A NOVEL TEXTURE DESCRIPTOR USING FUSED MULTI-RESOLUTION LBP AND TAMURA FEATURES FOR IMAGE RETRIEVAL SYSTEM

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Abstract: Texture analysis plays an important role in computer vision cases such as object recognition, surface defect detection, pattern recognition, medical image analysis, etc. In this paper, a new algorithm which is based on the discrete wavelet transformation and different texture features for content based texture image classification is proposed. Three techniques (LBP , DWT and Tamura) are combined together to create an effective hybrid function vector to obtain the finest information of texture. In this paper LBP and Tamura features are extracted in two ways by using wavelet transform and fusion to extract effective hybrid texture feature vector. Experiments with Brodatz database and MIT VisTex database show that the proposed approach has higher precision than a single feature texture algorithm and is also higher than the approach of Tamura texture features and wavelet transform features combined . Further the accuracy is higher for the approach with SVM classifier upto 99%.

1. Introduction

Due to the development of internet and technologies there is a huge growth of digital images. It is necessary to store and retrieve these images effectively. Image Retrieval dependent on Content (CBIR) is the most territory of image handling and PC vision. The generally utilized image highlights are shape, shading and texture. In the current situation, figuring the discriminative image highlights is harder assignment since images of various classes have various types of highlights. Appropriately, still there is a shortage for viable and flexible image include which is more helpful when the dataset comprises of various types of images. Descriptors are frequently assessed by utilizing the spatial data surface, shape and shadings and so on and worldwide descriptors are used for picture recovery. The use of the nearby descriptors increments in the ongoing years as these are stay consistent with comparative attributes, with the distinction that the neighborhood descriptors are extricated from the picture districts rather than the whole picture [1]. In the mid 70's Haralick et al [2] proposed coocurrence network portrayal of surface component. This methodology investigated dim level spatial ward of surface. Tamura et al [3] investigated surface portrayal from various point and proposed a computational estimation on six visual properties like coarseness, contrast, directionality, linelikeness, consistency and unpleasantness.

In the mid 90's, the wavelet change was presented for surface portrayal. Smith and Chang [4, 5] utilized the insights, for example, mean and fluctuation highlights are separated from wavelet subbands as surface portrayal. Net et al [6] utilized Wavelet Transform along with KL extension and kohenon guides to perform surface examination. Thygagarajan et al [7] and Kundu et al joined wavelet change with coocurrence framework to take the benefits of insights based and change based surface investigation. Mama and Manjunath [8] assessed surface picture explanation by utilizing different wavelet surface portrayal including symmetrical and bi-symmetrical wavelet change, tree organized wavelet change and Gabor wavelet change. The surface range was at first utilized as a surface separating approach [9]. The significance of the surface range strategy is dictated by the extraction of neighborhood surface data for every pixel and of the portrayal of textural part of a computerized image as a range. Likewise, Ojala et al. [10] proposed the formally dressed nearby parallel examples (LBP) way to deal with extricating revolution and histogram evening out invariant highlights, which was stretched out by Huang, Li and Wang [11]by figuring the subsidiary based neighborhood twofold examples and applied it to the

utilization of face arrangement. The methodology of the customary LBP is basic and proficient which considers the uniform examples in the pictures which will be nearby highlights of a picture. A noise invariant local ternary pattern (LTP) was proposed in [12], which functions in three states to identify and extract distinctions between the central pixel and its neighbourhood.
Recently, Shefali Dhingra et al [13] proposed a image recovery framework utilizing half breed highlight vector Local two fold example, Color second and Automatic division measure individually. Every one of these highlights consolidated for the arrangement of a half and half component vector by using the cycle of standardization. Support vector machine (SVM) have likewise been utilized for arrangement reason. Over the last few years the intensive research is carried out in characterizing the texture pattern as it is very challenging and demanding task in the area of image processing. The LBP texture descriptor has build up very much attention due to its less computational complexity and high selectivity ability [14]. Due to these properties of LBP technique it has been successfully employed in different applications like image analysis, pattern recognition and in CBIR systems. The second texture predictor which is used here is discrete wavelet transform [15]. These functions produce the optimized resolution in both frequency and spatial domains so this wavelet transform extracts the local features due to multi-orientation and multi-resolutional properties [16]. Dhingraa et. al [13] proposed a CBIR system which extract the finest details of texture by merging (LBP and DWT) together for the creation of an efficient hybrid feature vector. The performances of SVM and ELM machine learning classifiers are compared on two benchmark datasets i.e. Brodatz and MIT VisTex .

