International Journal of Electrical and Computer Engineering (IJECE)
Vol. 6, No. 3, June 2016, pp. 1176 ~ 1182
ISSN: 2088-8708, DOI: 10.11591/ijece.v6i3.8922

Walsh Transform Based Feature Vector Generation for Image Database Classification

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Article Info

Article history:

Received Oct 28, 2015
Revised May 4, 2016
Accepted May 20, 2016

Keyword:

Feature Vector
Image Classification
Vector Quantization
Walsh Transform
Wavelet Transform

ABSTRACT

Thousands of images are generated everyday, which implies the need to build an easy, faster, automated classifier to classify and organize these images. Classification means selecting an appropriate class for a given image from a set of pre-defined classes. The main objective of this work is to explore feature vector generation using Walsh transform for classification. In the first method, we applied Walsh transform on the columns of an image to generate feature vectors. In second method, Walsh wavelet matrix is used for feature vector generation. In third method we proposed to apply vector quantization (VQ) on feature vectors generated by earlier methods. It gives better accuracy, fast computation and less storage space as compared with the earlier methods. Nearest neighbor and nearest mean classification algorithms are used to classify input test image. Image database used for the experimentation contains 2000 images. All these methods generate large number of outputs for single test image by considering four similarity measures, six sizes of feature vector, two ways of classification, four VQ techniques, three sizes of codebook, and five combinations of wavelet transform matrix generation. We observed improvement in accuracy from 63.22% to 74% (55% training data) through the series of techniques.

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1. INTRODUCTION

Recent increases in storage capacity, processing power, and display resolution have enabled large image database development. Due to advancement in internet technologies, these databases have tremendously grown further. The task of accessing, processing, analyzing, and sharing these images has become more difficult. If images are properly organized, then accessing these images will be fast. Hence, with the large availability of high quality digital images, the need of classifying/categorizing images automatically is becoming increasingly important and challenging nowadays. Human beings easily classify images even if the images are poorly illuminated, partially occluded, and noisy. However, the classification task is not easy for machine. Hence, to design generic image classifier remains an elusive goal. The term image classification is a process of assigning an image to one of the predefined class. Manual classification of relevant images from a large database is time consuming, laborious, expensive, and subjective. So many researchers have focused on automatic (machine) classification of images. Content-based image retrieval (CBIR) is a system of retrieving a set of images similar to query image from a large image database. A successful classification of images will greatly enhance the performance of CBIR system by filtering out images from irrelevant classes during matching [1]. The problem of classifying images in database into predefined category has many levels of generality [2]. It can be as broad as separating indoor and outdoor images [3] or different outdoor scenes [4], it can be as generic as separating car, flower, elephant classes, or it can be finer [5] as separating different types of cloud images [6]. In one class classification (Unary classification) problem, image of an object is classified as genuine object or an outlier object. This classification is useful in some data mining applications like outlier detection and anomaly detection [7],[8]. In two-class classification (binary classification) problem, test image is assign to one of the predefined two classes [9]. This method has an application in medical field to detect the abnormality in medical images [10]. If the classification is for more than two classes then we get multi class classification. Classification is also classified as supervised and unsupervised classification [11],[12]. In general, automatic supervised image classification contains two steps: 1. Feature Extraction 2. Build Classifier [13]. The simplest way to represent an image in fewer coefficients is to extract color, shape and texture information from an image and represent it in a compact form [14]-[17]. Global features are extracted from entire image whereas local features are extracted from parts of an image [18]. Feature extraction can be done in spatial domain or transform domain. Image transform such as Walsh Transform has a property of energy compaction. Maximum energy accumulated in fewer coefficients; hence, reduced feature vector size. Once the feature vector generated, classification procedures such as nearest neighbor classification [19], classification using artificial neural network [20], and support vector machine [21] build the classifier.

We proposed a system in which initially Walsh transform [22], applied to the columns of an image. Then row mean vectors for three planes combined to make feature vector of that image [23]. To make effective and compact representation of training set feature vectors, different techniques of vector quantization (VQ) are applied on training set. Nearest neighbor (NN) classifier and nearest mean (NM) classifier with different similarity measures [24] assign the output class for a test image. To enhance the accuracy of classifier model, second method suggests applying Walsh wavelet to the columns of an image instead of simple Walsh transform. Addition of VQ techniques increases accuracy further decreases time and storage required. The paper is organized as follows: Section 2 explains detailed procedure of proposed system. Section 3 discusses all the results of implementation. The conclusion is given in section 4 followed by references.

