
D_3^3	0.0231	0.0242	0.0240	2.1824
D_3^4	0.0033	0.0030	0.0032	0.0906

Table(7) represents the maximum eigenvalues computed for different tested images using DWT at different scale and resolutions. These results will identify any tested image with respect to its eigen structure. Table(8) represents the maximum eigenvalues computed for different tested images using CWT at different scale of original image. These results will identify any tested image with respect to its eigen structure. In this table we proved that the results are very smooth of nearing from original image. This is regard to the CWT, which provides all details information from original tested image at that scale. We must remark that the time consumed here is very long.

Table(7): The eigen structure computed for 4 images under test

Sub_image	Maximum	Maximum	Maximum	Maximum

resolution	eigenvalue Object45^O *1Exp3	eigenvalue Object35^O *1Exp3	eigenvalue Object225^O *1Exp3	eigenvalue Object315^O *1Exp3
L_0^0	7.693	7.686	7.688	7.661
L_0^1	1.796	1.800	1.790	1.790
L_0^2	0.391	0.392	0.399	0.388
L_0^3	0.071	0.0721	0.070	0.070
L_0^4	0.006	0.0064	0.0060	0.006
D_1^0	8.0937	8.113	8.0994	8.108
D_1^1	1.818	1.8162	1.8093	1.8172
D_1^2	0.392	0.392	0.392	0.3940
D_1^3	0.072	0.072	0.073	0.073
D_1^4	0.0061	0.0063	0.0060	0.0060
D_2^0	7.967	7.9686	7.966	7.9631
D_2^1	1.8102	1.8098	1.8102	1.8103
D_2^2	0.3920	0.393	0.392	0.3922
D_2^3	0.0720	0.0720	0.0725	0.073
D_2^4	0.0065	0.0063	0.0062	0.0062
D_3^0	9.0575	9.0525	9.0553	9.0548
D_3^1	1.8255	1.824	1.824	1.8232
D_3^2	0.394	0.394	0.393	0.395
D_3^3	0.073	0.72	0.0741	0.071
D_3^4	0.0064	0.0063	0.0061	0.0061

Table(8): The eigen structure computed for 4 images under test

Details coeff. After applying CWT	Maximum eigenvalue Object45^O *1Exp4	Maximum eigenvalue Object35^O *1Exp4	Maximum eigenvalue Object225^O *1Exp4	Maximum eigenvalue Object315^O *1Exp4
Details at scale(1:2)	4.0040	3.9983	3.99962	3.99840
Details at scale(1:2)	4.00396	3.998531	3.998526	3.99402
Details at scale(1:2)	4.0040	3.99853	3.998262	3.99490

Table(9) represents the relationship between any eigenvalue and others, thus the calculating of the CFG will specify the range of eigenvalues that must be selected. We see that the selected eigenvalues must be laying in the one and second values only.

Table(9): The eigen structure computed for 4 images under test. Each image represents after applying CWT(Mexican Hat) the recursive form of it at that scale.

Details Coeff. After Applying CWT	Maximum eigenvalue Object256 *1Exp3	Maximum eigenvalue Object_35^O *1Exp3	Maximum eigenvalue Object_215^O *1Exp3	Maximum eigenvalue Object1 *1Exp3
Details at scale(1:4)	6.0010	5.99983	5.999862	340.6513
Details at scale(1:16)	6.00096	5.999851	5.999561	339.872

From table(10) we can say that the eigenstructure of any image will decay rapidly, thus we must find an accurate technique for estimating the range of these eigenvalues (i.e. developed AIC). These selected eigenvalues are never affected by different noise type, thus the whole image characteristic will be represented by its maximum eigenvector. In this table the first two values of the eigenvalues must be selected to represent image at this depth(depth$_2$) .

