Content-Based Image Retrieval Using Multiresolution XCSLDP and Tamura Features

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Abstract - Recently, multi-resolution texture approaches have gained prominence in the area of computer vision, such as CBIR. This paper therefore proposes a multi-resolution texture descriptor that incorporates wavelet transformation powers, local and global texture characteristics. To be precise, a discreet wavelet transformation is used to generate multi-resolution subbands at different levels. Multi-scale Local texture descriptor is extracted from estimated coefficient values at each phase and on all sub-bands by discrete wavelet transformation. Further multi-scale Tamura texture elements are extracted. Finally, in order to represent the texture, the two histograms are concatenated using Min-Max normalization. We present a comparative analysis of the performance of the CBIR method using the XCSLDP multi-resolution functionality on multiple datasets. Unprecedentedly, the experimental results show high mean accuracies (99.9%,100% and 93.5%) using the proposed feature of Corel-1K, Brodatz and MIT-VisTex datasets respectively.

Keywords: Content based image retrieval, wavelets, Tamura features, multi resolution.

I.INTRODUCTION

Nowadays, a multitude of digital images are being acquired and processed in libraries in diverse fields of our lives, social media, biometrics, forensics, medicine, education, etc. CBIR is a well-defined technique for finding and extracting images in a broad data set based on their visual information. Image retrieval is distinguished by local or global characteristics dependent on visual information. Global characteristics are defined by the properties of pictures, such as color, form and texture[1]. Texture is also an essential property of the surfaces in photographs and is characterized by the resemblance of the visual patterns, which reflects the most important details relevant to the surface of the image, such as bricks, tiles, clouds, etc. Such descriptors are also ideal for the retrieval of medical images. The local features of the image have been used successfully for the identification and classification of groups of objects and have been recovered from the collection of points of interest and regions[2]. Since the 1990s, the recovery of images from data sets using visual material has become a particularly complex research subject. However, the majority of experiments do not properly consider the semantic aspect of the images, which is the basic semantic difference between the data returned to the device and the interpretation of the individual. The use of local descriptors has risen in recent years as they remain constant with identical characteristics, with the exception that local descriptors are derived from the image regions instead of the whole image[3].

Local binary pattern (LBP) is proposed for computing local information of each point of interest based on its neighbors[4], LBP with rotational invariant capability is suggested in[5], numerous variants of LBP have been recorded in [6-12], biomedical image indexing and retrieval is done using the directional binary wavelet pattern. The further improvement of LBP is the Local Ternary Pattern (LTP)[14] and is resistant to noise. Improved LTP[15] is the more upgrade to the LTP. The definition of the Local Tetra Pattern (LTrP) is set out in [16]. The Local Diagonal Severe Pattern (LDEP) is proposed for the retrieval of CT images in [17]. The Local Maximum Binary Edge Pattern

(LMEBP) is presented for the estimation of patterns in [18]. It has already been seen that the directional features are very useful for image retrieval applications [19–21]. However, the work in DLEP and LDP found second-order derivative and reciprocal knowledge of all eight neighbors of a single pixel for its binary representation. More CSLMDP[22] fascinated with directional highlights. The effect of adjacent pixels on the measurement of a binary pattern has not yet been thoroughly investigated. The first order derivative in four directions, including directional information dependent on the location of the neighbor pixels, is considered in CSLDEP[23].similar to XCSLDP[24], which encodes weak edges and strong edges of the image based on local second order derivative variations. This pattern is obtained by integrating second-order derivative knowledge in two ways and combining to produce a pattern of LBP dimension.

The multi-resolution and rotation invariant technique based on texture extraction was introduced in [25] and this invariance was accomplished by aligning the main texture direction with the reference axis. The gabor functions are very much applicable to the study of textures, because their orientation and frequency representation are close to human visual systems and thus have high retrieval precision or performance[26]. The SVM-based hybrid CBIR framework was developed to remove color, texture and edge features from the Corel database. The SVM multiclass method is used to make the system more reliable and faster[27]. This paper proposes a novel and efficient CBIR method based on the combined methodology of LBP and DWT along with two machine learning classifiers, i.e. SVM and ELM[28], respectively. A novel CBIR system using a multi-resolution texture descriptor derived from the fusion of multi-scale LBP and multi-resolution Tamura texture features is proposed in [29]. Though a considerable amount of work has been done in the combination of dwt and texture features for image retrieval, existing systems still suffer from immense vector features, space, time complexity, real-time applications, and web-based device locking. This inspired us to create a new methodology to produce appropriate functionality that would boost the retrieval efficiency without increasing the vector size of the feature.

