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Column Transform based Feature Generation for Classification of Image Database

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ABSTRACT

Designing computer programs to automatically classify images using low level or high level features is a challenging task in image processing. This paper proposes an efficient classification technique which is based on image transforms and nearest neighbor classification. The database of images which has been used for experimentation is large containing 2000 images (20 classes) with wide variety in them. Since the performance of classifier is largely depends on the feature vector, a lot of research is going on the feature generation methods. This paper analyses the different transforms in this application domain. Initially Transforms like Discrete Fourier Transform(DFT), Discrete Cosine Transform(DCT), Discrete Sine Transform(DST), Hartley Transform , Walsh Transform and Kekre Transform applied to the columns of three planes of color image. Then using fusion technique, feature vector is generated. For more dimension reduction, the size of vector is further reduced. Nearest neighbor classification with Euclidean distance as similarity measure is used for classification task. The performance of other similarity measures like Manhattan distance, Cosine correlation measure and Bray-Curtis distance are also tested. The paper also discusses the accuracy obtained for variation in the size of feature vector, the size of training set and its impact on the result.

Keywords: Image classification, Image Transform, Nearest neighbor Classifier, Similarity Measure, Feature vector generation, Row mean vector

1. INTRODUCTION

The term image classification refers to the labeling of an image into one of the predefined classes. Manual classification of relevant images from a large database is time consuming and subjective. So many researchers have focused on automatic classification of images. Applications of image classification are multitudinous such as digital libraries, space science, web searching, geographic information systems, biomedicine, surveillance and sensor systems. Although there are many different classification models, most approaches follow the same basic process for classifying. First the feature generation and then the classifier or predictor is applied to the features. Feature generation should reduce amount of data and maintain important visual information. There are various types of features for image classification such as color, shape, textures as proposed by Anantharatnasamy P., et al.[1], H B Kekre, et al.[2] and A.Kadir, et al. [3], key point based features given by Zuo Yuanyuan, et al. [4], Hierarchical feature extraction by M H Tsai, et al.[5] etc. Also H B Kekre, et al. [6] and Smith J.R., et al. [7] have shown that the transforms can be used to generate feature vector. Boiman, O, et al. [8] has shown that, the nearest neighbor method is simple but effective classification method. The other methods like Support Vector Machine (SVM), Artificial Neural Network given by Le Hoang Thai, et al.[9] and Li Zhang, et al.[10] are also popular. In this paper, we first apply transform to the columns of an image. Then row mean vector for each plane of an image is generated and using fusion method entire feature vector is generated. This feature vector applied to nearest neighbor classifier for classification. The rest of the paper is organized as follows: section II describes the image transforms; section III discusses different similarity measures. In section IV, we present the proposed technique and section V gives the results and discussion followed by conclusions and references.

2. IMAGE TRANSFORMS

Most Unitary transforms pack a large fraction of the energy of the image into relatively few of the transform coefficients. This means that these coefficients have significant values. So this property is very useful for the generation of feature vector. The paper uses some sinusoidal and non sinusoidal transforms. Table 1 shows the equations for sinusoidal transforms. The discrete Fourier transform (DFT) is one of the most important transforms that is used in image processing [11]. The discrete cosine transform (DCT), introduced by Ahmed, Natarajan and Rao [12]. The DCT is real, orthogonal, separable transform. It has an excellent energy compaction property, so widely used in image compression. The discrete sine transform (DST- I) was introduced by A. K. Jain in 1974[13]. DST II and its inverse, DST III have been introduced by Kekre and Solanki[14]. Discrete Sine transform has been widely used in signal and image Processing [15]. The Hartley transform proposed by Hartley [16] is closely related to the Fourier transform. It has some advantages over the Fourier transform in the analysis of real signals as it avoids the use of complex arithmetic.