2. RESEARCH METHOD

The paper gives three different methods to generate training set of feature vectors as explained in section 2.1, 2.2, and 2.3.

2.1. ‘Walsh Transform over Row mean’ based Feature vector Generation

The stepwise procedure for the first method is as follows:

1. Apply Walsh Transform to the columns of three planes (R, G, and B) of training image.
2. Calculate the average of each row of transformed image planes. This will give one row mean vector of size 256x1 for each plane (size of each image 256x256) [25].
3. Organize first 'Z' values of these three vectors one below the other to generate feature vector of size ‘3Zx1’. By taking the value of 'Z' as 25, 50,100,150, 200 and 256, we get feature vector of different sizes such as 75x1, 150x1, 300x1, 450x1, 600x1 and 768x1 respectively. Above three steps are repeated for each training image. This will generate the training set.
4. Apply the above procedure for test image
5. Apply nearest neighbor (NN) classifier where all training feature vectors are used and apply nearest mean (NM) classifier where average feature vector of each class is used as training set. Figure 1 shows the procedures for these two classifiers. Different distance measures such as Euclidean distance, Manhattan distance, Cosine correlation similarity, and Bray-Curtis [26]-[28] are used to calculate distance between training feature vector and testing feature vector.

2.2. Walsh Wavelet Transform based Feature vector Generation

This method uses the procedure of generation of wavelet matrix from two orthogonal transform matrices. The algorithm is as follows:

1. Create Walsh wavelet matrix from two Walsh matrices [29]. To generate wavelet matrix of size 256x256, we can take two Walsh matrices of sizes '4x4 and 64x64' or '8x8 and 32x32' or '16x16 and 16x16'.
2. Apply steps 1 to step 5 from section 2.1 by replacing Walsh matrix with Walsh Wavelet matrix.
3. If wavelet matrix is created from two matrices of Walsh transform with sizes 8x8 and 32x32, and NN classifier is used for classification then the results are shown under the name Walsh_wavelet_8X32_NN and if NM classifier is used, the results are shown under the name Walsh_wavelet_8x32_NM.
4. Apply the above procedure for test image
5. Apply nearest neighbor (NN) classifier and nearest mean (NM) classifier.

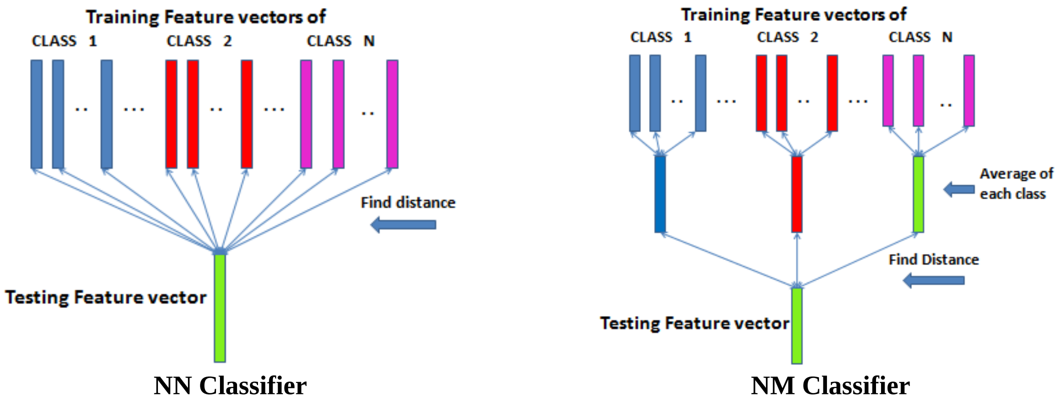

Figure 1. Nearest neighbour (NN) and nearest mean (NM) classifier

2.3. Proposed method of Feature vector Generation

The detailed procedure for method is as follows:

1. Apply first three steps from section 2.1 to generate training set.
2. Each feature vector of size 'Mx1' in a training set is a training point in 'M' dimensional space. Apply vector quantization techniques [30] such as Linde-Buzo-Gray (LBG) [31], Kekre's proportionate error (KPE) [32], Kekre's Fast Code book Generation (KFCG) [33] and Kekre's median codebook generation (KMCG) [34] algorithms to the training points of each class separately.
3. Generate the codebooks of size 4, 8 and 16. The code vectors are representative of the classes. Hence, the code vectors form the training set.
4. Apply NN classifier to find the class of test image.