The main objective of this work is to upgrade the performance of texture feature based image retrieval systems by making an intelligent and novel hybrid CBIR system which is the combination of well known texture extraction techniques i.e. Local Binary Pattern (LBP), Tamura features and Discrete Wavelet Transform . The chosen texture descriptors are capable of representing the texture properly and also have the property of compensating variations such as rotation, scale changes because these kinds of variations can distort the original appearance of the images. The remaining part of the paper is systematically structured as follows: a brief survey relating to this work is described in section 2. Detailed views on LBP, Tamura, DWT and SVM are given in Section 3. The proposed method is defined in detail in section 4 below. In section 5, experimental setup and outcomes are shown. Finally, the final description and possible work that can be discussed is described in the final section 6.
2. Related work
Texture is one of the most influential low level features of an image. It provides the spatial arrangement of the visual patterns presents in the images. Different CBIR systems are studied in literature using various texture features such as DWT, Gabor Transform, Grey Level Co-occurrence Matrix (GLCM), LBP , Tamura etc. Adaptive tartlet transform texture based retrieval technique was proposed which provides very good texture information. The best combination of tetrominoes was elected which provides the better geometry of the image at all level [18].The new technique was proposed entitled Local tetra patterns for image indexing and image retrieval for CBIR systems in the different way [19]. In order to decrease the information level of the images the new technique was proposed known as Local Derivative Radial Pattern (LDRP) [20]. It uses multi-level coding as the replacement of binary coding in different directions which decreases the loss of information along with increase in somewhat accuracy. Tamura feature extraction technique was used in [21] which uses the fuzzy humming distance to measure the similarity between the images. Andre Ricardo Backes et al.[12] designed a method by using LBP maps technique which extracts the new and more information from the query image. After that it computes the descriptors with the help of fractal dimension. In[24] the authors described a hybrid CBIR system based on texture and color. Wavelet decomposition technique was used to extract the texture feature and the characterization of texture classes with the variations in higher frequency

coefficients. Haralick recommended GLCM which gives more spatial information regarding the texture analysis by determining the co-relation between the neighbor pixels[2] . Murala et al. proposed Local Tetra pattern (LTP) in which second order derivatives are calculated in both horizontal and vertical directions [17] . Texture descriptor based on combination of LTP and GLCM was developed known as CoALTP by integrating the feature vectors of both [18]. Image retrieval by texture was described in[25] in which both the dual tree complex and rotated wavelets were used which makes this method rotation invariant in twelve directions. Energy and standard deviations were used as texture features. Another color and texture based retrieval system had been proposed by employing local extreme features which were able to capture the important information from the images[26] . The multi-resolution and rotation invariant technique based on texture retrieval was proposed in[27] and this invariance was achieved through aligning the principal texture direction with the reference axis. LBP was proposed to extract the local properties of every pixel with its neighboring pixels and basically used to classify the texture[28] . In this binary pattern technique, the magnitude of the centre pixel is compared with the neighbor pixels and finally a decimal value is created by which histogram is generated with pixel values of LBP. Despite of all these advantages LBP does not take into consideration the directional information[29]. In order to extract the edge information in the four directions Directional Local Extrema Pattern was proposed[30] . The gabor functions are very much applicable for the analysis of texture as its orientation and frequency representation resembles with the human visual systems and thus having high retrieval accuracy or performance [14]. Dihuang et al. presented the survey regarding the LBP technique about its applications and analysis in the domain of image processing [11] SVM based hybrid CBIR system was designed in which color, texture and edge features are extracted from Corel database. To make the system more accurate and speedy multiclass SVM is applied [31]. A unique and effective CBIR system is proposed based on the combined approach of LBP and DWT features using Tamura technique along with SVM machine learning classifier. This complete approach is applied on two standard datasets i.e. Brodatz and MIT VisTex and the results obtained outperformed the other state of art methods. The LBP, DWT and SVM are described below in this section.