Table 1: Sinusoidal Transforms

Transform	Equation	Eq. No.
DFT	$F(u,v) = \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x,y) e^{-j2\pi\left(\frac{ux}{N}+\frac{vy}{N}\right)}$ for $0 \le u,v \le N-1$	(1)
DCT	$F(u,v) = \alpha(u)\,\alpha(v) \sum\sum f(x,y) \cos\left[\frac{(2x+1)u\pi}{2N}\right] \cos\left[\frac{(2y+1)v\pi}{2N}\right]$ for $0 \le u,v \le N-1$ Where $\alpha(u) = 1/\sqrt{N}$ for $u = 0$ $\alpha(u) = \sqrt{\frac{2}{N}}$ for $1 \le u \le N-1$ $\alpha(v) = 1/\sqrt{N}$ for $v = 0$ $\alpha(v) = \sqrt{\frac{2}{N}}$ for $1 \le v \le N-1$	(2)
DST	$F(u,v) = \frac{2}{N+1} \sum\sum f(x,y) \sin\left[\frac{(x+1)(u+1)\pi}{N+1}\right] \sin\left[\frac{(y+1)(v+1)\pi}{N+1}\right]$ for $0 \le u,v \le N-1$	(3)
Hartley	$F(u,v) = \frac{1}{N} \sum\sum f(x,y)\, cas\left[\frac{2\pi}{N}(ux+vy)\right]$ where $cas\,\theta = \cos\theta + \sin\theta$	(4)

Unlike the Fourier transform which is based on trigonometric terms, the Walsh Transform given by J.L.Walsh [17] consists of a series expansion of basis functions whose values are only -1 or 1 and they have the form of square waves. These functions can be implemented more efficiently in a digital environment than the exponential basis function of Fourier transform. The forward and inverse Walsh kernels are identical for 2-D signals. This is because the array formed by the kernels is a symmetric matrix having orthogonal rows and columns. The Kekre's transform proposed by H B Kekre is real and orthogonal transform [18]. It has a fast algorithm to compute.

3. Similarity Measures

Many distance measures have been proposed in literature for image classification. Some of them have explained by X.Chen., et al.[19], E.Deza and M.Deza[20] and John P.Van De Geer [21]. Table 2 gives the formula for different distance measures. Consider $P=(P_1,P_2,\ldots,P_n)$ and $Q=(Q_1,Q_2,\ldots,Q_n)$ are two feature vectors, then the Minkowski distance of order p between them is given by Eq.5.

$$D_{Mink}(P,Q)=\sqrt[p]{\sum_{i=1}^{n}\left|P_i-Q_i\right|^p} \tag{5}$$

The L_1 (1-norm) Minkowski distance is the Manhattan distance and the L_2 distance is the Euclidean distance. Cosine similarity is a measure of similarity between two vectors by measuring the cosine of the angle between them. The Bray–Curtis dissimilarity, named after J. Roger Bray and John T. Curtis [22]

Table 2: Similarity measures

Similarity Measure	Equation	Eq. No.
Euclidean	$D_{Euc}(P,Q)=\sqrt{\sum_{i=1}^{n}\left\|P_i-Q_i\right\|^2}$	(6)
Manhattan	$D_{Man}(P,Q)=\sum_{i=1}^{n}\left\|P_i-Q_i\right\|$	(7)
Cosine Correlation	$D_{Corr}(P,Q)=\frac{\sum_{i=1}^{n}P_iQ_i}{\sqrt{\sum_{i=1}^{n}P_i^2}\sqrt{\sum_{i=1}^{n}Q_i^2}}$	(8)
Bray-Curtis	$D_{BC}(P,Q)=\frac{\sum_{i=1}^{n}\left\|P_i-Q_i\right\|}{\sum_{i=1}^{n}(P_i+Q_i)}$	(9)

4.Proposed Technique

Database is divided into two sets of images : training set, for which the classification is already known and testing set, for which the classification is to be done.

Proposed algorithm :

1. Apply various transforms such as DCT, DFT, DST, Hartley, Walsh and Kekre transform, to the columns of three planes of each training image.
2. Calculate the row mean vector of each transformed plane of that image[23].
3. Make a feature vector of size 75x1 by fusion of first 25 values of each plane row mean vector one below the other.
4. By fusing first 50 values of each transformed image plane, we get the feature vector of size 150x1. Different sizes of feature vector such as 300x1, 450x1, 600x1 and 768x1, are considered for analysis of the performance.