The same procedure is applied on second method (Walsh wavelet based training set).

3. RESULTS AND DISCUSSION

For experimentation, large image database is constructed. This database contains total 2000 images (20 classes, 100 images per class). Six classes (bus, dinosaur, elephant, rose, horse, and mountain) are directly taken from Wang database [35]. Images of remaining fourteen classes (ibis bird, sunset, bonsai, car, panda, sunflower, airplane, coin, scooter, schooner, kingfisher bird, starfish, Windsor chair, and cup-saucer) are downloaded from the web related to the class keyword. Images are selected in such a way that they have many variations within the class and among the classes. Figure 2 shows the sample images of training database and testing database. Accuracy of classification is calculated as per equation (1). Initially 35 images per class are used for training purpose and remaining 65 images are used for testing purpose.Then training images increased by 10 for two times (45 images per class and then 55 images per class). It has been observed that as the number of training images increased accuracy increases. Table 1 indicates the size of training set, time required for generation of training set and time required for classification for single test image for different methods when we have used 35 images per class for training purpose. It shows that number of training feature vector reduces because of vector quantization hence reduces the classification time. Table 2 specifies highest accuracy obtained for all three methods for 55 training images and 45 testing images per class. Table 3 shows the variations in different factors considered for classification. Table 4 shows the confusion matrix obtained for ‘Walsh_wavelet_32X8_NN’ method (similarity criteria: Manhattan, number of training images: 55 images/class). This table shows the individual class performance.

$$\%Accuracy = \frac{Number\ of\ correctly\ classified\ images}{Total\ number\ of\ testing\ images} \times 100 \qquad (1)$$

The sizes of codebook we have tried are 4, 8 and 16 because the minimum number of training images is 35 per class. It has been observed that the proposed method of VQ gives better results compared to earlier methods.

Table 1. Number of training feature vectors and corresponding time required for each method for 35 training images/class

Method	Number of training images : 700 (35 images/class) Size of each feature vector : 768x1		Time required for generation of all training feature vectors (in sec)	Time required for classification of single testing feature vector (in sec)
	No. of training feature vectors/class	Total training feature vectors		
Walsh+Row mean+NN	35	700	34.79	4.24
Walsh+Row mean+NM	1	20	35.48	0.12
Walsh_wavelet+NN	35	700	38.72	4.24
Walsh_wavelet+NM	1	20	39.32	0.12
Proposed VQ(CB size 4)	**4**	**80**	**37.48**	**0.50**
Proposed VQ(CB size 8)	**8**	**160**	**38.34**	**1.01**
Proposed VQ(CB size 16)	**16**	**320**	**40.57**	**1.92**

Observations: 'NM' method requires least classification time and least storage space as the size of training set is only 20 training vectors. 'NN' method requires high classification time and large storage space as the size of training set is 700 training vectors. Proposed 'VQ' method generates training set of codebook (CB) size. It requires more classification time as compared to 'NM' method but it is quite less than 'NN' method.