In this paper, a specific and efficient CBIR method is proposed based on the combined approach of LBP and Tamura features extracted using DWT along with SVM classifier.This complete strategy is applied to two traditional datasets, i.e. The other state of the art approaches were outperformed by Brodatz and MIT VisTex and the outcomes obtained. In this segment, the LBP, Tamura Features,DWT and SVM are listed below.

3.1. Local binary pattern (LBP)

Local Binary Pattern operator is a simple yet very efficient texture operator which labels the pixels of an image by threshold the neighborhood of each pixel with the value of the center pixel and considers the result as a binary number. The original LBP method is a complementary measure for local image contrast. LBP extracts texture feature in spatial domain.

For each input image local binary pattern is applied and the transformed images and calculating code are shown in figure 2.

P7	P6	P5
P0	CP	P4
P1	P2	P3

binary code

30	66	7
0	53	68
59	13	255

Local at cp=

0	1	0
0		1
1	0	1

2^7	2^6	2^5
2^0		2^4
2^1	2^2	2^3

128*0+64*1+32*0+16*1+8*1+4*0+2*1+0*0=90

Figure 2: Calculation of Local Binary Pattern for every pixel.

The LBP texture descriptor is extensively used currently due to its simplicity, dynamic and rotational invariant properties. The designed intelligent system uses LBP technique for the extraction of the texture features from the images. In this technique the pre-processing step is done in which the RGB space of the image is transformed to grey scale. After that the image is subdivided into smaller sub matrices of size 3x3 from which the feature extraction take place. All the features obtained by sub matrices are integrated to form a single feature histogram which represents the whole image [32]. Its working is based on the difference between the center value of the pixel and the neighbor pixel. The binary code for every pixel is produced by the step of thresholding of neighbor pixel with the centre pixel as given in Equation (1) and Equation (2) which is shown in Figure 2.

$$\mathrm{LBPN}=\sum_{i=0}^{N-1} f(pi-cp)2^{i} \qquad (1)$$

$$F(p)= \begin{cases} 0 & p<0 \\ 1 & p\geq 0 \end{cases} \qquad (2)$$

$$\mathrm{Histi}=\sum_{x=1}^{M}\sum_{y=1}^{N} f2(LBP(x,y),k) \qquad (3)$$

LBP's are obtained for the individual images in the dataset and after that the histogram of LBP image represent the texture of the image. The histogram of each bin, as shown in Equation (3), is computed by summing the image pixel numbers. LBP (x, y) is the value of the pixel location of the image in the x row and the y column. The unwanted edge information is ignored in order to minimise false information when measuring the code for an image using LBP [22].

3.2.Tamura Feature Extraction.

Tamura et al took the approach of devising texture features that correspond to human visual perception [2]. They defined six textural features (coarseness, contrast, directionality, line-likeness, regularity and roughness) and compared them with psychological measurements for human subjects. The first three attained very successful results and are used in our evaluation, both separately and as joint values.
Coarseness has a direct relationship to scale and repetition rates and was seen by Tamura et al as the most fundamental texture feature. An image will contain textures at several scales; coarseness aims to identify the largest size at which a texture exists, even where a smaller micro texture exists.
Computationally one first takes averages at every point over neighbourhoods the linear size of which are powers of 2. The average over the neighbourhood of size 2k × 2k at the point (x, y) is given in (4)

$$\mathrm{Ak}(x, y) = \sum_{i=x-2^{k-1}}^{x+2^{k-1}-1}\sum_{j=y-2^{k-1}}^{y+2^{k-1}-1} f(i,j)/2\wedge(2k) \qquad (4)$$

