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Performance Comparison of Wavelet Transforms, Generated from Orthogonal Transforms, in Classification of Image Database

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Abstract— Thousands of images are generated every day, which implies the need to build an easy, faster, automated classifier to classify and organize these images. Classifying the images based on visual content is an important and challenging problem today. Feature extraction is a major step in a classification as the accuracy of the classification depends on it. This paper presents the use of wavelet transform to generate the feature vector. Wavelet transform is generated from orthogonal transform matrices of two different sizes. This wavelet transform is then applied to the columns of an image to generate feature vector which will represent that image. Feature extraction is done for training as well as testing images. Euclidean and Manhattan distance criteria are used as a similarity measure. Matching is done using nearest neighbor method. The paper also compares the performance of orthogonal transforms and their wavelet transforms in classification task. The results have shown that the performance of wavelet transform is far better than their respective orthogonal transform.

Keywords— Image classification; Wavelet transform; Similarity Measures; Image Transforms; Feature Vector; Nearest Neighbor Classifier; Euclidean Distance; Manhattan Distance; Row mean;

I. INTRODUCTION

Wavelets are mathematical tools that can be used to extract information from many different kinds of data, including images. A key advantage it has over Fourier transforms is temporal resolution i.e. it captures both frequency and location information. wavelets are localized in both time and frequency whereas the standard Fourier transform is only localized in frequency. Wavelet transforms are now being adopted replacing Fourier transform for multiple domains of image processing such as image retrieval[1][2], medical imaging[3][4][5], image watermarking[6][7], image compression [8] and many more. The wavelet analysis procedure is to adopt a wavelet prototype function, called an analyzing wave or mother wave. The other wavelets are contracted and translated copies (known as "daughter wavelets") of a mother wave. By contraction and translation we can generate infinite set of functions. But these functions must be orthogonal to qualify as a wavelet transform.

The first literature that relates to the wavelet transform is Haar wavelet. It was proposed by the mathematician Alfréd Haar in 1909. Earlier, wavelets of only Haar transform have been studied. But in recent work it can be seen that the wavelets of Walsh transform[9] ,DCT (Discrete Cosine Transform)[10] and Kekre transform[11] are developed and successfully used for applications such as CBIR(Content based image retrieval)[12], steganography[13], image fusion[14],finger print verification[15], image retrieval [16] etc. This paper proposes the use of such wavelet transforms for Image classification. The image classification process involves grouping of images into pre-defined classes. Images in one class are more similar to each other than to those in the other class. The research area of general image classification has always been very active. Many image classification methods have been successfully used for better organizing, representing and browsing images as well as to improve the performances of related applications, such as CBIR[17], image annotation[18], and image indexing[19]. Earlier orthogonal transforms have been used for image classification[20]. This paper presents the use of wavelet transform, generated from some orthogonal transforms such as DCT, DST(Discrete Sine transform)[21], DHT(Discrete Hartley Transform)[22], WALSH[23] and Kekre transform[24], to form feature vector. The matching is implemented using the nearest neighbor method. Two similarity measures used are Euclidean distance and Manhattan distance. The rest of the paper is organized as follows: section II explains the procedure to generate wavelet transform from orthogonal transform matrices of two different sizes. In section III, the paper presents the proposed methodology. Section IV discusses the results followed by conclusion in section V.

II. GENERATING WAVELET TRANSFORM FROM ORTHOGONAL TRANSFORM MATRICES OF TWO DIFFERENT SIZES

From two orthogonal transform matrices A_M of size MxM (as shown in Fig.1) and B_N of size NxN (as shown in Fig.2), we can generate wavelet transform matrix T of size MNxMN. For example, from orthogonal transform matrix A of size 32x32 and B of size 8x8 , we can generate wavelet transform matrix of size 256x256. To generate first N rows of wavelet transform matrix, multiply each column of matrix B with each coefficient of the first row of matrix A. To generate next N rows, second row of A is appended with zeros and then it is shift rotated. Similar procedure is repeated for remaining rows of A from third row onwards. This entire procedure is shown in Fig. 3.

$$A_M = \begin{bmatrix} A_{11} & A_{12} & \dots & A_{1M} \\ A_{21} & A_{22} & \dots & A_{2M} \\ : & : & \dots & : \\ A_{M1} & A_{M2} & \dots & A_{MM} \end{bmatrix}$$

