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# Color Image Retrieval Using Compacted Feature Vector with Mean-Count Tree

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## Abstract

Image Retrieval systems highly rely on the image signatures stored in database. Constructing Image signatures with optimal size and accurate representation of image is most interesting challenge here. High level image features like object and their characteristic are useful in sentiment image analysis but faces the limitations of domain specific feature vector. Low level image features like color, texture and shape are interesting and useful enough to represent the image in diverse image databases. Targeting to low level image feature: color, the image signatures created are of huge size, as those represents three color planes and their values. Image signatures vary, as the image size varies. Targeting towards creating the optimal image signatures with color feature, to reduce the size of feature vector is possible by considering images in frequency domain. Image transforms converts image in frequency domain, with compressed image data. This data is further reduced form by ignoring the low energy components. This paper discusses the approach to construct image signatures by considering high energy components of transformed image. Further the high energy components are bagged together. Here the intelligent mean-count tree is created based on image information. Performance of Image retrieval is tested using image feature database.

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*Keywords:* Mean-count tree ;Image Retrieval; Image Transform; Feature Extraction ;Low level features

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## 1. Introduction

CBIR systems are popular application of image processing to retrieve the Content similar images [1][2] [3] which have similar image signatures. Crucial phase of CBIR system is Feature Extraction. Feature Extraction phase

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extracts information hidden in image and represent it in the form of image signatures. If two image signatures are content wise similar, then those represents similar images. Major Image Features can be categorized as low level features and high level features. Various approaches are researched to create image signatures, which are helpful in retrieving similar images. Particularly low level features [1][2][3] like color, texture and shape are popular for representing images in terms of image signatures. In past few years the research was done for retrieving semantically similar images using High level feature components of image, and constructing image signatures based on those high level features like Objects inside image. Understanding semantics of image is depends on the Object present in image and their relationships. High Level Feature extraction faces the limitation of huge Object corpus size. Low level features provide generous way to represent the any image despite of diverse image classes and type. This paper discuss the frequency domain feature extraction using Image Transforms. Major objective of the work is to create the feature vectors with good discriminative power and with reduced dimension. Here low level feature extraction of Color is used on transformed image. In Image transforms possesses energy compaction property, and are proved very useful to study image internals. They provide effective way to create compact image signatures, if high energy components are considered for feature vector generation. Many researchers have observed the usage of Low level Feature like Shape and Texture. But these features face the limitation of domain dependency and ambiguity. Also these features are not invariant to rotation and scaling. Low level feature Color provides effective way to represent image with the invariance to scaling, rotation and translation. So image signatures, if created by analyzing Color Feature Components and the pattern of color distribution, are effective in image retrieval. Pattern of Color distribution can be represented in variety of ways like color histogram, color correlograms etc.

Mostly the statistical components are used to generate dimensionally reduced feature vector of minimal size. In [3][4][5][17] approaches Sectorization, Color Histogram, Vector Quantization are discussed to create feature vector with analysis of statistical components and with reduced dimensionality. But the statistical components used in these approaches represent the central tendency, which possess less discriminative power to distinguish between the images or to find similar images.

In CBIR, Feature vector, must be optimal enough and must possess good discrimination component. Understanding this fact, here discussed a new approach for feature vector generation using Mean–Count Tree. In mean-count tree, the statistical component-Mean is used to understand image. Instead of Global mean,  $n$  level means are calculated and stored in binary tree for feature vector generation. The tree holds  $n$  level means, which are calculated based on the pixel values of transformed color planes. LHS of the tree holds the Means of pixel with less values of global mean, RHS of tree holds the Means of pixels with greater values, than global mean.

In chapter 2, feature extraction using low level feature: color on transformed images is discussed. Different image transforms Hartly and Haar are analyzed for feature extraction creation, and its performance in image retrieval. Feature Vector preparation with Mean-Count Tree is discussed in chapter 3. Chapter 4 discusses about the Image database creation. Chapter 5 Discuss about the image retrieval performance evaluation, with the approach of Color feature extraction on transformed image with mean-count tree for feature vector preparation.

## 2. Feature extraction using Image Transforms

All Transform Domain Images when considering energy conservation property, provides effective way for optimal image signature generation. Different image transforms possesses different energy compaction property. We analyzed the energy compaction property of different transforms by ignoring 16, 32, 64...128 rows of bits with low energy components. If used the Transform Domain for feature extraction, Image with size  $N \times N \times 3$  will be optimally represented by considering only High Energy components of feature vector. Walsh Image transform is discussed here,

Walsh transform matrix [1,11,18,19,26,30] is defined as a set of  $N$  rows, denoted  $W_j$ , for  $j = 0, 1, \dots, N - 1$ , which have the following properties:

- $W_j$  takes on the values +1 and -1.
- $W_j[0] = 1$  for all  $j$ .
- $W_j \times W_k = 0$ , for  $j \neq k$  and  $W_j \times W_k = N$ , for  $j = k$ .
- $W_j$  has exactly  $j$  zero crossings, for  $j = 0, 1, \dots, N-1$ .