Do this process for all training images.

5. Perform steps 1,2,3 and 4 for a given test image to generate its feature vector.
6. Apply similarity measure such as Euclidean distance, Manhattan distance, Cosine correlation similarity and Bray-Curtis distance to find the nearest training feature vector for given test image feature vector
7. Assign the class of that training feature vector to the given test image (Nearest neighbor classification)

5.RESULTS

The implementation of the proposed technique is done in MATLAB 7.0 using a computer with Intel Core i5 and 6 GB RAM. The proposed technique is tested on the Augmented Wang image database. This database contains 20 classes, each class with 100 images , so total 2000 images. Wang database was created by the group of professor Wang [24] from the Pennsylvania State University. 6 classes (Bus, Dinosaur, Elephant, Rose flower, Horse and Mountain) are directly taken from Wang database. Other 14 classes (Ibis bird, Sunset, Bonsai, Car, Panda, Sunflower, Airplane, Coin, Scooter, Schooner, Kingfisher bird, Star fish, Windsor Chair and Cup-saucer) are taken from the Internet. Fig. 1 shows the sample database of training images and Fig. 2 shows the sample database of testing images. Each image is resized to 256 x 256. Initially 25 images from each class (total 500 images) are used for training and the remaining images (total 1500 images) are used for testing. Later, 10 more images from each class are added to the training set. So in all 700 images were considered for training and 1300 images for testing. At last again 10 more images from each class are added to training set. So training set contains 45 images from each class (total 900 images) and testing set contains 55 images from each class (total 1100 images).

Figure 1: Sample database of training images

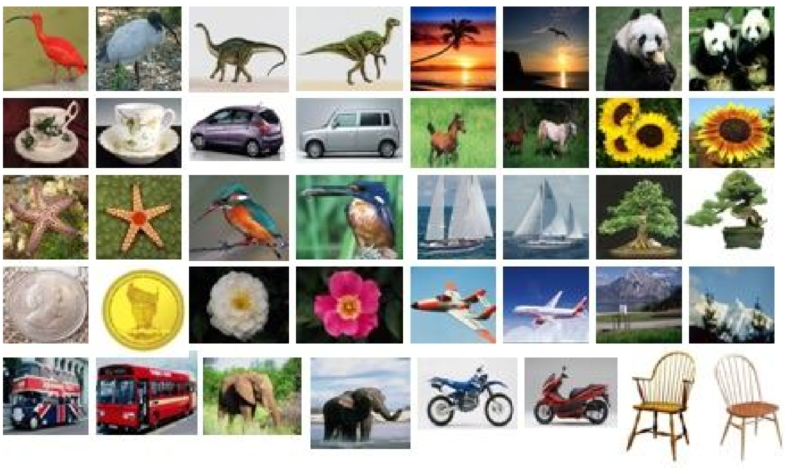

Figure 2: Sample database of testing images

Table 3,Table 4 and Table 5 shows the performance of different Transforms for 25, 35 and 45 training images per class respectively with 5 different sizes of feature vectors over 4 different similarity measure. Accuracy in each case is calculated from the Eq. no.10

$$\%\ \text{Accuracy} = \frac{No.of\ \ correctly\ \ classified\ \ images}{Total\ \ no.of\ \ testing\ \ images} * 100 \qquad (10)$$

The correctness of classification is visually checked. FIg.3 shows the accuracy in each individual class. Selected transform is DST, similarity measure is Cosine correlation, feature vector size is 768 and training images are 25 per class. Fig.4, 5, 6 and 7 shows the performance of similarity criteria such as Euclidean, Manhattan, Cosine-correlation and Bray-Curtis respectively for different transforms over all sizes of feature vector when 35 images per class are used for training. Table 6 shows the maximum accuracy achieved for each individual class and its corresponding transform, similarity measure, size of training set and feature vector size.