Fig. 1. MXM Orthogonal Transform Matrix A

$$B_N = \begin{bmatrix} B_{11} & B_{12} & \dots & B_{1N} \\ B_{21} & B_{22} & \dots & B_{2N} \\ : & : & \dots & : \\ B_{N1} & B_{N2} & \dots & B_{NN} \end{bmatrix}$$

Fig. 2. NXN Orthogonal Transform Matrix B

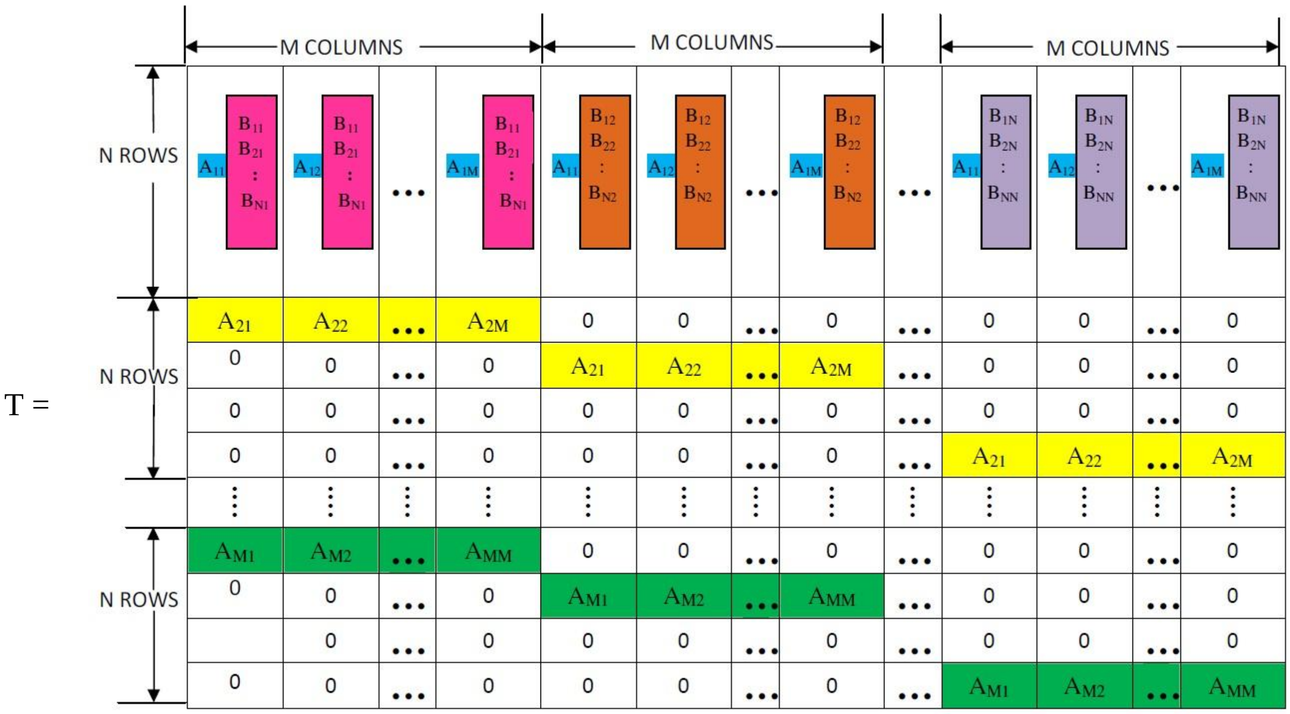

Fig. 3. Generation of wavelet transform T from orthogonal transforms A and B

III. Proposed Methodology

The first step of image classification is feature extraction. Every image in database is represented by feature vector.

A. *Generation of feature vector*

Step 1: Generate DCT wavelet transform matrices T (256x256) as per the procedure explained in section II from

a. A_{16}=DCT matrix(16x16) and B_{16}=DCT matrix(16x16)
b. A_8 = DCT matrix(8x8) and B_{32} = DCT matrix(32x32)
c. A_{32} = DCT matrix(32x32) and B_8 = DCT matrix(8x8)
d. A_4 = DCT matrix(4x4) and B_{64} = DCT matrix(64x64)
e. A_{64} = DCT matrix(64x64) and B_4 = DCT matrix(4x4)

Step 2: Apply these wavelet transform matrices on the columns of three planes of color image (R,G and B) to get three column transformed images.