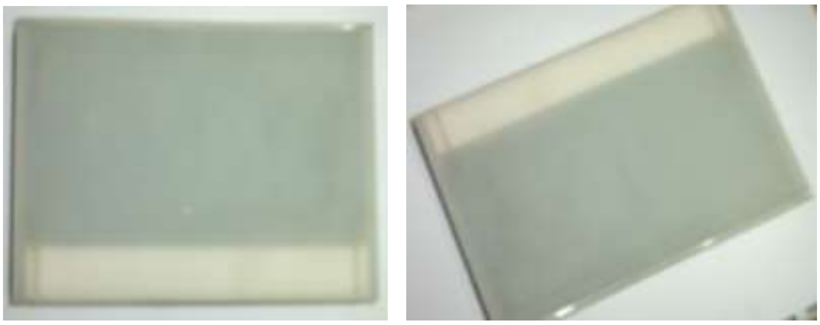
Table(10): The CFG(non-zero)values according to developed AIC algorithm, which is applied on reference images at depth$_3$ (16*16) of details coefficients from DWT. **Note** that * is referred to the minimum GFC values thus, there are two eigenvalues must be selected to represent image at this depth

Object5	Object2 (0.3%)	Object2 (0.5%)	Object2 (0.6%)
1.1553e+01	1.1184e+01	1.1182e+01	1.1185e+01
*1.0602e+01	*1.0880e+01	*1.0870e+01	*1.0830e+01
1.0178e+01	1.0707e+01	1.0997e+01	1.1151e+01
1.0452e+01	1.1743e+01	1.1943e+01	1.2036e+01
1.1052e+01	1.2746e+01	1.2876e+01	1.3032e+01
1.761e+01	1.3744e+01	1.3851e+01	1.3873e+01
1.2666e+01	1.4547e+01	1.4838e+01	1.9432e+01
1.3562e+01	1.5592e+01	1.5734e+01	1.5859e+01
1.4336e+01	1.6423e+01	1.6776e+01	1.6770e+01
1.5123e+01	1.7321e+01	1.7647e+01	1.7746e+01
1.6039e+01	1.8380e+01	1.8651e+01	1.8706e+01
1.6780e+01	1.9241e+01	1.9411e+01	1.9559e+01
1.7494e+01	2.00533e+01	2.0192e+01	2.0229e+01
1.8020e+0	2.0980e+01	2.1027e+01	2.0825e+01
2.8800e+01	2.0895e+01	2.1237e+01	2.1170e+01

Table(11): The eigenvalues according to the developed AIC algorithm, clearly the first two values are represent minimum GFC with maximum eigenvalues to the image at depth$_3$(16*16). **Note** that * is referred to maximum eigenvalues, which are used in the operation of recognition.

Object5	Object2 (0.3%)	Object2 (0.5%)	Object2 (0.6%)
3.0988e+10	1.3289e+10	1.3229e+10	1.3223e+10
*3.0109e+8	*5.7988e+8	*5.7988e+8	*5.7999e+8
9.9870e+06	4.2670e+07	7.9554e+07	1.1035e+08
1.6772e+06	3.8304e+07	6.0641e+07	7.4780e+07
5.9413e+05	3.2292e+07	4.5078e+07	6.2183e+07
2.7090e+05	2.6876e+07	3.6128e+07	3.8800e+07
1.7469e+05	1.5388e+07	2.9502e+07	3.6281e+07
1.2411e+05	1.3987e+07	2.0210e+07	2.6274e+07
6.4232e+04	8.3615e+06	1.8276e+07	1.8402e+07
3.4148e+04	5.7145e+06	1.1699e+07	1.4582e+07
2.3619e+04	5.3381e+06	9.7598e+06	1.1111e+07
1.1183e+04	3.2977e+06	4.8475e+06	6.6879e+06
4.9407e+03	1.8269e+06	2.4999e+06	2.6783e+06
1.4433e+03	1.2799e+06	1.4346e+06	9.0363e+05
7.28611e+02	9.0839e+04	1.9947e+05	1.7103e+05
7.4642e-11	4.7051e-09	7.4099e-09	1.3324e-008

Test Eight: Let us given image H1, H2 (Images from the same class with different direction). See figure (4) the same object with 10 different rotate angels, for each image we will be resulted the features vector as shown in table (12).