Table 3: %Accuracy for DFT, DCT, DST, HARTLEY and WALSH over different feature vector sizes using different similarity Measure. Training Set: Feature vectors of 25 images from each class (total 500 images)
Testing Set: Feature vectors of 75 images from each class (total 1500 images)

No. of Training Images per class	Transform	Similarity Measure	Feature Vector Size					
			75	150	300	450	600	768
			% Accuracy					
25	DCT	Euclidean	53.33	54.6	54.67	55.07	55.33	55.33
		Manhattan	53.67	54.4	54.47	54.8	54.67	54.47
		Cosine correlation	52	52.93	52.87	53.6	54.27	54.73
		Bray-Curtis	54.07	54.87	55.33	54.73	55.47	55.27
	DFT	Euclidean	50.27	50.6	51	51.93	52.6	52.4
		Manhattan	53.53	54.13	54.33	52.53	50.4	51.6
		Cosine correlation	47.8	48.67	49.67	50.27	50.87	50.4
		Bray-Curtis	53.53	53.6	53.53	53.07	51.47	51.67
	DST	Euclidean	57.47	57.73	57.87	58.4	58.6	58.87
		Manhattan	56.07	56.6	57.8	57.73	57.47	55.8
		Cosine correlation	56.93	57.8	58.87	59.33	59.67	59.47
		Bray-Curtis	55.87	56.8	57.07	58.07	57.53	56.33
	Hartley	Euclidean	48.6	48.87	48.93	49.13	49.73	54.53
		Manhattan	50.93	51.33	52.47	52.13	50.93	52.27
		Cosine correlation	44.73	45.93	46.87	46.73	47.2	51.87
		Bray-Curtis	51.2	52.2	52.47	52	50.8	52.93
	Walsh Transform	Euclidean	51.2	51.8	52.13	52.67	52.87	52.87
		Manhattan	52.33	53.4	54.2	54.27	54.47	53.93
		Cosine correlation	50.73	52.13	52.13	51.8	51.8	52
		Bray-Curtis	52.73	53.67	55.07	53.73	53.87	53.67
	Kekre Transform	Euclidean	43.33	44.47	48	51.2	52.93	55.8
		Manhattan	45.4	46.27	47.8	48.87	51.6	56.53
		Cosine correlation	42.93	46.07	48.53	50.27	50.93	53.4
		Bray-Curtis	45.93	45.67	47.4	47.93	50.8	55.93

Note : Yellow color indicates the highest performance for respective feature vector size. Pink color indicates the highest performance for corresponding transform.

Observations

By over all comparison, DST performs better than any other transform. In DST Cosine-correlation gives high performance in almost all size of feature vector. Euclidean measure tends to increase the accuracy as the increase in size of feature vector. Manhattan and Bray-Curtis measure gives good results for middle size of feature vector in first five transforms. In Kekre transform all similarity measure gives better performance for largest size of feature vector. Highest Accuracy achieved is **59.67%** and it is for DST, cosine correlation and 600 feature vector size

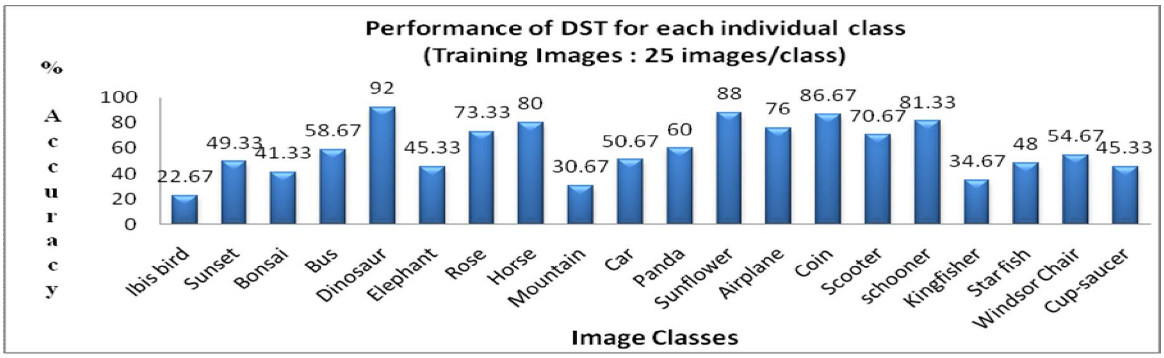

Figure 3: Performance of DST for individual class (Cosine correlation measure, Feature vector size 768)