- Each row  $W_j$  is even or odd with respect to its midpoint.

Walsh transform matrix is defined using a Hadamard matrix of order  $N$ . The Walsh transform matrix row is the row of the Hadamard matrix specified by the Walsh code index, which must be an integer in the range  $[0, \dots, N - 1]$ . For the Walsh code index equal to an integer  $j$ , the respective Hadamard output code has exactly  $j$  zero crossings, for  $j = 0, 1, \dots, N - 1$ .

Hartly and Walsh transforms are analyzed for the energy compaction property by Ignoring 16, 32, 48, 64, 80, 96, 112, 128 rows of bits with low energy components and its effect on RGB Image. Fig 1. Shows the Mean square error is displayed of Image with low energy components ignored along with Image Distortion for Hartly Transform.

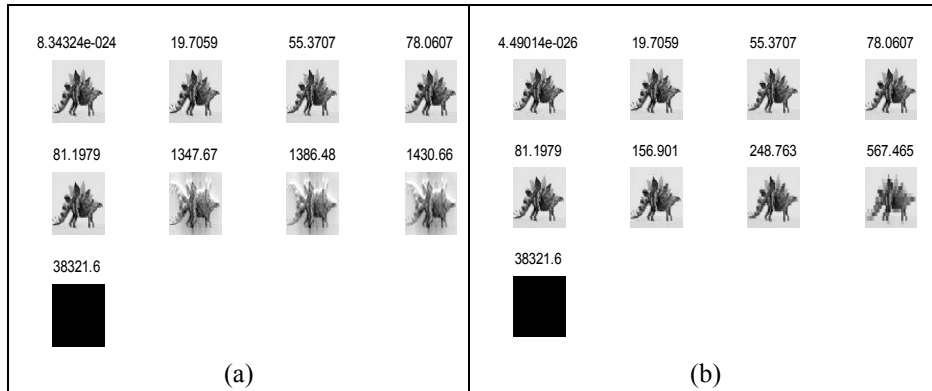


Fig. 1. Analysis of Image Quality Distortion, MSE Displayed for Images, with 16, 32, 48, 64, 80, 96, 112, 128 low component bits ignored. (a) Hartly Transform, (b) Walsh Transform

In Fig.1, MSE for Hartly and Walsh transform is displayed. Distortion in Hartly transform and Walsh transform is similar for bits of rows ignored 32, 48, 64, 80. Walsh transform possesses less distortion than Hartly for bits 96, 112. By using this analysis, it's observed that Image quality is retained, even if 64 low energy row bits are ignored in transformed image. While constructing Image signature, this finding is considered. So the Image Signature of image size  $[128 \times 128]$  can be reduced to  $[128 \times (128 - N)]$ , where  $N$  will be 16, 32, 48, 64.  $128 - N$  rows is called region of interest.

For Feature Vector creation with working on colour image, each color plane of transformed image is treated separately for feature vector creation. Methodology of feature vector creation is described in Fig.2, each image is represented by feature vector.