Then at each point one takes differences between pairs of averages corresponding to non-overlapping neighbourhoods on opposite sides of the point in both horizontal and vertical orientations. In the horizontal case this is as given below(5)

$$E_{k,h}(x, y) = |A_k(x + 2^{(k-1)}, y) - A_k(x - 2^{(k-1)}, y)| \qquad (5)$$

At each point, one then picks the best size which gives the highest output value, where k maximizes E in either direction. The coarseness measure is then the average of $S_{opt}(x, y)=2^{kopt}$ over the picture.
Contrast aims to capture the dynamic range of grey levels in an image, together with the polarisation of the distribution of black and white. The first is measured using the standard deviation of grey levels and the second the kurtosis α_4. The contrast measure is therefore defined as in (6)

$$F_{con} = \sigma/(\alpha_4)^{n} \qquad (6)$$

where $\alpha_4 = \mu_4/\sigma^4$, μ_4 is the fourth moment about the mean and σ^2 is the variance. Experimentally, Tamura found n = 1/4 to give the closest agreement to human measurements. This is the value we used in our experiments
Directionality (F_{dir})

Directionality is a global property over a region. The feature described does not aim to differentiate between different orientations or patterns, but measures the total degree of directionality. Two simple masks are used to detect edges in the image. At each pixel the angle and magnitude are calculated. A histogram, H_d, of edge probabilities is then built up by counting all points with magnitude greater than a threshold and quantizing by the edge angle. The histogram will reflect the degree of directionality. To extract a measure from H_d the sharpness of the peaks are computed from their second moments.

3.3 . Discrete wavelets transformation

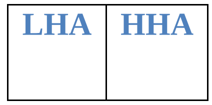
Wavelets are the small waves with changing frequency. Its duration is very limited [23]. These are used in multi resolution analysis. At multiple resolutions all the images are analyzed and represented. Small sized and low contrasted objects are observed at the high resolution and huge are huge and high contrasted objects are analyzed at the coarse level. The idea of multi-resolution analysis is useful when a picture comprises of small and large and also has low and high contrast objects. All images at multi-resolution are useful. Undetected features at one resolution can be identified at other resolution. DWT is simpler to implement and gives adequate data for the analysis and for the synthesis. The signals are decomposed into the approximation coefficients and in the detailed coefficients in which detailed coefficients are computed in horizontal, diagonal direction and also separately formed the feature vector. This feature vector can be utilized for retrieving the same type of images and can be combined with other for CBIR. At different resolutions the signals with different bands are analyzed and at the next resolution, approximation coefficients are further brake which creates three detailed co-efficient. Features left in last step decomposition are extracted by the coefficients and form the feature vector for retrieval. Discrete Wavelet transform is superior to the Fourier transform as it is capable to analyze the components of a non stationary signal. It allows the decomposition of complicated and complex information regarding, patterns, images, speech etc to elementary forms at different scales and positions and then reconstruct the signal with high accuracy. These transforms are stand on small waves known as wavelets. These transforms can represent the images at different resolutions depending on the chosen frequencies [33]. Due to this ability some important features which are generally ignored in different resolutions are taken into consideration. For extracting the texture features from DWT the coefficient distribution of the mother wavelet is calculated. This wavelet Ψ (t) when translated by b and scaled by a is given in Equation 7.

$$\Psi_{a,b}(t)= 1/\sqrt{a}\ \Psi(t-a/b) \qquad ---(7)$$

DWT decomposes the image using orthogonal basis function into the set known as wavelet coefficients. These sets provide the details of four parts such as horizontal, diagonal, vertical and approximation and therefore it can provide the fine details of the image [34]. The low frequency components are the approximation part while other three are the components of high frequencies. With the application of this technique an image is divided into four sub-bands and one sub-sampled band which is clearly shown in Figure 3.