Table 4: %Accuracy for DFT, DCT, DST, HARTLEY and WALSH over different feature vector sizes using different similarity Measure. Training Set: Feature vectors of 35 images from each class (total 700 images) Testing Set: Feature vectors of 65 images from each class (total 1300 images)

No. of Training Images per class	Transform	Similarity Measure	Feature Vector Size					
			75	150	300	450	600	768
			% Accuracy					
35	DCT	Euclidean	56	56.92	57.69	57.62	57.69	57.77
		Manhattan	56.92	56	57.23	57.92	57.92	58.15
		Cosine correlation	55.23	56	56.46	57	57.15	57.08
		Bray-Curtis	56.54	57.62	57.46	57.15	57.77	**58.31**
	DFT	Euclidean	52.08	53	53.23	53.92	54.23	54.62
		Manhattan	54.77	**55.77**	55.23	55.31	54.46	54.85
		Cosine correlation	50.38	50.54	51.54	52.69	53.38	53.54
		Bray-Curtis	55.15	54.85	55	55.46	55.15	54.08
	DST	Euclidean	58.8	59.08	59.54	60.15	60.15	60.38
		Manhattan	57.62	58.38	60.23	60.54	60.54	58.85
		Cosine correlation	**60.15**	**60.46**	**61.38**	**61.92**	**62.08**	**62**
		Bray-Curtis	57.4	58.85	60.38	60.62	60.15	60.38
	Hartley	Euclidean	50.69	50.69	50.54	50.69	51.31	55
		Manhattan	53.08	52.46	53.38	54.08	52.69	**54.77**
		Cosine correlation	47.77	48.31	49.46	49.46	49.92	53.85
		Bray-Curtis	52.69	52.38	53.15	54.38	54	54.69
	Walsh Transform	Euclidean	54.08	55.38	55.6	55.69	56	56
		Manhattan	54.31	56.15	55.85	55.54	55.08	55.54
		Cosine correlation	54.31	55.08	55.38	55.54	55.62	55.54
		Bray-Curtis	54.15	55.77	**57**	55.92	55.54	56.31
	Kekre Transform	Euclidean	44.31	45.77	50.15	54.08	56.46	**58.69**
		Manhattan	46.92	48.23	49.46	51.31	53.92	58
		Cosine correlation	43.69	46.85	50.31	52.54	53.92	56.69
		Bray-Curtis	46.69	48	49.15	51.85	54.54	57.08

Note : Yellow color indicates the highest performance for respective feature vector size. Pink color indicates the highest performance for corresponding transform.

Observations

For all sizes of feature vector, DST with Cosine-correlation similarity measure performs the best. Highest accuracy achieved is **62.08%** and it is for DST, cosine correlation and 600 feature vector size.

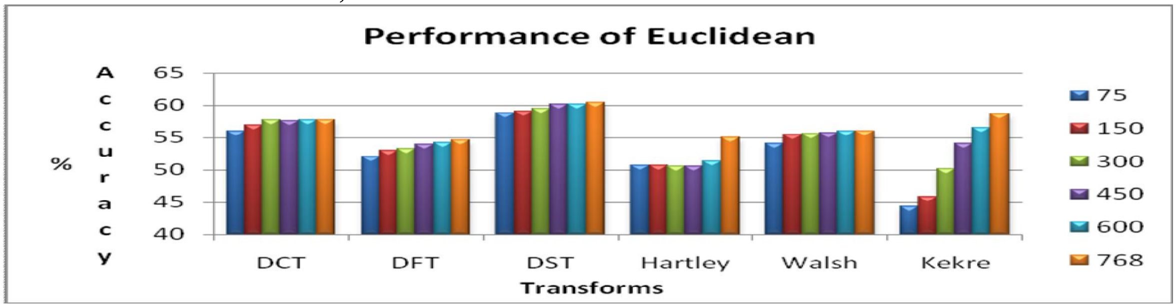

Figure 4: Performance of Euclidean for 6 transforms over variation of feature vector size(Training size:35 per class)