Thus, in this article, we are implementing a framework for retrieving images using multi-resolution texture features using the XCSLDP and Tamura texture features. In specific, these texture characteristics are used from more than one image resolution and we conducted a multi-resolution analysis using db4 discrete wave transformation. The remainder of this paper is structured as follows: Section 2 outlines the transition of the wavelet, the Tamura features and the xcsldp features in more detail. The propsed frame and evaluation parameters are defined in Section 3. The experimental setup and findings are also defined in Sections 4. The conclusion is given in Section 5.

II.FEATURES

2.1 *Discrete Wavelet Transform*

Wavelets are tiny waves with a shifting pitch. It has a rather short duration[30]. These are used in a multi-resolution study. The wavelets were well positioned in time and frequency. Both images are processed and represented at multiple resolution. Tiny and low contrast objects are studied at high resolution, and big, large, high contrast objects are analyzed at a rough range The principle of multi-resolution analysis is useful where the image is small and wide and often has low and high contrast artifacts. Both multi-resolution files are helpful. Unidentified characteristics may be identified at one resolution at another resolution. DWT is faster to implement and offers sufficient data for analysis and 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. Signals are decomposed into the approximation coefficients and the detailed coefficients in which the detailed coefficients are determined in horizontal, diagonal direction and the characteristic vector is also developed separately. This vector function can be used to obtain the same form of images and can be paired with another one for CBIR. At different resolutions, the signals of different bands are evaluated and at the next resolution, the approximation coefficients are further brakes, generating three detailed coefficients of co-efficiency. The features left in the last step of decomposition are extracted by the coefficients and form the retrieval vector function.

Wavelets are in different sizes and types, such as Morlet, Daubechies, Coiflets, Biorthogonal, Mexican Hat, and Symlets. The low-pass filter (L) and the high-pass filter (H) are two filters for use in wavelet transformation. As a consequence, wavelet decomposition at level-one is four sub-bands (LL, HL, LH, and HH). In our experiments, we used three steps of decomposition (db4) as seen in the figure. 1

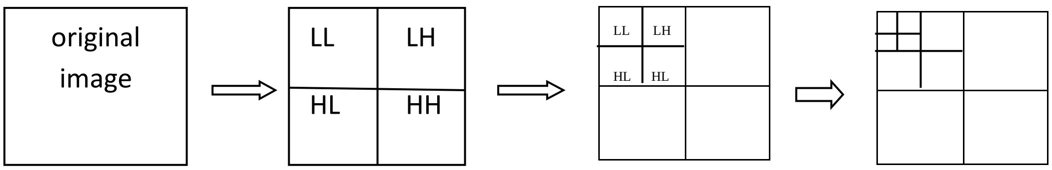


Figure . 1 Wavelet decomposition of a sample image for 3 levels

2.2. *TAMURA TEXTURE FEATURES*

Tamura features texture approaches by creating texture features that suit human sensory expectations. Tamura texture has six characteristics of texture (coarseness, contrast, directionality, line-likeness, regularity, and roughness) and is compared to psychological dimensions.

Roughness: Roughness has a clear relationship to the scale and the repeat rate of this feature in Tamura's extraction feature is the most simple texture feature.

$$A_k(x,y)= \sum_{i=x-2^{k-1}}^{x+2^{k-1}} \sum_{j=y-2^{k-1}}^{y+2^{k+1}} \frac{f(i,j)}{2^{2k}} \quad \text{---(1)}$$

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

Contrast: aims to capture the dynamic range of the gray level in the image, along with the black and white distribution polarization. The first is measured using the standard deviation of the gray level and the two α4 kurtoses. The size of the contrast is defined as.

$$F_{con=} \frac{\sigma}{(\alpha 4)^n} \qquad (3)$$

where $\alpha_4 = \mu_4 / \sigma^4$

Directionality: is a global commodity in a region. The defined function is not intended to differentiate between different orientations or patterns, but rather the overall phase of the directionality level. The pixel and the magnitude are measured at each angle. A histogram, Hd, likelihood edge is then constructed by measuring all points of magnitude greater than the threshold and quantifying the edges of the edge. The histogram will reflect the level of directionality [31].