In this Figure LHA, HHA, HLA describes the finest details of coefficients of the wavelet while the coefficients of the coarse level are represented by sub-band LLA which means an approximate idea of an image. The sub-band LLA is further divided for getting the other level of wavelet coefficients. This is also shown in Figure 3. The process remains in continuation until the final scale is obtained. These both values of approximation and of detailed images are very useful and important for the extraction of the texture features and provide a high value of precision when image is taken at different resolutions.

LLA	HLA



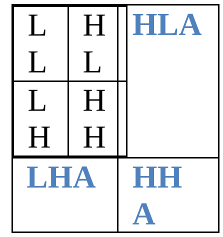


Figure 3: DWT showing its sub-band.

3.4. Support vector machine (SVM)

It is a machine learning method based on the learning theory, (Vapnik-Chervonenkis dimension theory) and the principle of structural-risk minimization. It can effectively deal with the regression (time series analysis), pattern recognition ,classification problem, discriminate analysis and many other problems. SVM is popular in the field of prediction and comprehensive evaluation. It works well to solve the small sampling problems, non-linear problems, and the high-dimensional pattern recognition problems. It also has many unique advantages, overcoming by the “curse of dimensionality”, “over-learning” and other problems.

4. Proposed Framework

A novel CBIR system is presented in Figure. 4, which is based on incorporating the properties of two leading techniques LBP and Tamura to get the finer details of texture. while the DWT has the multi-resolution and multi-orientation properties. It is able to extract the information regarding shape of the image over a higher scale, thus increasing the retrieval rate. Features of the database images at multi resolution and multi scale are extracted by both (LBP and Tamura) techniques and are combined by the process of normalization. The steps involved in the system are given below.

4.1. System Framework Algorithm:

Part 1: Feature vector construction Input: An Image from the database.

Output: Feature vector.

1) Take an image from the image database and convert it into gray scale image if the image is colored.

2) Apply DWT and compute sub band images.

3) Apply LBP for approximate coeffiecent image and compute the histogram.

4) Apply Tamura features for all the sub band images and compute the histogram

5) Concatenate the two histograms obtained in step-2 to step- 4 to obtain the feature vector using Max-Min normalization.

Part 2: Image retrieval using LBP and Tamura features :

Query image from the database Output: Retrieved images based on similarity measure

5) Take the query image as input.

6) Perform step-2 to step-5 in part 1 to extract the feature vector of the query image.

7) Perform the similarity measure to compute the similarity index of the query image vector with every database images using different similarity measures.

8) Sort the similarity indices from highest to lowest to get the set of similar images.

9) Evaluate the performance using the metrics

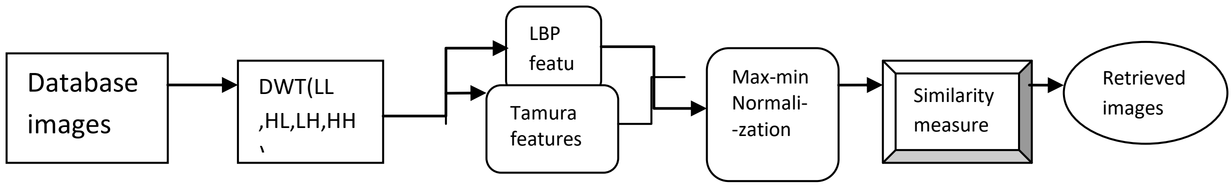


Figure 4: Block diagram of CBIR system.

4.2. Similarity Measure:

In addition to feature vector estimation, similarity test also plays an important role in recovering the images in a content-based image recovery technique. This similarity measure gives the distance between the query image feature vector and the feature of each image from the database after measuring the feature vectors, i.e., the dissimilarity between the images is found. Focused on the Indexing of this calculation is performed and indices are sorted out as the collection of retrieved images with lower measurements. D1 distance measure is used for calculation of similarity matching.