Step 3: Calculate the row mean vector[25] of each column transformed image. We get three row mean vectors say R_{MV}, G_{MV} and B_{MV}..

Step 4: Make a feature vector by fusing the values of row mean vector of three column transformed images. For example feature vector of size 300 is made by fusing first 100 values of R_{MV} followed by first 100 values of G_{MV} followed by first 100 values of B_{MV} vectors.

The different values of feature vector size are also considered to study the effect of feature vector size on the performance. Similarly the wavelets of other transforms like DST, DHT, Walsh and Kekre transform are also used to generate feature vector by applying the procedure given in step1 to step4.

B. Classification

For each training and testing image, its feature vector is generated. Nearest neighbor classifier is used for classification. Two similarity criteria are used: Euclidean distance and Manhattan distance[26]. They are given by equation 1 and 2 respectively. Other distances such as correlation distance, bray-curtis distance have been used for image classification [27].

$$D_{Euc}(P,Q)=\sqrt{\sum_{i=1}^{n}\left|P_i-Q_i\right|^2} \qquad (1)$$

$$D_{Man}(P,Q)=\sum_{i=1}^{n}\left|P_i-Q_i\right| \qquad (2)$$

Minimum distance between testing image and training image indicates the most similar training image for the corresponding testing image. Then the given testing image is assigned to the class of corresponding training image. There are two types of training sets used. One training set consists the feature vectors of all training images. The other set is made up of an average of feature vectors of training images of each class.

IV. RESULT

The Algorithms discussed in previous section were implemented on 256x256 color images. Images from Wang image database are used for this purpose. This database was created by the group of professor Wang from the Pennsylvania State University [28]. Sample of testing images and training images are shown in Fig. 4 and 5 respectively. Training image database consists of 5 images per class (8 classes, so total 40 images). Testing image database consists of 30 images per class (8 classes, so total 240 images). Initially column transform is applied on image and the row mean is calculated as a feature vector. After feature extraction, training set consists of 40 feature vectors and testing set consists of 240 feature vectors . All the algorithms are also implemented using another training set where only 8 feature vectors (average of feature vectors of 5 images from each class) were used for training. Matching is done using two distance criteria-Euclidean distance and Manhattan distance. Table I , III, V, VII and IX shows the number of correctly classified images (out of 240 images) for different transforms, their wavelets, for various feature vector size and for two types of training sets. The correctness of classification is visually checked.

Fig. 4. Sample of Testing images(8 classes : Monument, rose, horse, elephant, dinosaur, snow mountain, beach, bus)

Fig. 5. Sample of Training images

TABLE I. NUMBER OF CORRECTLY CLASSIFIED IMAGES (OUT OF 240) FOR DCT

Training set 1: 40 Feature vectors (5 images from each class)												
Feature vector size	Euclidean Distance						Manhattan Distance					
	DCT	DCT WAVELET					DCT	DCT WAVELET				
		A_{16},B_{16}	A_8,B_{32}	A_{32},B_8	A_4,B_{64}	A_{64},B_4		A_{16},B_{16}	A_8,B_{32}	A_{32},B_8	A_4,B_{64}	A_{64},B_4
25R+25G+25B	151	149	152	156	151	**163**	163	164	163	169	163	**171**
50R+50G+50B	156	153	152	158	154	**166**	167	167	167	171	168	**173**
75R+75G+75B	159	154	157	158	157	**166**	169	160	169	167	171	**177**
100R+100G+100B	162	156	156	159	156	**168**	170	162	167	162	**176**	174
150R+150G+150B	162	159	158	158	160	**169**	164	160	163	159	**170**	169
256R+256G+256B	163	159	158	158	160	**170**	163	149	156	163	**165**	162
Training set 2: 8 Feature Vectors (Average of feature vectors of 5 images from each class)												
Feature vector size	Euclidean Distance						Manhattan Distance					
	DCT	DCT WAVELET					DCT	DCT WAVELET				
		A_{16},B_{16}	A_8,B_{32}	A_{32},B_8	A_4,B_{64}	A_{64},B_4		A_{16},B_{16}	A_8,B_{32}	A_{32},B_8	A_4,B_{64}	A_{64},B_4
25R+25G+25B	156	156	155	**157**	156	**157**	171	172	173	177	172	**179**
50R+50G+50B	158	157	156	158	158	**159**	172	172	176	175	176	**177**
75R+75G+75B	157	157	158	157	158	**161**	169	170	171	**176**	171	173
100R+100G+100B	159	159	157	157	157	**161**	168	169	171	**175**	172	**175**
150R+150G+150B	**160**	158	158	**160**	158	**160**	163	170	169	170	**171**	170
256R+256G+256B	160	159	160	160	158	**162**	156	149	**170**	162	168	167