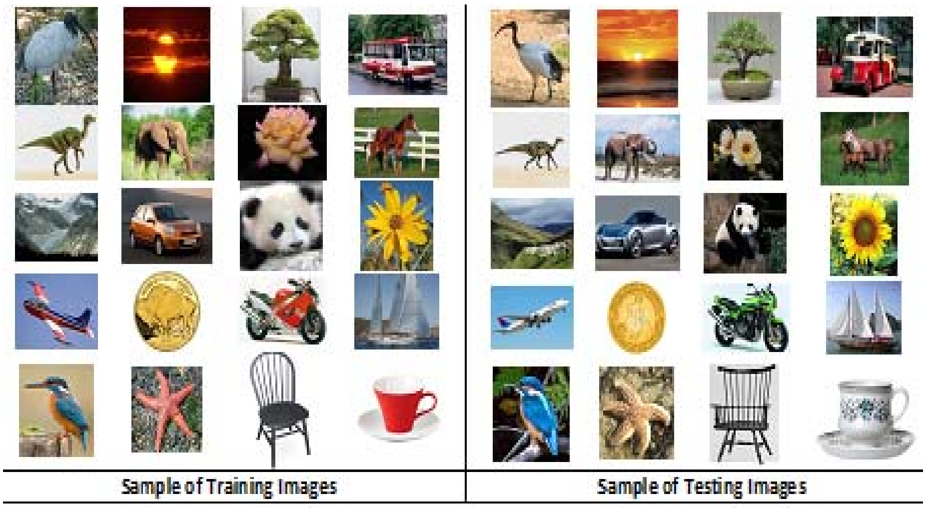

Figure 2. Sample images of training and testing Database

Table 2. Comparison of highest Overall Classification accuracy acheived for all the methods
No. of training images: 1100(55/class) No. of testing images : 900(45/class)

Method	Highest %accuracy achieved	Corresponding feature vector size	Corresponding similarity criteria	VQ method/ Wavelet method
Walsh+Row mean+NN	61.22	600x1	Euclidean	-
Walsh+Row mean+NM	52.67	300x1	Cosine correlation	-
Proposed VQ(CB size 16)	**63.22**	450x1	Manhattan	**Walsh+Row mean+LBG**
Walsh_wavelet+NN	72.78	768x1	Manhattan	Walsh_wavelet_32X8_NN
Walsh_wavelet+NM	63.89	768x1	Manhattan	Walsh_wavelet_32X8_NM
Proposed VQ(CB size 16)	**74%**	768x1	Bray-Curtis	**Walsh_wavelet_32X8+KMCG**

Observations: Accuracy increases from 52.67% to 74%. Highest accuracy achieved with proposed technique applied on second method of Walsh wavelet.

Table 3. Variations in different factors considered for Classification.

Sr. No.	Factors	No. of Variations	Variations
1	Feature Vector size	6	75x1, 150x1, 300x1, 450x1, 600x1, 768x1
2	Similarity Criteria	4	Euclidean, Manhattan, Cosine correlation, Bray-Curtis
3	Code book size	3	4, 8, 16
4	Classifiers	2	NN & NM Classifier
5	VQ methods	4	LBG, KPE, KFCG, KMCG
6	Walsh Wavelet matrix generation	5	4x64, 8x32, 16x16, 32x8, 64x4

Observations: ‘Walsh transform+row mean’ method with factors 1,2 and 4 generates 48 results for single test image. Proposed VQ technique over the ‘Walsh transform+row mean’ method with factors 1,2,3 and 5 generates 288 results for single test image. Walsh wavelet method with factors 1,2,4 and 6 generates 240 results for single test image. Proposed VQ technique over the Walsh wavelet method with factors 1,2,3,5 and 6 generates 1440 results for single test image.

Due to space constraint it is not possible to show the results of all the methods with all factor variation. But after implementing all the methods, it has been observed that proposed method of applying VQ over the earlier methods gives highest accuracy in most of the classes. In some classes like Bus, Dinosaur, Rose, Horse and Airplane, 'NM' method gives better results. It means that those classes are compact and they can be best represented by single feature vector. Bray-Curtis and Manhattan performance is almost similar and they both give better performance than other two similarity criteria in most classes. Euclidean and Cosine correlation shows similar performance. In sunset class and scooter class, cosine similarity gives better performance than any other distances.

Table 4. Confusion Matrix for Walsh_wavelet_32X8_NN method (Feature vector size: 768x1, Similarity measure: Manhattan distance, No. of training images: 55/class)