5. Experimental results and analysis

On the basis of precision and recall, the efficiency of the proposed method for image retrieval is evaluated. By comparing it with some recent texture patterns for image retrieval in terms of the evaluation metrics described earlier, the superiority of the proposed method was confirmed. Some images were retrieved based on a query image for each database. Each and every database image has been handled once for each database as a query image.

The experiments test the most critical CBIR system parameters that are measured as equations, precision and recall. (9) as well as (10).

$$\text{Precision}(P_r)=\frac{Total\ no\ of\ relevant\ images\ retrieved\ from\ the\ database}{Total\ no\ of\ images\ in\ the\ database(N)} \qquad (9)$$

$$\text{Recall }(R_r)=\frac{Total\ no\ of\ relevant\ images\ retrieved\ from\ thre\ database}{Total\ no\ of\ relevant\ images\ present\ in\ the\ database} \qquad (10)$$

For each category average value of precision and recall can be figure out as Equations. (11) and (12).

$$P_{avg}=1/L\sum_{r=1}^{L} Pr \qquad (11)$$

$$R_{avg}=1/L\sum_{r=1}^{L} Rr \qquad (12)$$

On similar terms, we can compute the total precision and total recall for our experiment using eqn. 13 and 14.

$$P_{\ total}=\frac{1}{k}\sum_{c=1}^{k} Pavg(c) \qquad (13)$$

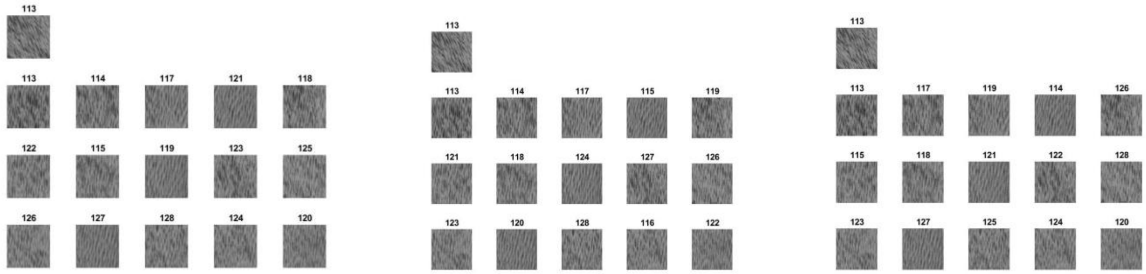
$$R_{total}\ =\frac{1}{k}\sum_{c=1}^{k} Ravg(c) \qquad (14)$$

Two touchstone databases Brodatz and VisTex are taken for conducting the experiments. In every experiment the parameters precision and recall are evaluated by the combination of LBP and DWT technique

5.1. Experiment 1

The Brodatz texture database, which comprises 13 different groups of images such as bark, brick, grass, raffia etc. with a scale of 512 x 512, is rotated in the first experiment and each class consists of 7 images with orientations (0◦, 30◦, 60◦, 90◦, 120◦, 150◦, 200◦). Every image is subsequently subdivided into 16 smaller images, and the total database now comprises 1456 images, each 128 x 128 in size. In Figure 6, some sample images from this database are shown. The top 25, 35, 45, 55, 65 images are retrieved by taking each image from the full database as a query image.