Observations: DCT wavelet gives better performance compared to DCT in all criteria. DCT wavelet generated from DCT matrix A of size 64x64 and B of size 4x4 outperforms, for Euclidean distance. Highest number of correctly classified images for DCT wavelet for two training sets and for two similarity measures are shown in table II.

TABLE II. HIGHEST NUMBER OF CORRECTLY CLASSIFIED IMAGES (OUT OF 240)

Training Sets	Similarity Measure	
	Euclidean Distance	Manhattan Distance
Training set 1:40 Feature vectors	**170(70.83%)** **DCT wavelet(A_{64},B_4)** Feature Vector Size:768	**177(73.75%)** **DCT wavelet(A_{64},B_4)** Feature Vector Size:225
Training Set 2: 8 Feature Vectors	**162(67.5%)** **DCT wavelet(A_{64},B_4)** Feature Vector Size:768	**179(74.58%)** **DCT wavelet(A_{64},B_4)** Feature Vector Size:75

Observations : Best performance of DCT Wavelet is given by Manhattan distance criteria at much lower feature vector size with training set 2.

TABLE III. NUMBER OF CORRECTLY CLASSIFIED IMAGES (OUT OF 240) FOR DST

Training set: 40 Feature vectors (5 images from each class)												
Feature vector size	Euclidean Distance						Manhattan Distance					
	DST	DST WAVELET					DST	DST WAVELET				
		A_{16},B_{16}	A_8,B_{32}	A_{32},B_8	A_4,B_{64}	A_{64},B_4		A_{16},B_{16}	A_8,B_{32}	A_{32},B_8	A_4,B_{64}	A_{64},B_4
25R+25G+25B	151	158	158	**159**	158	157	163	**169**	166	166	164	**169**
50R+50G+50B	156	**163**	160	160	160	155	167	173	168	171	**174**	**174**
75R+75G+75B	159	**165**	**165**	160	160	156	169	175	176	172	**177**	173

100R+100G+100B	162	165	**166**	159	161	157	170	**176**	173	**176**	175	173
150R+150G+150B	162	164	**165**	159	162	157	164	176	176	174	**177**	174
256R+256G+256B	163	163	**166**	162	164	159	163	173	173	174	**177**	173
Training set: 8 Feature Vectors (Average of feature vectors of 5 images from each class)												
Feature vector size	**Euclidean Distance**						**Manhattan Distance**					
	DST	**DST WAVELET**					**DST**	**DST WAVELET**				
		A_{16},B_{16}	**A_8,B_{32}**	**A_{32},B_8**	**A_4,B_{64}**	**A_{64},B_4**		**A_{16},B_{16}**	**A_8,B_{32}**	**A_{32},B_8**	**A_4,B_{64}**	**A_{64},B_4**
25R+25G+25B	161	**165**	162	162	161	158	161	**169**	159	168	159	**169**
50R+50G+50B	160	161	**162**	**162**	160	159	162	170	**173**	170	164	171
75R+75G+75B	160	160	161	**163**	161	160	168	164	161	170	**172**	171
100R+100G+100B	159	**162**	**162**	**162**	**162**	160	169	161	167	169	**175**	172
150R+150G+150B	161	**163**	159	**163**	161	160	169	164	163	167	164	**175**
256R+256G+256B	161	**164**	160	**164**	160	160	164	160	163	**167**	166	**167**

Observations: DST wavelet improves the results in all cases in comparison with DST. In this case their is no specific combination of matrix sizes which outperforms others.