	Ibis bird	Sunset	Bonsai	Bus	Dinosaur	Elephant	Rose	Horse	Mountain	Car	Panda	Sunflower	Air plane	Coin	Scooter	Schooner	Kingfisher	Star Fish	Windsor Chair	Cup-saucer
Ibis bird	**17**	0	2	0	0	5	0	4	1	0	1	0	1	0	1	1	9	3	0	0
Sunset	0	**28**	0	1	0	3	6	1	0	0	1	2	0	0	0	0	1	2	0	0
Bonsai	1	0	**26**	1	0	2	0	2	0	0	2	0	0	3	1	0	3	1	1	2
Bus	0	0	1	**27**	0	1	0	3	2	0	2	0	0	0	4	0	1	4	0	0
Dinosaur	0	0	0	0	**44**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Elephant	2	0	0	0	2	**32**	0	0	1	0	1	0	1	0	2	0	0	2	0	2
Rose	0	0	0	0	0	0	**41**	1	0	0	2	0	0	0	0	0	0	1	0	0
Horse	2	0	0	0	0	0	0	**43**	0	0	0	0	0	0	0	0	0	0	0	0
Mountain	3	0	1	4	0	3	0	4	**20**	0	1	0	1	0	3	2	2	1	0	0
Car	0	0	0	5	0	3	1	1	2	**23**	2	1	1	0	4	0	2	0	0	0
Panda	1	0	0	1	0	0	0	3	1	2	**36**	0	0	0	1	0	0	0	0	0
Sunflower	0	0	0	0	0	0	0	0	0	0	0	**43**	0	0	0	0	0	1	0	1
Air plane	0	0	1	0	2	0	0	1	1	0	0	0	**40**	0	0	0	0	0	0	0
Coin	1	0	0	0	0	2	0	0	0	0	0	0	0	**40**	0	0	1	1	0	0
Scooter	0	0	1	1	0	0	0	0	1	0	0	0	0	0	**41**	0	0	1	0	0
Schooner	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	**44**	0	0	0	0
Kingfisher	0	0	0	0	0	2	3	4	0	0	4	0	0	0	0	0	**27**	3	0	2
Star Fish	0	0	0	4	0	3	1	2	0	0	3	0	0	2	0	0	0	**26**	1	3
Windsor Chair	2	0	0	0	3	0	0	0	0	0	1	0	0	0	0	0	0	2	**37**	0
Cup-saucer	2	0	0	0	4	2	0	1	0	0	3	0	0	0	1	0	8	3	1	**20**

Observations: Classes whose accuracy is more than 90% are Dinosaur (98%), Rose (91%), Horse (96%), Sunflower (96%), Scooter(91%) and Schooner (98%). Worst performing classes are Ibis bird class with 38% and cup-saucer class with 44% accuracy. Few of Ibis bird images are misclassified as Kingfisher bird images due to similarity in structure and shape. Few of the cup-saucer class images are misclassified as Dinosaur class because of their plane background. Therefore, the accuracy of those classes degrades.

After Walsh transform applied to each column of an image, low frequency components get stored in the first few coefficients of each column. Hence maximum feature vector size is not required to get highest accuracy in first method. But in Walsh wavelet method, the low frequency components are spread. Hence, highest accuracy is obtained with feature vector of size 768x1.

4. CONCLUSION

The paper gives methods for generation of training set using Walsh Transform for classification of image database. If we increase training data, the accuracy of classification increases. In the paper, we have shown the results for 55% of database (1100 images) for training, and tried to increase accuracy by implementing different techniques of feature vector generation. For classification, a simple and fast method, Nearest Neighbor classifier, is used. It has been observed that classes like dinosaur, rose give the better results with NM classifier than NN classifier. While the other classes give better performance with NN classifier. As we were analyzing this fact, it has been found that classes like dinosaur and rose are compact and close i.e. low intra-class distance and high inter-class distance compared to other training classes. After a lot of experimentation, we realized that instead of all training vectors per class or average training vector per class, there is a need to represent the class by few but more effective training feature vectors. It resulted in proposed method of applying vector quantization on ‘Walsh transform+row mean+NN’ method. This method increases accuracy from 61.22% to 63.22% and it has great advantage of reducing time required and storage space required for classification. However, in thirst of more accuracy, better feature vector representation is generated using wavelet transform. It has been observed that Walsh wavelet has increased an overall accuracy from 63.22% to 72.78%. Manhattan and Bray-Curtis distance are more suitable similarity measures for this application. Walsh_wavelet_32x8_NN method gives highest accuracy of 72.78%. In all VQ techniques it has been observed that KMCG with codebook size of 16 has given better performance. Hence, KMCG is applied on feature vectors generated by Walsh wavelet. The accuracy increased upto 74% for codebook size of 16. Thus the proposed technique not only increases accuracy but also drastically reduces the size of training set (from 900 training vectors to 320 training vectors) results in less storage space required and faster classification.

ACKNOWLEDGEMENTS

We are extremely grateful to our research guide late Dr. H.B.Kekre for his valuable guidance, scholarly suggestions and consistent encouragement. Sir had always clarified our doubts despite his busy schedules and provided academic support and facilities to carry out this research work. We acknowledge our deep sense of gratitude towards him. Though he is not physically present with us, his work, words and blessings will remain with us forever.

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