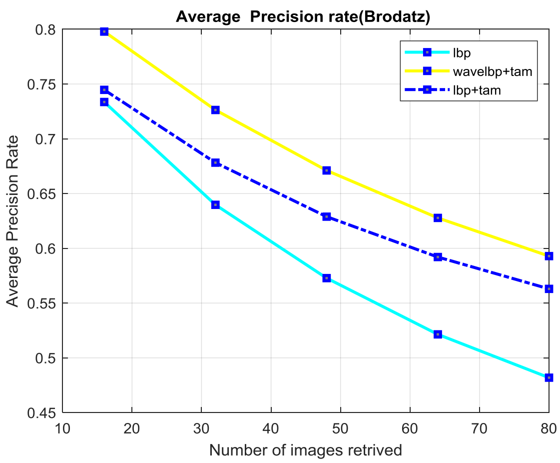
Graphs are obtained for average precision and recall from the combination of DWT and LBP and also for with SVM which shows that the performance of the proposed framework is much superior to the simple combined approach of both texture techniques.

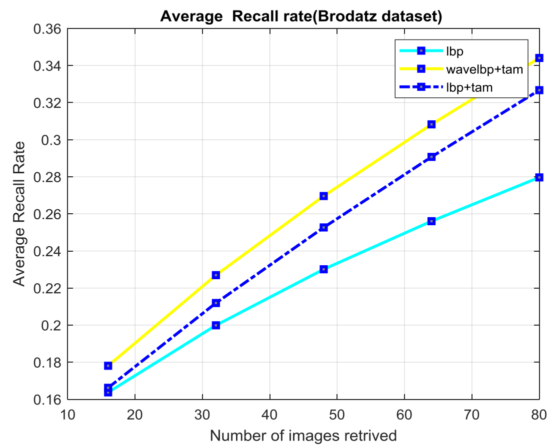


(a)LBP (b) wavelbp+Tamura (c) LBP+Tamura

Figure : Retrieved top 15 images from Brodatz database by proposed methods.

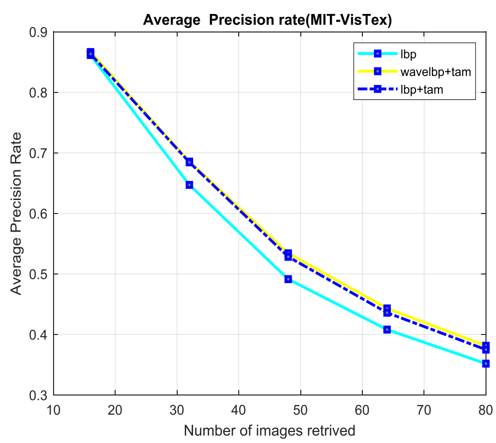
For each input image local binary pattern is applied and the transformed images and calculating code are shown in figure 2.