2.3 *Extended Centre Symmetric Local Derivative Pattern (XCSLDP)*

LBP encodes the binary pattern of the first-order derivative between local neighbors by considering the basic threshold function seen in (4), which is unsuccessful in explaining more detailed information. Extended Center Symmetric Local Derivative Pattern is proposed to collect texture statics from the input image. It extracts the directional information of all 3 x 3 patterns of the given input image by measuring two local second order variations between the middle pixel and its local symmetrical pixel local neighbours (defined in Eq. 4).

$$LBP_{P,R}=\sum_{i=0}^{P-1}(Ii-Ic)\, x\, 2^{i} \quad \text{--(4)}$$

Unlike LBP encoding binary derivative gradient directions, CSLDP encodes a transition in neighborhood derivative directions, which is the second-order pattern information in the local area. In Xcsldp, in addition to the derivative directional information, the magnitude difference of the second order derivative term is determined. After that, the middle symmetrical local derivative sequence along 00,450, 900, 1350 directions is obtained as follows:

$$\text{XCS-LDP}_{P,R}=\sum_{i=0}^{(P/2)-1} f1\left[(\mathrm{Ii}-\mathrm{Ic})\left(\mathrm{Ic}-\mathrm{I}_{(i+(P/2))}\right)\right] x2^{i} + f2\left[\left(Ii+\mathrm{I}_{(i+(P/2))}-2Ic\right)2^{(i+(P/2))}\right] \quad (5)$$

where the parameters I_c, I_i, $I_{i+(P/2)}$, P, R are the same as above.
The threshold function f(x1; x2) is used to determine the types of local pattern transition and is defined as:

$$f1(x1; x2) = \begin{cases} 0 & \text{if } x1 * x2 > 0 \\ 1 & \text{if } x1 * x2 \leq 0 \end{cases} \quad (6)$$

$$f2(x1; x2) = \begin{cases} 0 & \text{if } (x1 - x2) > 0 \\ 1 & \text{if } (x1 - x2) \leq 0 \end{cases} \quad (7)$$

The detailed representation of XCSLDP can be seen in Figure 2. Eventually, the given image is converted to XCSLDP images with values ranging from 0 to 255.After calculation of XCSLDP, the whole image is represented by building a histogram supported by Eq. (8).

$$\text{XCSLDP}\,(l)=\sum_{j=1}^{N1}\sum_{k=1}^{N2} f2(\,\text{XCSLDP}(\,j,k)\,,l);\ l \in [0,\,255] \quad (8)$$

where the size of input image is N1 × N2.

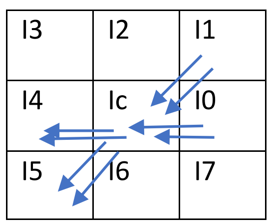


Figure 2

III. EXPERIMENTS

This section clarifies a framework of proposed algorithm that was followed and performance evaluation parameters that were used in experiments for result analysis.

3.1. *Framework Proposal*

Figure.3 displays the phases of the proposed algorithm, the extraction function. A smart and novel CBIR process, focused on the fusion of different multi-resolution texture features, is suggested on texture-based images to obtain finer texture detail. Extension of LBP, Xcsldp, method has a larger scope for discrimination and a lower computational complexity. It captures the correct local appearance of the pixel, while the DWT has multi-resolution and multi-orientation properties. Thereby, the Xcsldp multi-resolution function is extracted from the approximate coefficients, LL subband, of dwt. It can extract information on the shape of the image on a higher scale, thus raising the recovery rate using the Tamura texture features. Both techniques delete the characteristics of the database images and are paired with the normalization technique. The Min-Max standardization approach is used here for combining, since this technique maintains the correspondence of all data values. The next move that is proposed here, after that, is grouping. The features obtained are categorized using the SVM classifier.