TABLE IV. HIGHEST NUMBER OF CORRECTLY CLASSIFIED IMAGES (OUT OF 240)

Training Sets	**Similarity Measure**	
	Euclidean Distance	**Manhattan Distance**
Training set 1:40 Feature vectors	**166(69.16%)** **DST wavelet(A_8,B_{32})** Feature Vector Size:300,768	**177(73.75%)** **DST wavelet(A_4,B_{64})** Feature Vector Size:225,450,768
Training Set 2: 8 Feature Vectors	**164(68.33%)** **DST wavelet(A_{16},B_{16} and A_{32},B_8)** Feature Vector Size:768	**175(72.92%)** **DST wavelet(A_{64},B_4 and A_4,B_{64})** Feature Vector Size:300,450

Observations: Table IV indicates that the maximum number of correctly classified images are obtained with feature vector training set 1 and using Manhattan distance similarity.

TABLE V. NUMBER OF CORRECTLY CLASSIFIED IMAGES (OUT OF 240) FOR DHT

Training set: 40 Feature vectors (5 images from each class)												
Feature vector size	**Euclidean Distance**						**Manhattan Distance**					
	DHT	**DHT WAVELET**					**DHT**	**DHT WAVELET**				
		A_{16},B_{16}	**A_8,B_{32}**	**A_{32},B_8**	**A_4,B_{64}**	**A_{64},B_4**		**A_{16},B_{16}**	**A_8,B_{32}**	**A_{32},B_8**	**A_4,B_{64}**	**A_{64},B_4**
25R+25G+25B	148	**152**	146	144	146	**152**	154	158	159	162	154	**169**
50R+50G+50B	150	**158**	156	150	148	154	162	166	164	169	165	**172**
75R+75G+75B	151	**159**	**159**	150	157	154	165	170	169	163	**172**	**172**
100R+100G+100B	151	158	**160**	150	158	155	167	168	**172**	163	**172**	**172**
150R+150G+150B	152	158	**160**	151	158	157	161	161	165	163	**173**	171
256R+256G+256B	158	**163**	**163**	161	157	**163**	161	158	156	160	162	**166**
Training set: 8 Feature Vectors (Average of feature vectors of 5 images from each class)												
Feature vector size	**Euclidean Distance**						**Manhattan Distance**					
	DHT	**DHT WAVELET**					**DHT**	**DHT WAVELET**				
		A_{16},B_{16}	**A_8,B_{32}**	**A_{32},B_8**	**A_4,B_{64}**	**A_{64},B_4**		**A_{16},B_{16}**	**A_8,B_{32}**	**A_{32},B_8**	**A_4,B_{64}**	**A_{64},B_4**
25R+25G+25B	159	159	159	**162**	159	153	169	174	170	**179**	167	175
50R+50G+50B	162	**163**	161	162	159	154	168	172	174	**179**	173	177

75R+75G+75B	161	163	162	162	**164**	154	172	172	174	**178**	175	175
100R+100G+100B	162	163	164	162	**166**	154	171	174	173	**180**	173	176
150R+150G+150B	163	164	164	163	**166**	153	168	172	172	**179**	173	176
256R+256G+256B	167	168	166	165	**169**	163	164	169	169	171	167	**172**

Observations: DHT wavelet gives the better performance than DHT in all cases. In average feature vector database and with Manhattan distance, DHT wavelet generated from DHT matrix A of size 32x32 and B of size 8x8 outperforms better. Table VI shows the highest number of correctly classified images for DHT wavelet in all combinations of distance and training set.

TABLE VI. HIGHEST NUMBER OF CORRECTLY CLASSIFIED IMAGES (OUT OF 240)

Training Sets	**Similarity Measure**	
	Euclidean Distance	**Manhattan Distance**
Training set 1:40 Feature vectors	**163(67.92%)** **DHT wavelet(A_{16},B_{16} and A_8,B_{32} and A_{64},B_4)** Feature Vector Size:768	**173(72.08%)** **DHT wavelet(A_4,B_{64})** Feature Vector Size:450
Training Set 2: 8 Feature Vectors	**169(70.42%)** **DHT wavelet(A_4,B_{64})** Feature Vector Size:768	**180(75%)** **DHT wavelet(A_{32},B_8)** Feature Vector Size:300

Observations: The best performance of DHT wavelet is obtained with Manhattan distance and training set 2.