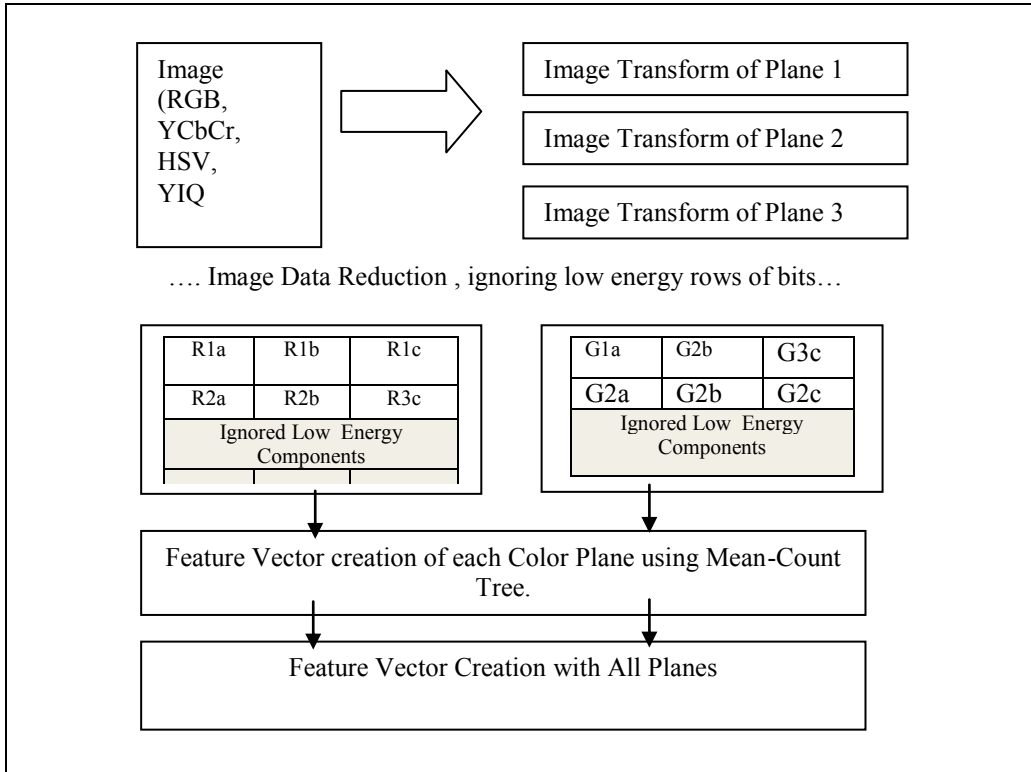


Fig.2. Feature Vector Preparation Methodology

### 3. Feature creation using Mean-Count Tree

Mean Count Tree Construction as explained in Fig.3 is used to construct optimized feature vector. Here, the General mean of ROI image is calculated and considered as ROOT node. RHS of tree will have all pixel with energy value more than mean, and LHS of tree hold all pixels with energy value less than mean. Again the mean of LHS and RHS is calculated, and same method is repeated. Mean count tree evaluates the energy distribution and pixel quantization with level wise mean calculated.

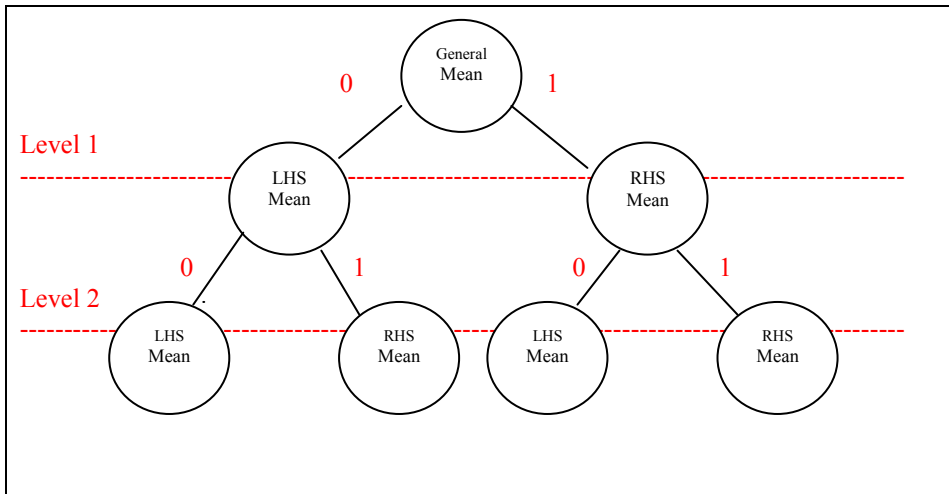


Fig.3. Mean-Count Tree

### Steps for Level Wise Mean Calculation and Tree Creation

1. Root Node :Calculate Global Mean of transformed Image for color plane 1[output of step 2 , in Fig.2] and assign it to root node
2. LHS: Identify Pixels with values less than Root, Calculate their Mean ,assign it to LHS node of Root
3. RHS: Identify Pixels with values greater than Root, Calculate their Mean, assign it to RHS node of Root
4. Repeat 2 and 3 for each node.
5. Exit when Count of Pixel < 30

Quantization is done by traversing the tree edges. Mean-Count Buckets are formed for each edge like:

0={Mean( pixels on first level LHS)}  
 1={ Mean, ( pixels on first level RHS)}  
 00={Mean( pixels on second level LHS of LHS)}  
 01={ Mean, ( pixels on second level RHS of LHS)}  
 10={ Mean, ( pixels on second level LHS of RHS)}  
 11={ Mean, ( pixels on second level RHS of RHS)}

F(Color Plane1) = Values of Bucket {0,1,00,01,10,11}  
 F (Color Plane2) = Values of Bucket {0,1,00,01,10,11}  
 F (Color Plane3) = Values of Bucket {0,1,00,01,10,11}  
 FV = { F (CP1), F (CP2), F (CP3) }

Here, CP=Color Plane of Different Color Spaces.