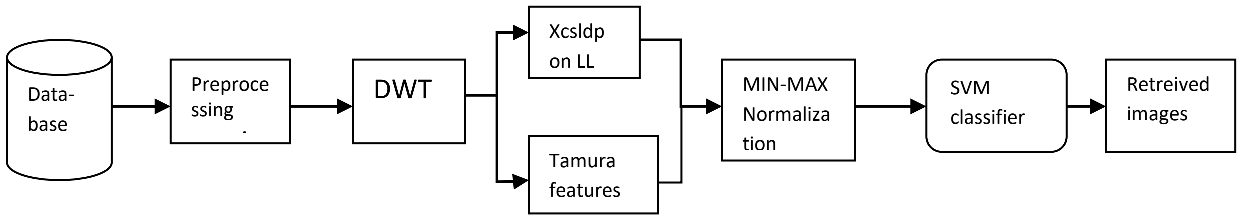


Figure 3 Basic structure of proposed algorithm

3.2 *Performance evaluation*

Both objective and subjective performance evaluation has been a crucial part of image retrieval process. The performance of the proposed method is measured in terms of average precision/ average retrieval precision (ARP), average recall/average retrieval rate (ARR) as shown below:

$$\text{Precision: } P(Iq)=\frac{Number\ of\ relevant\ images\ retrieved}{Total\ Number\ of\ images\ retrieved} \qquad (9)$$

$$\text{Average Retrieval Precision: } ARP=\frac{1}{|DB|}\sum_{i=1}^{DB} P(I_i) \qquad (10)$$

$$\text{Recall: } R(Iq)=\frac{Number\ of\ relevant\ images\ retrieved}{Total\ Number\ of\ relevant\ images\ in\ the\ database} \qquad (11)$$

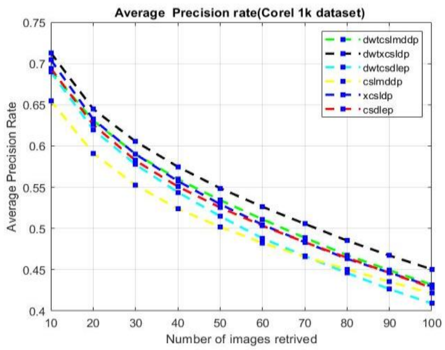
$$\text{Average Retrieval Rate: } ARR=\frac{1}{|DB|}\sum_{i=1}^{DB} R(I_i) \qquad (12)$$

4. Experiments, Results and Analysis

Three regular corel1 k, Brodatz and MIT-VisTex databases were chosen to perform the experiments. Precision and recall parameters are evaluated in each experiment by a mixture of multi-resolution Xcsldp and Tamura using the db4 dwt technique. Furthermore, the accuracy, precision and recall parameters are tested using a distance of d1 and compared to that of the SVM classifier.

4.1 *Experiment #1*

WANG standard color database images[32] that are part of the Corel 1K database and freely accessible to researchers. The basic database includes 1000 images in JPEG format which are separated into 10 groups (Elephants, Flowers, Buses, Foods, Horses, Mountains, African people, Beach, Buildings, and Dinosaurs). Each group has 100 images in (256x384) and (384 x 256) formats. The top 10,20,30...100 images are recovered by taking each image from the complete database as a query image. Precision and recall curves are tested using a distance of d1 and seen in Figure 4. Table 1 reveals that the overall performance of the process using the xcsldp texture function is 99.46 percent using the SVM classifier.



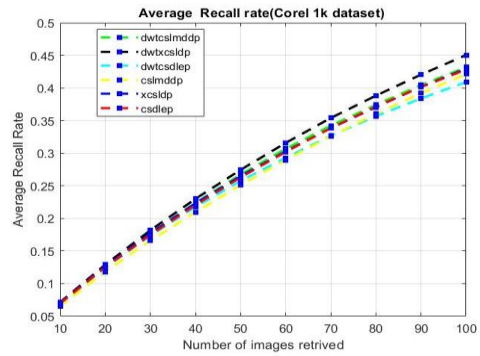


Figure 4 Avg. Precision rate (left) and Avg. Recall Rate(right) vs. number of retrieved images

Table 1. Results using proposed method on three datasets using SVM classifier

Dataset	Dwtcslmddp +Tamura+SVM	Dwtcsdlep +Tamura+SVM	Dwtxcsldp +Tamura+SVM
Corel1 k	98.2	97.02	99.46
Brodatz	99.99	99.78	100
MIT-VisTex	93.44	93	93.5

4.2 *Experiment #2*

The Brodatz texture[34] database, which consists of 13 separate classes of pictures, such as bark, stone, 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 0, 300, 600, 900, 1200, 1500, 2000). Every image is subdivided into 16 smaller images and the cumulative archive currently consists of 1456 images, each 128 x 128 in resolution. The top 25, 35, 45, 55, 65 images are recovered by taking each image from the complete database as a query image. Graphs (Figure 5) are obtained from the proposed precision and recall function using d1 distance, which indicates that the performance of the proposed structure is much superior to other texture techniques such as CSLMDDP and CSDELP.