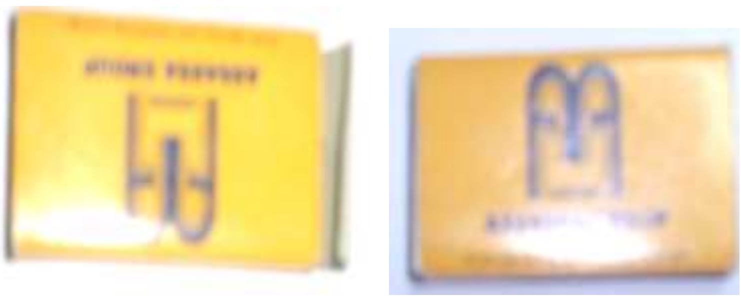
H1 H2

Figure(4) Images from the same class with different situations

Table(12) represent the features vector of the images in fig(4)

Rotate angle	H1				H2			
	Mean	STD	VAR	Max Eigen	Mean	STD	VAR	Max Eigen
0	501.2	194.9	13311.4	0.378	525.9	212.9	15983.5	0.356
36	510.4	198.9	14421.3	0.382	532.3	217.4	16983.3	0.360
72	509.2	192.1	13991.2	0.366	529.9	209.9	15773.5	0.344
108	513.5	196.2	14430.7	0.372	535.8	215.7	16885.5	0.350
144	507.9	195.3	13980.2	0.381	527.5	213.9	15663.2	0.359
180	501.4	194.1	13300.6	0.377	524.5	211.8	15889.9	0.355
216	519.4	199.7	14479.7	0.368	539.4	216.9	16999.5	0.364
252	522.2	201.1	15500.4	0.370	542.2	220.7	17483.4	0.368
288	516.4	197.2	14427.5	0.380	5362.9	217.3	16963.7	0.378
324	517.4	195.6	14476.2	0.384	538.1	219.2	17283.3	0.382
360	501.4	194.1	13309.9	0.378	525.7	212.2	15200.9	0.356

Test Nine: Let us given image H3,H4 (Images from the different classes). See figure (5) H3 is different from H1 with 10 different rotate angels, for each image we will be resulted the features vector as shown in table(13).



H3 H4

Figure(5) Images from the different classes

Table(13) represent the features vector of the images in fig(5)

Rotate angle	H1				H2			
	Mean	STD	VAR	Max Eigen	Mean	STD	VAR	Max Eigen
0	378.9	141.7	12712.4	0.135	312.7	130.3	12090.1	0.152
36	379.3	140.6	13727.6	0.140	313.4	128.1	13192.6	0.155
72	370.6	146.6	13210.2	0.146	306.9	134.5	12770.1	0.169
108	375.3	144.9	13760.8	0.129	311.7	129.3	13200.4	0.142
144	373.9	142.2	13270.4	0.131	309.4	135.8	12720.8	0.149
180	376.2	139.7	12690.3	0.134	311.5	129.9	12099.9	0.150
216	372.6	145.2	13698.4	0.139	308.7	136.6	13220.5	0.153
252	371.9	144.7	14602.6	0.137	307.2	137.9	14304.5	0.144
288	374.2	145.8	13527.1	0.130	310.5	133.6	13270.6	0.147
324	372.4	144.7	14630.7	0.133	309.6	136.4	13292.7	0.157
360	378.9	141.7	12712.1	0.135	312.7	130.3	12091.4	0.152

<u>Test Ten</u> :The unknown image is entered, see figure(6).

- Multiwavelet 2-level decomposition of two-dimensional image into 24-subimages.
- Feature extraction: Detect the features vector for each sub-image from the previous step.
- Classification: Calculate minimum Mahalanobis distance between the unknown image and all the feature vectors stored in the reference set. Table(14) below shows the computed distance with the reference set.The smallest distance was =5.6767e-021

The unknown image is classified as class label 14

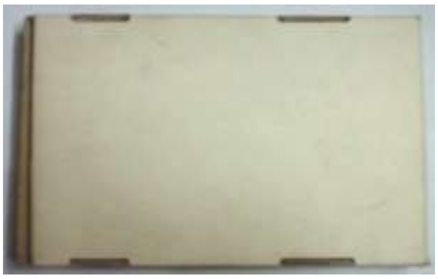


Figure (6) unknown image

Table(14)