TABLE VII. NUMBER OF CORRECTLY CLASSIFIED IMAGES (OUT OF 240) FOR WALSH

Training set: 40 Feature vectors (5 images from each class)												
Feature vector size	**Euclidean Distance**						**Manhattan Distance**					
	Walsh	**Walsh WAVELET**					**Walsh**	**Walsh WAVELET**				
		A_{16},B_{16}	**A_8,B_{32}**	**A_{32},B_8**	**A_4,B_{64}**	**A_{64},B_4**		**A_{16},B_{16}**	**A_8,B_{32}**	**A_{32},B_8**	**A_4,B_{64}**	**A_{64},B_4**
25R+25G+25B	149	143	149	151	149	**155**	160	160	160	159	160	**168**
50R+50G+50B	152	158	155	152	152	**161**	162	168	160	163	162	**170**
75R+75G+75B	155	160	157	155	155	**161**	166	166	162	165	167	**176**
100R+100G+100B	156	161	159	155	157	**162**	170	166	169	163	168	**176**
150R+150G+150B	160	159	161	157	160	**165**	171	162	164	163	168	**172**
256R+256G+256B	161	160	159	160	160	**164**	**170**	160	158	165	167	162
Training set: 8 Feature Vectors (Average of feature vectors of 5 images from each class)												
Feature vector size	**Euclidean Distance**						**Manhattan Distance**					
	Walsh	**Walsh WAVELET**					**Walsh**	**WALSH WAVELET**				
		A_{16},B_{16}	**A_8,B_{32}**	**A_{32},B_8**	**A_4,B_{64}**	**A_{64},B_4**		**A_{16},B_{16}**	**A_8,B_{32}**	**A_{32},B_8**	**A_4,B_{64}**	**A_{64},B_4**
25R+25G+25B	155	156	155	156	155	**157**	179	173	179	177	179	**183**
50R+50G+50B	157	155	156	156	157	**160**	175	173	**178**	174	175	**178**
75R+75G+75B	158	158	157	158	158	**161**	173	171	**175**	174	**175**	**175**
100R+100G+100B	158	158	157	158	158	**161**	169	169	**177**	172	171	175
150R+150G+150B	158	158	156	158	157	**162**	169	170	169	**174**	**174**	172
256R+256G+256B	159	158	157	159	156	**163**	159	165	166	**171**	168	166

Observations: With Euclidean distance as a similarity criteria, Walsh wavelet generated from two Walsh transform matrices A of size 64x64 and B of size 4x4 gives best performance in both types of training sets and for all sizes of feature vectors. With Manhattan distance as a similarity criteria, Walsh wavelet works well in most of the cases. Table VIII shows the highest number of correctly classified images for four different cases.

TABLE VIII. HIGHEST NUMBER OF CORRECTLY CLASSIFIED IMAGES (OUT OF 240)

Training Sets	**Similarity Measure**	
	Euclidean Distance	**Manhattan Distance**
Training set 1:40 Feature vectors	**165(68.75%)** **Walsh Wavelet(A_{64},B_4)** Feature Vector Size:450	**176(73.33%)** **Walsh Wavelet(A_{64},B_4)** Feature Vector Size:225,300
Training Set 2: 8 Feature Vectors	**163(67.92%)** **Walsh Wavelet(A_{64},B_4)** Feature Vector Size:768	**183(76.25%)** **Walsh Wavelet(A_{64},B_4)** Feature Vector Size:75

Observations: Best performance of Walsh wavelet (76.25%) is obtained with Manhattan distance similarity and with average feature vector training set.