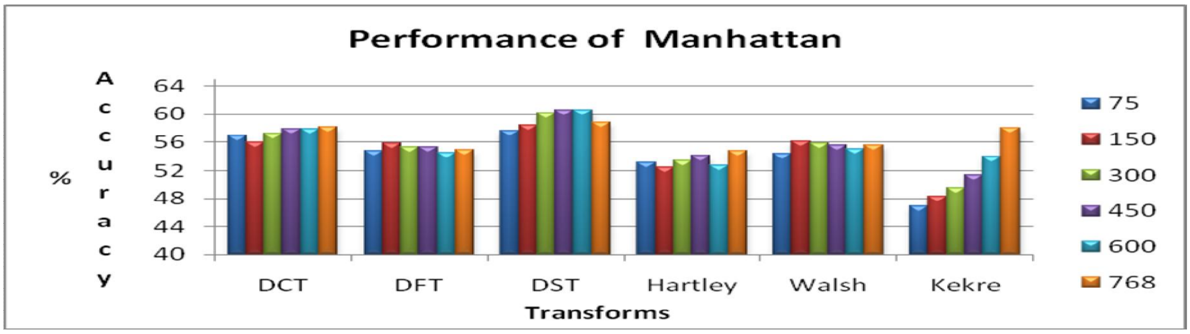

Figure 5: Performance of Manhattan for 6 transforms over variation of feature vector size(Training size:35 per class)

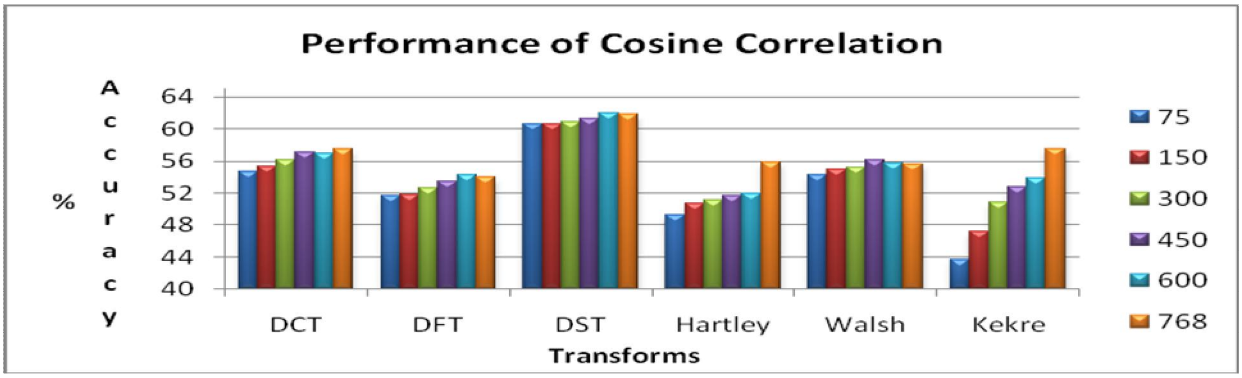

Figure 6 Performance of Cosine Correlation for 6 transforms over variation of feature vector size(Training size:35 per class)