Using Mean-Count tree, the pixels in each tree branch and mean of all values, is calculated and collected in feature vector. Separate Feature vector for each of three color planes are created. Combine Feature vector of all colors is created and Image retrieval and performance is tested.

## 4. Image Database Creation

WANG image database [15] is tested for the discussed approach. Evaluated the retrieval performance for two image transforms on RGB image. 1000 Images of 10 different classes are tested for performance measurement. 10 classes of images with 100 images of each class, are considered. 4 Feature vectors are created for each Image. Image retrieval is tested for each. Precision measure is used for testing performance. Following are Feature Vectors evaluated for each color space in Performance measurement.

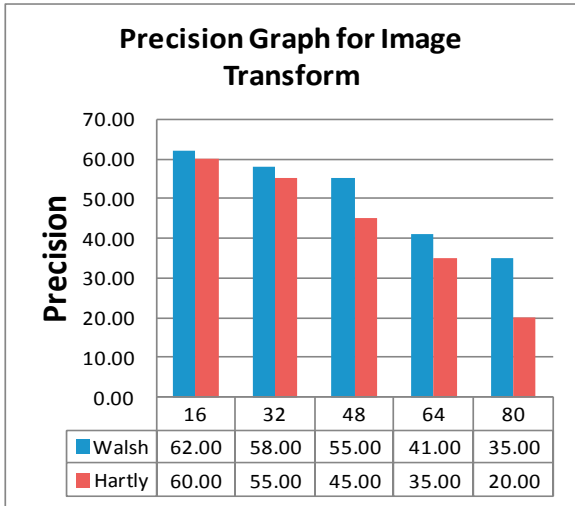
FV\_Red:: Values of Bucket {0,1,00,01,10,11}  
 FV\_Green:: Values of Bucket {0,1,00,01,10,11}  
 FV\_Blue:: Values of Bucket {0,1,00,01,10,11}  
 FV\_ALL:: {FV\_Red, FV\_Green, FV\_Blue}

Feature vector size is reduced in 2 steps, In first step, by ignoring low energy component, the size is reduced from  $[128*128] \rightarrow [128*(128-N)]$ , where N will be 16,32,48,64. In next step , this reduced feature vector is quantized using Mean-Count Tree. Feature Vector size will be  $2^{N-1}$ , where N will be levels in Tree. N=5 is demonstrated in performance measurement.

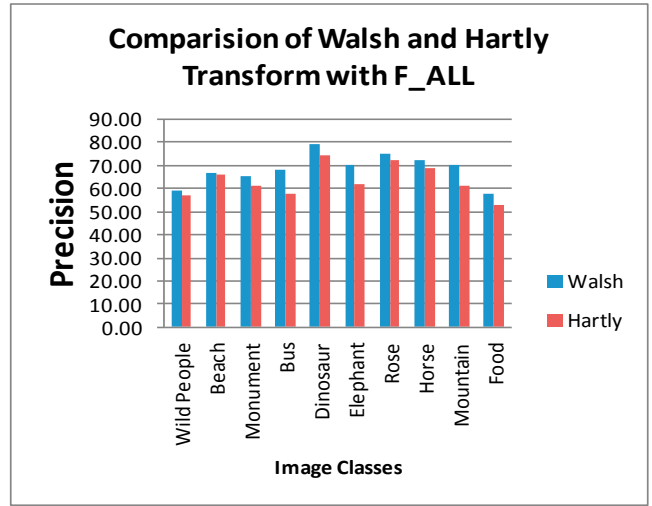
## 5. Performance Measurement

Euclidian Measure is popular measures for Image Similarity measurement [7]. Using Euclidian Measure performance of Image retrieval is measured for different feature vectors. Following performance measures are used to test the performance of the Image retrieval, Using Eq.1, Precision is evaluated for each color plane against Phase and Magnitude.