Ref. Img.	Distance to test image	Ref. Img.	Distance to test image	Ref. Img.	Distance to test image	Ref. Img.	Distance to test image	Ref. Img.	Distance to test image
M1	0.4242	M21	0.4119	M41	0.5451	M61	0.5710	M81	0.2622
M2	0.3509	M22	0.2388	M42	0.4654	M62	0.1433	M82	0.2833
M3	0.4904	M23	0.5704	M43	0.5913	M63	0.4655	M83	0.5276
M4	0.4689	M24	0.5456	M44	0.2738	M64	0.3532	M84	0.4233
M5	0.5291	M25	0.5151	M45	0.5435	M65	0.4888	M85	0.4048
M6	0.5109	M26	0.5479	M46	0.5803	M66	0.5644	M86	0.4708
M7	0.1678	M27	0.4208	M47	0.1748	M67	0.2110	M87	0.5421
M8	0.5494	M28	0.5627	M48	0.1434	M68	0.1489	M88	0.6977
M9	1.2162	M29	0.4699	M49	0.1625	M69	0.1374	M89	0.4982
M10	6.6924	M30	0.5599	M50	0.5962	M70	0.4420	M90	0.0007
M11	0.7569	M31	0.4691	M51	0.4501	M71	0.2027	M91	0.5749
M12	0.5782	M32	0.4883	M52	0.2504	M72	0.4210	M92	0.2493
M13	2.3594	M33	0.1956	M53	0.2586	M73	0.2754	M93	0.7773
M14	0.0000	M34	0.3138	M54	0.5412	M74	0.5606	M94	0.6292
M15	0.2064	M35	0.2539	M55	0.4305	M75	0.1827	M95	0.5430
M16	0.5466	M36	0.5267	M56	0.5775	M76	0.3966	M96	0.2988
M17	0.7062	M37	0.5447	M57	0.5415	M77	0.0963	M97	0.2531
M18	0.2827	M38	0.5857	M58	0.5258	M78	0.9341	M98	0.2131
M19	0.5557	M39	0.6151	M59	0.5846	M79	0.2384	M99	0.3205
M20	0.7605	M40	0.5132	M60	0.2534	M80	0.9662	M100	0.5569

As was mentioned in section three that we have classified different images with respect to the local features, these local features are calculated based on wavelet domain. In this domain we benefit from its two ways:

- In DMWT the input image will be studied and tested at different scales of this

image and different resolutions(approximated, vertical, horizontal, and diagonal) related to each scale.. After this the correlation form is call covariance matrix, in which each column of a given resolution must correlated with its transform, and then subtraction from the mean of this column multiplied by its transform. In this new covariance form of a given resolution the calculation of local features is very easy. This form is symmetrical diagonal and orthogonal. At this step we provide a tool for study image at different scales of it. This means that texture features are calculated on different scales of original image. This will lead to increase the ability of recognition when classified it with respect to the others. As a conclusion the separable nature of the DMWT is reducing the ability of recognition when it is compared with CWT.

- Time consumed through this transform. Consider DMWT as real time transform

because the operations at each step of DMWT are very easy. As a conclusion the small time consuming when applying DMWT rather than CWT in which the time consumed is very long this consumed time is due to the step taken to apply the CWT on a vector of data (not two dimension data). Excellent result are obtained when apply CWT(at scale 2,4 and 16)in recognition task while compare with the results obtained from DMWT(at depth 0,1,2,3 and 4). But still the DMWT is very effective domain for calculating best image at different resolution and scales.

- The form of recursive is very efficient domain for calculating local features. To improve the weak points of this recursive form must find an adaptive form for representing the same image only even when image is suffering from rotating, noise, and a shift in direction (evaluate invariant features). This technique can be obtained by increasing the connectivity between each two-pixel frame and the next pixel frame in a row wise direction for any test image. Besides to the high-speed performance of DMWT in transformation image at different scales and resolutions, but the time consuming through calculating different texture features is very long too. As a conclusion the new adaptive-recursive form for representing DMWT coefficients provides good domain for calculating PCA features. These features will represent invariant parameters. Finally see the better result obtained using CWT And DMWT , but the time consumed through applying CWT is very long(about 4 times that consumed by DMWT). Thus we must adopt different ideas of pattern recognition and then apply it on the DMWT at different scales. As a conclusion DMWT provides different sub images resolution and depth represents the optimum depth for recognizing the image itself using KL transform. In section three, the proposed methods of recognition dependent on the PCA. The major problems effect the image recognition is the huge image size. Thus, in the first method of recognition we adopted an idea of reducing the huge image size to the small size(4*4) using DMWT(Mallat algorithm). At this point we must apply PCA to compute the eigen structure of the sub image after applying QL algorithm to find the eigenvalues from correlated or covariance matrix of this sub image.