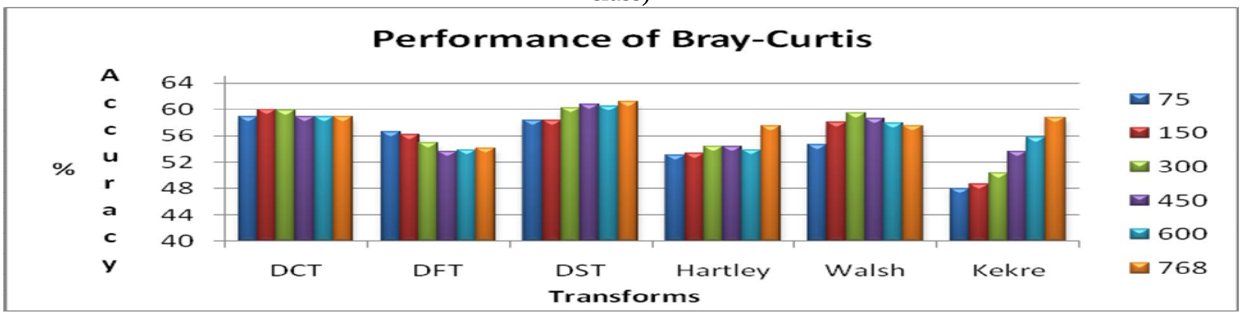

Figure 7: Performance of Bray-Curtis for 6 transforms over variation of feature vector size(Training size:35 per class)

Observations

In Kekre transform, for all similarity measures, the accuracy increases as the size of feature vector increase. The incremental change is significant. For other transforms, in Euclidean and Cosine correlation measure, the performance goes slightly higher as the size of feature vector goes high and in Manhattan and Bray Curtis similarity performance is better for middle size of feature vector.

Table 5 : %Accuracy for DFT, DCT, DST, HARTLEY and WALSH over different feature vector sizes using different similarity Measure. Training Set: Feature vectors of 45 images from each class (total 900 images) Testing Set: Feature vectors of 55 images from each class (total 1100 images)

No. of Training Images per class	Transform	Similarity Measure	Feature Vector Size					
			75	150	300	450	600	768
			% Accuracy					
45	DCT	Euclidean	56.45	56.55	57.55	57.55	57.73	57.82
		Manhattan	58.82	58.73	58.73	59	58.73	58.27
		Cosine correlation	54.64	55.36	56.18	57.09	57	57.45
		Bray-Curtis	58.82	59.91	59.82	58.91	58.82	58.82
	DFT	Euclidean	52.09	53.36	54	55	55.09	56.09
		Manhattan	56.27	56.45	55	54.55	53.64	54.18
		Cosine correlation	51.73	51.82	52.64	53.45	54.27	54
		Bray-Curtis	56.55	56.09	54.91	53.64	53.91	54.09
	DST	Euclidean	59.45	60.36	60.73	61.36	61.45	61.73
		Manhattan	57.64	58.82	59.64	60.91	61.45	59.45
		Cosine correlation	60.64	60.64	60.91	61.36	62	61.91
		Bray-Curtis	58.36	58.36	60.27	60.82	60.45	61.18
	Hartley	Euclidean	50.36	51.09	51.55	51.27	51.27	55.55
		Manhattan	52.55	53.18	54.64	54.45	52.82	56.82
		Cosine correlation	49.27	50.73	51.18	51.64	51.91	55.82
		Bray-Curtis	53.09	53.27	54.45	54.45	53.91	57.45
	Walsh Transform	Euclidean	54.18	55.45	56.45	56.45	56.64	56.91
		Manhattan	54.82	58.09	57.64	58	57	56.73
		Cosine correlation	54.27	54.91	55.27	56.09	55.73	55.64
		Bray-Curtis	54.64	58.09	59.36	58.55	57.91	57.55
	Kekre Transform	Euclidean	44.64	47.64	50.36	54.18	56.64	58.82
		Manhattan	47.91	49.09	50.82	53.36	56.27	59.27
		Cosine correlation	43.64	47.18	50.91	52.73	53.91	57.55
		Bray-Curtis	48	48.64	50.27	53.64	55.73	58.73

Note : Yellow indicates the highest performance for respective feature vector size. Pink indicates the highest performance for corresponding transform.

Observations

For all sizes of feature vector, DST with Cosine-correlation similarity measure performs the best. Highest accuracy achieved is **62%** and it is for DST, cosine correlation and 600 feature vector size. Hartley and Kekre Transform gives their best performance for the feature vector size 768. Walsh transform comparatively performs better than them at smaller size of feature vector.