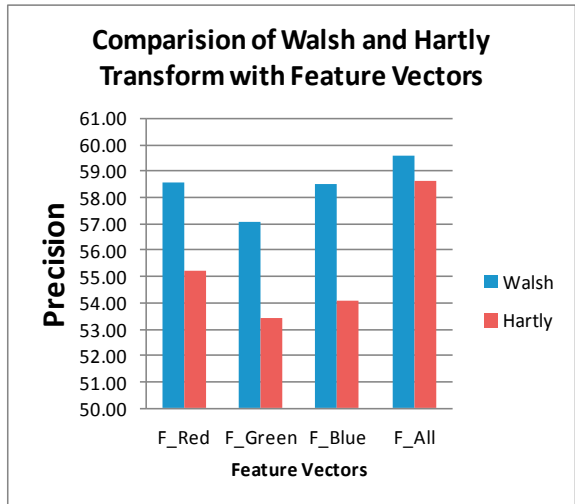
Precision = no of Images correctly retrieved/Total no of retrieved images (1)



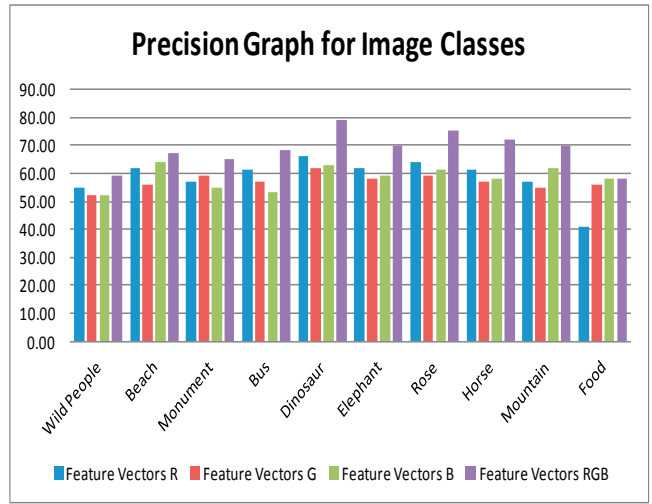
(a)



(b)



(c)



(d)

**Fig. 4** Performance of Image Retrieval(a)Comparison of Precision for Walsh Transform and Hartly Transform w.r.t Low energy components ignored(b) Comparison of Precision for Walsh Transform and Hartly Transform w.r.t Image Classes(c) Comparison of Precision for Walsh Transform and Hartly Transform w.r.t Facture Vectors(d) Comparison of Precision for different image classes with Walsh transform

As shown in Fig. 4 (a), Precision Graph comparing Feature vector created using Walsh and Hartly. All feature vectors are evaluated separately for RGB colour space by ignoring Low energy component’s rows in sequence 16, 32, 48, 64, 80. In the graph Walsh Transformed Images are observed performing better for 48, 64 and 80 low energy component rows than the Hartly Transformed Image. For 16, 32 both the transform performs same for Image Retrieval. Understanding the Impact of Transform on Image Data, 16, 32 low energy rows can be ignored to reduce

the feature vector.

Fig 4 (b) shows the comparison of Precision for Walsh Transform and Hartly Transform w.r.t Image Classes considering 32 rows of low energy components ignored and F\_All. Image Classes: Dinosaur, Rose shows better retrieval performance than the other image classes. As per the observation, these classes possess less diverse objects and colour inside it.

As observed in Fig.4(c) Precision for Walsh Transform is better than Hartly Transform w.r.t Feature Vectors F\_Red, F\_Blue and F\_Green. F\_All shows better performance than the remaining feature vectors.

Fig, 4(d) shows the Precision graph of Image retrieval for Image Classes with Walsh Transform. FVRed, FVBlue, FVGreen feature vectors individually tested for Image Retrieval FV\_ALL is also tested for Image Retrieval. F\_R and FRGB feature vectors are showing good retrieval performance as compared to FVGreen, FVBlue. It is upto 65% for classes “Beach”, “Dinosaur” and “Rose”.

## 6. Conclusion

Image Transforms possess energy compaction property, which is effectively used to reduce the Image Feature Vector size. Performance of Image Retrieval observed on Walsh and Hartly transform, and tested their energy compaction property. Walsh Transforms performs better in Image Retrieval, when Feature vector is created based on that. Mean-Count Trees are applied on Transformed and Reduced Image Data, to extract the image data distribution Pattern with level-wise mean calculated. With this method entire image is represented using Mean-Count Tree, with dimensionally reduced feature vector. The compact feature vectors are generated using Image Transforms and Mean-Count Tree. Retrieval performance is successfully tested to observe effective use of Image Transform in Feature Vector Generation. Mean-Count Tree is successfully used for feature vector generation, and tested each generated feature vectors to analyze retrieval performance. When compared the performance Combine Feature vector, with individual color plane, by selecting random images of any class, FVRGB feature vector gives 70% and above precision. FVGreen and FVBlue performance observed less than FVRed. Feature vector created Ignoring 16, 32 rows gives better retrieval performance than 64, 80, 112. Feature Vector is tremendously optimized by this multimodal approach of Image Transform Compaction property and Mean-Count Tree Data Representation.

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