4.3 *Experiment #3*

The MIT VisTex[33] database was used in the second experiment in which 40 different texture images of 512 x 512 sizes were picked. After this, each image was subdivided into 16 bits, each 128 x 128 in size, and the final archive comprises 640 images. Like the first experiment, all the photos are taken as the query picture and the images are recovered at the top 16, 32, 48, 64 and 80. The combination of the xcsldp dependent wavelet and the Tamura function is evaluated. The contrast of graphs given with precision and retrieval at different image retrievals in Figure 6 is evaluated. As seen in the graphs obtained, the results of the proposed approach use d1 distance similarity. Further SVM classifier also provide the best results compared to the others in this dataset as mentioned in Table1.

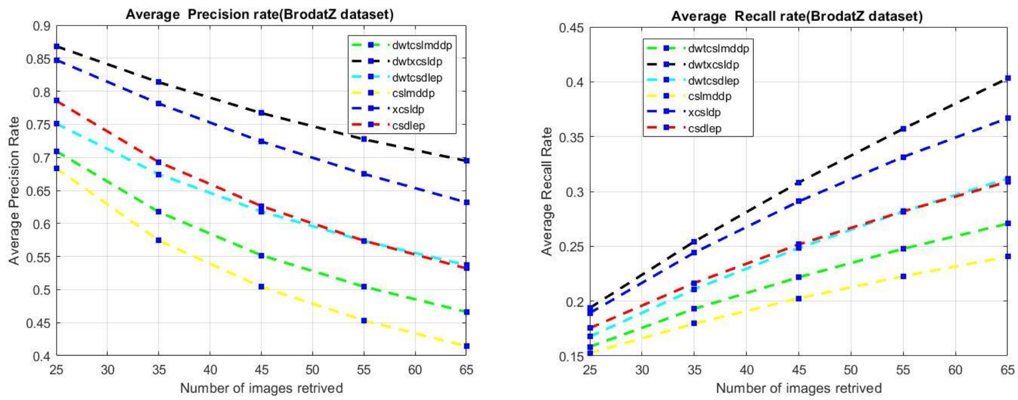


Figure 5 Avg. Precision rate (left) and Avg. Recall Rate(right) vs. number of retrieved images

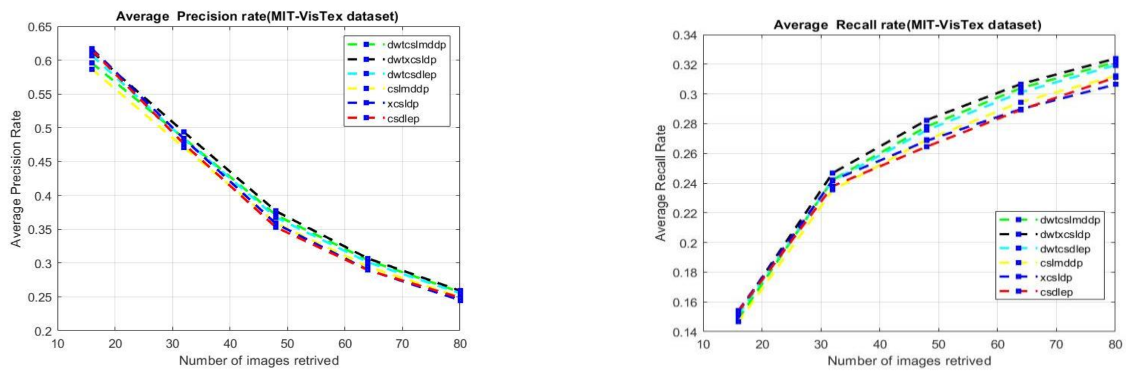


Figure 6 Avg. Precision rate (left) and Avg. Recall Rate(right) vs. number of retrieved images

V. CONCLUSION

In this article, various multi-resolution properties of low-frequency decomposed image components are obtained from wavelet transformation. Experiments have been carried out on a particular form of image database. After removing the attributes, the classification is carried out using the help vector machine classifier, which very effectively classifies the images into various classes. Results have shown that our proposed CBIR system is more reliable and reminiscent in comparison. The review of the results reveals that this proposed solution performs well in terms of precision, recall and accuracy over the individual features of the classified methods and other existing ones.

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