Wavelet Transform Derived Dominant Descriptors for Rotation Invariant Image Retrieval

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Abstract

In this paper, we introduce a new global level and geometrically invariant descriptor, coined as dominant edgels descriptor (DED). The proposed DED is integrated with geometrically invariant dominant local binary pattern (DRLBP) and dominant color descriptor (DCD) for photo, texture and histopathological image retrieval. The DRLBP and DED are exploited from multi-resolution domain and DCD is computed from RGB image. Experiments are conducted exhaustively on benchmark databases and it proves that proposed integration of geometrically invariant feature descriptors gives better results than the state-of-the-art methods.

Keywords:—*Dominant rotated local binary pattern, Dominant color descriptor, Dominant Edgel descriptor, Daubechies-4.*

1. Introduction

Nowadays, voluminous quantities of digital images are generated at an incredible rate due to the introduction of variety of digital imaging and storage devices and its cost reduction. All together, as more and more use of information in digital images is also increasing rapidly in all domains, efficient and precise image retrieval has drawn the interest of researchers to a huge extent and has been more active research field since 1970s. Since archiving, indexing and retrieving of images based on textual and semantic contents is more difficult, laborious and time demanding task [1,2], many advances in content based image retrieval (CBIR) has been proposed to retrieve desired images more exactly from huge image archives based on image contents which refers to texture, color, spatial information and shape. The retrieval process performs matching of features of images in archives and query given by the user.

Since image contains more complex details, various combination of image contents have been combined in the literature for efficient retrieval. In this paper, we focus on texture, shape and color combination based image retrieval with rotation invariant. Among the various image contents used to describe the image, texture is a significant and prominent visual content and has been widely used in the applications of computer vision. Many texture features has been suggested in the literature including gray level co-occurrence statistics suggested by Haralick [3] computes the frequency of pair of pixels with same gray level values depends on angular and distance spatial relationship, gray level run length matrix reported by Galloway measures the numbers of successive pixels having same gray levels based on angular spatial relationship and it exploits 11 texture features [4], Kamarasan and Sathiamoorthy suggested a histogram of BDIPs and BVLCs in [5] and it is extended by computing the local spatial correlations of BDIPs and BVLCs in [6], Zhao et al. introduced multi-trend structure descriptor which computes the relation among the local structures in the form of small, large and equal trends [7] and its advances is reported in [8], distribution and orientation representation of Gabor filter is used in [9] for classification and retrieval due to its similarity with human visual system, composite sub-band gradient vector and energy distribution pattern strings computed from

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wavelet sub band images are used in [10] for image retrieval, Liu and Yang described co-occurrence of textons in specific spatial relation, called Texton co-occurrence matrix which is further enhanced by integrating co-occurrence with histogram in [11]. Though several texture features has been reported, local binary pattern (LBP) suggested by Ojala et al. [12] has attracted more researchers and applied in various vision applications owing to its discriminative power, low computation cost and resilient to illumination changes. The LBP captures the sign of difference between center and its neighboring pixels with a threshold value and the obtained binary numbers are formed as string which is converted to decimal value and is used to construct a histogram to represent the image. Inspired by LBP, numbers of its extended variants have been reported in the literature including complete local binary pattern [13] which includes both signs and magnitudes instead of considering the only the signs of difference between center and its neighboring pixels and thus it results in rich texture information; center-symmetric LBP (CS-LBP) introduced in [14] considers the difference among center pixels and its neighboring pixels in center symmetric direction to exploit the patterns and it reduces number of comparisons but maintains the efficiency; spatial extended CS-LBP (SCS-LBP) is presented in [15] and it exploits texture, spatial details of textures and temporal details for identifying objects in video sequences and its computational cost is too less than LBP; instead of finding the differences among each neighboring pixels with center pixel, the difference among each closet neighbor pixel with center pixel and two most adjacent neighborhood pixels either at horizontal or vertical directions is computed and named as local tri-directional pattern (LTriDP) in [16]; an interval rather than single threshold value is used in [17] to attain a new extended variation of LBP and is called local ternary pattern (LTP); like CS-LBP, CS-LTP is also suggested in [18] by computing the difference among each closet pixel in center symmetric direction with neighbor pixel in horizontal or vertical direction and center pixel, and it is reported that its sensitiveness to noise is less in uniform image regions; co-occurrences of CS-LBP is presented in [19] which computes frequency of co-occurrence of neighboring CS-LBPs at specific spatial relationship based on distance and directions, and it attains the advantage of CS-LBP and GLCM; local derivative pattern (LDP) derived from LBP in different directions is defined by Zhang et al. in [20] for face recognition which not only exploits first order derivative patterns like LBP, also exploits second or more order derivative patterns and thus it is reported as more discriminative than LBP but it is not resilient to rotation. Completed robust local binary pattern (RLBP) is described using Gabour wavelets in [21] and it encompasses sign and magnitude of local patterns. LTrP suggested in [22] is an extended variant of LDP from 1D spatial relationship to 2D; geometric moments of LTrP is presented in [23]; co-occurrences of LTrP is suggested to attain high retrieval rate for medical images [24] and completed LTrP is suggested in [25] for medical, scene and event images; center-symmetric LTrP and extended center-symmetric LTrP are presented in [26] and [27]; local vector pattern (LVP) is introduced by Fan and Hung [28] to increase the precision and to avoid high redundancy in LTrP and they also reduced the dimension of LTrP by using comparative space transform algorithm which uses dynamic linear function to compute features with more details; co-occurrences of both LTP is described by Murala et al. [29] which integrates the discriminative capability of LTP and LDP with GLCM respectively; local oppugnant pattern is reported in [26] which is an extension of LTP into RGB color space; Pyramid local binary pattern (PLBP) suggested in [27] computes LBP from low pass of wavelet transformed image followed by pyramid CS-LBP and pyramid LTP are suggested in [28] and [29] respectively and are more efficient in time cost than CS-LBP and LTP and extract gradient information also; in [30], LBP is computed from Haar transformed image and it computes polarity of differences between center and its adjacent pixels instead of magnitude; binary wavelet and LBP is suggested for face and biomedical images in [31]. In line with this, various LBP variants and similar to LBP approach are presented in literature and attempted to tackle the challenges that arises due to changes in illumination, rotation, noise, etc. Among the various variants of LBP, dominant rotated LBP suggested by Mehtaa and Egiazariana [32] is resilient to rotation and have significantly high discriminative power. In [32], Mehta and Egiazarian described that discarding non-uniform patterns results in loss of information and it leads to significant drop in discriminative power. Hence, they addressed the issues of pattern selection by presenting a novel feature selection approach by considering the cumulative distribution of patterns which results in less dimensionality and by eliminating the repeated patterns it also improves the discriminative power. In accordance with [32], we presented DRLBP with fuzzy k-NN and integrated DRLBP with distribution of dominant edgels and SOM in [33] and [34] respectively. The systems presented by us in [33] and [34] considerably improve the accuracy of retrieval for texture and histology images.