- Thus whole spectral characteristic of image is performed by the maximum eigenvector of the selected sub image only. As a conclusion if the image under test represent scaled version of the original one, there is no need for stating invariant space from the DMWT coefficients.So all propsed methods for image recognition depended on calculating the PCA features from image on different resolutions and scales(DMWT). These features will represent the image itself with small number of coefficient and without loosing time. Thus any matching procedure like(Mahalanobis distance measurement) will work efficiently to classify different images under test even when image is noisy version of original. Because the first eigenvalue dominates, being an order of magnitude larger than the succeeding eigenvalues, and the first eigenvector represents the dominated spectral characteristic of the image. Thus noise component does not effect the maximum eigenvalue and related eigenvector. The weak point of this adaptive method recognition will appear when the input huge image is rotated in angle. We need to analyze image from other side in order to find and calculate local features from PCA. These local features are calculated on the different image resolutions at different scale. The range of maximum eigenvalues will represent these local features here; these eigenvalues are selected from the diagonal details at each scale of image. This method represents an adaptive speed method for classifying different shifted, noisy, and rotated images. We proposed an adaptive new method of representing any sub image after applying DMWT by adaptive recursive form in order to enlarge the feature space to the optimum and in order to recognize different image rotated at different angles. In this method we find that the efficiency of recognition is increased to optimum because the local PCA features are calculated on the different invariant domains after applying DMWT(5-depth with 4 resolution of each depth) or CWT(scale 1,2,4, and 16).

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طرق مقترحة لتمييز الصور بالاعتماد على تحليل العوامل الاساسية

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الخلاصة:
تم اقتراح طريقتين في التمييز الصوري، تعتمد هذه الطرق في أساس عملها على استخلاص العوامل الرئيسية من تفاصيل الصورة الناتجة من المحول المويجي المتعدد عند كل قياس لها.اقترحت الطريقة الأولى زيادة عدد العوامل الرئيسية المستخلصة من الصورة من خلال حساب هذه العوامل من تفاصيلها القطرية والناتجة من المحول المويجي عند خمس قياسات منه.ثم تحديد العوامل الرئيسية والمؤثرة فقط في عملية التمييز الصوري. اقترحت الطريقة الثانية على تمثيل أي من تفاصيل الصورة الناتجة من المحول المويجي عند أربع قياسات منه إلى مستوى ثابت يدعى(recursive form). لذلك فمهما تعرضت الصورة إلى مشكل من تدوير أو إزاحة فسوف لن يؤثر ذلك كثيراً على طبيعة هذا المستوى الثابت الممثل لكل التفاصيل الناتجة من المحول المويجي. ثم يتم تحديد العوامل الرئيسية والمؤثرة فقط في عملية التمييز الصوري. الطرق الموظفة هنا بمحول مويجي متعدد لتمييز صورة مجهولة بواسطة قياس اقصر مسافة بينه وبين قاعدة بيانات المرجع الثابت الذي تم بناءه للنظام والذي يتضمن متجه الخصائص لجميع الصور الموجودة ضمن قاعدة البيانات. لقد تم اختبار كفاءة الطرق المقترحة أعلاه على صور عديدة ، وقد أثبتت كفاءتها العالية في تمييزها بأقل وقت ممكن.التأثير الذي أحدثه الربط بين هذه التقنيات قد نوقش في كل طريقة وتحت تأثيرات مختلفة مثل الضوضاء، الليل والنهار، الجو صحواً أم ضباب، وايضاً تزحيف الصورة في مختلف الاتجاهات وبنسب مئوية مختلفة.حيث قدمت اختبارات الكفاءة مع القيم التجريبية.