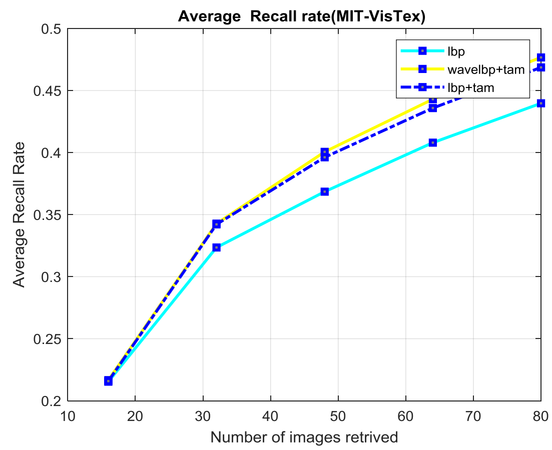


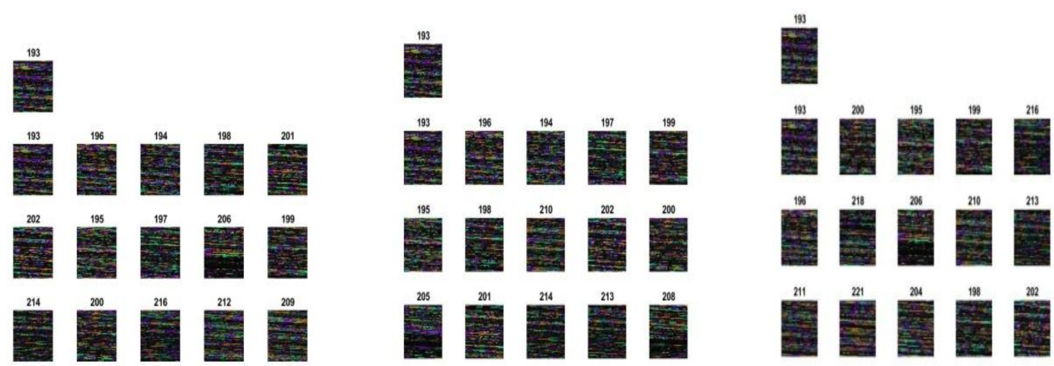


5.2. Experiment 2

The MIT VisTex database was taken in the second experiment in which 40 separate texture images of 512 x 512 sizes were chosen. After this, each image has been subdivided into 16 bits, each 128 x 128 in size, and 640 images are in the final database. Like the first experiment, all the photographs are taken as the question image and pictures are retrieved at the top 16, 32, 48, 64 and 80. In Figure 9, sample images of this dataset are shown. The combination of LBP+Tamura using DWT and the suggested techniques assesses average accuracy and recall. Comparison graphs that are provided for accuracy and recall at various image retrievals in Figure 10 and Figure 11 are evaluated. As per the graphs obtained, the results of the proposed method with the SVM classifier also provide the best results compared to the others in this dataset.







(a)LBP (b) Wavelbp +Tamura (c) LBP+Tamura

Figure : Retrieved top 15 images from MIT-VisTex database by proposed methods

5.3. Performance comparison of the proposed methods with other existing techniques

In order to authenticate the novelty in terms of precision of our proposed work, its comparison with other latest state-of-art methods is tabulated in Table 1 for both Brodatz and MIT-VisTex datasets on retrieval of top 25 and 16 images respectively.

Table 1: Avreage precision rate and ac=verage recall Rate for Brodatz and VisTex database

Dataset	Parameter/Feature	LBP	Wavelbp+Tamura	LBP+Tamura
BrodatZ	APR	58.98	68.3	64.7
BrodatZ	ARR	22.6	26.5	25.3
MIT-VisTex	APR	55.2	58.2	57.7
MIT-VisTex	ARR	35.1	37.6	37.2

Table 2: Average precision comparison of proposed methods with others when number of retrieval is 25 and 16 for Brodatz and VisTex database

Database	Parameter/Feature	LBP	Wavelbp+Tamura	LBP+Tamura
BrodatZ	Average Precision	73.4	79.9	74.5
BrodatZ	Average Recall	16.4	17.8	16.6
MIT-VisTex	Average	86.2	86.6	86.3

	Precision			
MIT-VisTex	Average Recall	21.5	21.7	21.6

Features with SVM classifier	Accuracy for Brodatz dataset	Accuracy for MIT-VisTex dataset
Wavelbp+Tamura+SVM	100	99.8
DWT+Tamura+SVM	98.73	97.6

From Table 1 it is clear that the values obtained of the average precision rate (APR) by our proposed method are remarkably higher than other existing texture descriptor techniques in CBIR systems. In case of MIT-Vistex average precision is nearly same with all three techniques. But in case of Brodatz database average precision is higher with proposed method. From Table 3 it is clear that the accuracy is highest with SVM classifier for both methods for both datasets.

6. Conclusion

An hybrid CBIR system is proposed for texture based images to increase the overall precision and accuracy of the system. The combination of features and classifications plays the supreme role in this designed framework. For obtaining the finest details of texture, two features LBP and Tamura using dwt extracted and merged together for the creation of an efficient hybrid feature vector. performance of CBIR system using d1 distance compared with SVM classifier. The performance of SVM classifiers is compared here. This new overall system is experimented on two benchmark datasets i.e. Brodatz and MIT VisTex and similarity between the images is determined by applying Euclidean distance. The results obtained spectacles that the performance of the proposed system is superior to other texture based methods with SVM classifier.

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