Table 6 : % Maximum accuracy achieved for each individual class.

Class	Max Accuracy Achieved (%)	Size of training set	Transform	Similarity Measure	Feature vector size
Ibis bird	**40**	35	DST	Manhattan	300
		45	DST	Manhattan	600
Sunset	**67.27**	45	DFT	Euclidean	75,150
			Kekre	Cosine-correlation	75
Bonsai	**60**	45	Kekre	Cosine-correlation	450
Bus	**74.55**	45	DFT	Bray-Curtis	600
Dinosaur	**100**	25	DST	Euclidean, Manhattan	75
			DST	Manhattan	150
		45	DST	Euclidean	75,150,300,450
				Manhattan	150
			Kekre	Euclidean	75,150
				Manhattan	75,150
				Bray-Curtis	75,150
Elephant	**65.45**	45	DCT	Bray-Curtis	600
Rose	**95.38**	35	DCT	Manhattan	768
			DFT	Manhattan	600,768
			Hartley	Manhattan	300
Horse	**98.18**	45	Walsh	Manhattan	300
Mountain	**60**	45	DCT	Manhattan	75
				Bray-Curtis	75
Car	**54.55**	45	DST	Cosine-correlation	75
Panda	**78.67**	25	Walsh	Bray-Curtis	75
Sunflower	**93.85**	35	DCT	Manhattan	300
				Bray-Curtis	300
Airplane	**85.45**	45	DST	Manhattan	450
			Walsh	Manhattan	600
Coin	**89.23**	35	Kekre	Manhattan	768
				Bray-Curtis	768
Scooter	**80**	45	DST	Cosine-correlation	300,450,600
Schooner	**90.91**	45	DST	Cosine-correlation	768
Kingfisher Bird	**50.91**	45	Kekre	Manhattan	768
Star Fish	**56.92**	35	DST	Euclidean	768
Windsor Chair	**70.77**	35	WALSH	Cosine-correlation	75
Cup-Saucer	**50.77**	35	DST	Cosine-correlation	75

Observations

Maximum accuracy achieved in 5 classes like Dinosaur, Rose, Horse, Sunflower and Schooner is above 90% . Most of the classes give their best performance with DST. In similarity measure, Manhattan followed by cosine correlation measures performs better. Training set of 45 images per class gives maximum accuracy in most of the classes.

6. CONCLUSIONS

This paper proposes the use of column transform to generate feature vector. Since a column transform and not a full transform is used, the computation is fast. The paper gives detailed study and analysis of different transforms over 4 similarity measure for three sets of training and testing images. A large database of 2000 general images with wide variety has been used to perform the experiment. When the size of training images increase from 25 per class to 35 per class, the accuracy level goes up in most of the cases. When the size of training images increase to 45 images per class, there is no significant increase in accuracy. With DFT, DCT, Hartley and Kekre, Manhattan and Bray-Curtis similarity performs better than other two similarity criteria. With DST, Cosine-correlation similarity gives higher accuracy. Bray-Curtis measure gives good results with Walsh transform in most of the cases. In Kekre transform with any similarity measure, accuracy increases with the increase in size of feature vector from 75 to 768. So Kekre transform performs its best at the largest size of feature vector. Comparatively, in any other transform, Manhattan and Bray-Curtis measure gives their best performance at the smaller size (300,450) of feature vector. With Euclidean distance, as the size of feature vector increases, the accuracy increases. But the increment is very less in all transforms except in Kekre Transform. In all training sets of 25,35,45 images per class, overall maximum accuracy achieved is with the combination of **DST, Cosine Correlation similarity and feature vector of size 600**. These accuracies are 59.67%, 62.08% and 62% respectively. After analyzing individual class performance, it can be seen in most cases like Ibis bird, Dinosaur, Car, Airplane, Scooter, Schooner, Star fish, and Cup-saucer class, the best accuracy is obtained with DST.

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