TABLE IX. NUMBER OF CORRECTLY CLASSIFIED IMAGES (OUT OF 240) FOR KEKRE TRANSFORM

Training set: 40 Feature vectors (5 images from each class)												
Feature vector size	**Euclidean Distance**						**Manhattan Distance**					
	Kekre	**Kekre WAVELET**					**Kekre**	**Kekre WAVELET**				
		A_{16},B_{16}	**A_8,B_{32}**	**A_{32},B_8**	**A_4,B_{64}**	**A_{64},B_4**		**A_{16},B_{16}**	**A_8,B_{32}**	**A_{32},B_8**	**A_4,B_{64}**	**A_{64},B_4**
25R+25G+25B	135	**147**	142	143	139	141	135	155	148	151	132	**158**
50R+50G+50B	139	145	148	143	**150**	146	129	**165**	157	161	147	155
75R+75G+75B	141	148	151	143	**154**	149	131	**166**	162	165	157	157
100R+100G+100B	139	149	**157**	147	155	153	132	160	**166**	165	159	160
150R+150G+150B	144	151	157	152	158	**159**	141	154	**167**	156	162	157
256R+256G+256B	155	156	156	158	158	**168**	140	152	153	152	**160**	156
Training set: 8 Feature Vectors (Average of feature vectors of 5 images from each class)												
Feature vector size	**Euclidean Distance**						**Manhattan Distance**					
	Kekre	**Kekre WAVELET**					**Kekre**	**Kekre WAVELET**				
		A_{16},B_{16}	**A_8,B_{32}**	**A_{32},B_8**	**A_4,B_{64}**	**A_{64},B_4**		**A_{16},B_{16}**	**A_8,B_{32}**	**A_{32},B_8**	**A_4,B_{64}**	**A_{64},B_4**
25R+25G+25B	151	147	154	**155**	150	151	141	155	168	**174**	154	170
50R+50G+50B	150	145	**159**	156	156	152	137	165	176	**176**	165	176
75R+75G+75B	152	148	**159**	156	**159**	154	133	166	**179**	177	164	171
100R+100G+100B	152	149	159	159	**160**	153	140	160	**180**	177	170	170
150R+150G+150B	153	151	160	**162**	160	158	149	154	**182**	172	175	168
256R+256G+256B	161	156	161	**165**	160	164	151	152	171	168	**176**	162

Observations : With Manhattan distance similarity measure, Kekre wavelet gives extremely good performance compared to kekre transform. Also with Euclidean distance, Kekre wavelet performs better than Kekre transform in both the training database. Table X shows the highset number of correctly classified images for Kekre wavelet.

TABLE X. HIGHEST NUMBER OF CORRECTLY CLASSIFIED IMAGES (OUT OF 240)

Training Sets	**Similarity Measure**	
	Euclidean Distance	**Manhattan Distance**
Training set 1:40 Feature vectors	**168(70%)** **KEKRE Wavelet(A_{64},B_4)** Feature Vector Size:768	**167(69.58%)** **KEKRE Wavelet(A_8,B_{32})** Feature Vector Size:450
Training Set 2: 8 Feature Vectors	**165(68.75%)** **KEKRE Wavelet(A_{32},B_8)** Feature Vector Size:768	**182(75.83%)** **KEKRE Wavelet(A_8,B_{32})** Feature Vector Size:450

Observations: The combination of Manhattan distance and average training set 2 improves the performance of Kekre wavelet significantly.

V. CONCLUSIONS

In this paper the efficiency of classifying the general images is analyzed using wavelet transform and compared to traditional orthogonal transforms. The paper proposes to generate the wavelet transform from orthogonal transform matrices (of same type) of two different sizes and use it for making of feature vector for image classification. This transform is applied to only the columns of an image as compared to full image, thus saving time and number of calculations. The performance of different wavelet transform generated from DCT, DST, DHT, Walsh and Kekre transform is tested thoroughly with different feature vector sizes (75 , 150, 225, 300, 450 and 768). Two types of similarity measures (Euclidean distance and Manhattan distance) are used. Two types of training sets (feature vectors of 40 training images and average of feature vectors of training images in a class) are used. The best performance for each wavelet transform is shown in table XI.

TABLE XI. BEST PERFORMANCE FOR EACH WAVELET TRANSFORM

Transform	**Highest number of correctly classified images**	**Similarity Measure**	***Training set***
DCT Wavelet	179(74.58%)	Manhattan Distance	Training Set 2
DST Wavelet	177(73.75%)	Manhattan Distance	Training Set 1
DHT Wavelet	180(75%)	Manhattan Distance	Training Set 2
WALSH Wavelet	**183(76.25%)**	**Manhattan Distance**	**Training Set 2**
KEKRE Wavelet	182(75.83%)	Manhattan Distance	Training Set 2

As may be seen from the table that almost all wavelet transform give their best performance with Manhattan distance similarity and Training set 2. Since this set contains only the average of feature vectors, it reduces number of calculations and time required for classification. Walsh wavelet gives the highest accuracy of 76.25% followed by Kekre Wavelet. The feature vector size required for the best performance is lowest that is 75 for Walsh wavelet. The best similarity measure is Manhattan distance which also requires much lower feature vector size. Thus the Walsh wavelet with feature vector 75 using Manhattan similarity criteria and for training set 2 is the best combination. The paper also presents the comparison between the performance of wavelet transform and their corresponding orthogonal transform in classification of images. Results have indicated that the proposed method of using wavelets for feature generation improves the image classification task.

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