Color information has been demonstrated to be very noteworthy in image retrieval because of their more informative and high distinguishing power and is geometrically invariant. Color information such as color moments [1], color histogram [35], color tuple histogram [36], spatial chromatic histogram [37], dominant color descriptor (DCD) [38], scalable color descriptor [38], color layout descriptor [38], color correlogram [39], color autocorrelogram [40-43], color anglogram [44], etc. has been described for image retrieval. Although color information is geometrically invariant, it is highly sensitive to lightning conditions. Among a variety of color information, as DCD is constructed based on dominant colors, it remains as dominant while lighting vary, and thus it is considerably invariant to lightning variation. Besides, DCD is trade-off between compactness, accuracy and time.

Since shape is more stable feature than texture and color information of image i.e., it does not varies substantially with variations in contrast and brightness, it is employed extensively for image retrieval. But shape is significantly affected by geometrical variations, noise and deformation. Thus, characterizing the shape is challenging one. Apart from that, characterization of shape information must be simple, compact and robustness to noise and geometrical transformations. It is very hard to develop a shape feature with all the aforementioned qualities. So, depends on the application, researchers employed or developed shape descriptors. In the literature, shapes features are divided into contour and region based and the use of contour based shapes are extensive than region based shapes because human identifies the object more easily based on shapes. During the past decade, several shape characterization approaches are described like shape context [45], scale space [46], Fourier descriptors [47], Contour points distribution histogram [48], shape salience descriptor [49], variant of edge direction histogram [50], Legendre moments of LBP codes [51], Fu et al. [52] combined Gabor filter with Zernike moments for retrieval, Rotation invariant wavelet descriptor [53], autocorrelogram based chordiogram image descriptor reported in [54] exploits shape and its underlying texture details, orthogonal Fourier-Mellin moments reported in [55] pack the entire image details in very less number of coefficients and is effective and efficient. However, all the aforementioned approaches are either compactness and simple or high in accuracy or invariant to geometrical transformations or robustness to noise or robustness to deformations, but not satisfying all the aforementioned criteria for image retrieval. Keeping all these in mind, we propose novel shape information based on dominant edgels and we coined it as dominant edgels descriptor (DED).

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Aside from the use of color, texture, and shape individually, high number of retrieval systems rely on integration of various features to have notably better performance. Therefore, in this paper, we integrated DRLBP, DCD and DED for image retrieval. The texture and shape information are computed from Daubechies-4 wavelet transformed image. The proposed texture and shape information are computed at various resolutions and various scales and thus the information that are left over in one resolution are identified at another resolution. Exhaustive experimentations have been done to verify the competence of proposed and state-of-the-art systems [51, 56-58] and the results shown clear evidence that proposed system is better in terms accuracy, time and storage cost, robustness to geometric variations.

The rest of the paper is structured as follows: Section 2 described proposed feature extraction methods, measure of divergence and measure of accuracy. Section 3 deals with experiments and results. Finally, proposed work is summarized in section 4.

2. Proposed Feature Extraction Method

The proposed feature estimation methodologies are described in this section. The framework of proposed retrieval system for images is shown in Figure 1. In the proposed work, we employed SOM [34] in the classification phase.

2.1.Daubechies Wavelet

Multi-resolution analysis attracted the researchers in recent years owing to its ability [59 - 61]. Therefore, in this paper, we employed Daubechies-4 wavelet [62, 63] for the computation of proposed texture and shape features. The Daubechies-4 wavelet has 4 wavelet and scaling coefficients. Generally, Daubechies wavelets are written as DbN where Db represents the surname and N represents the order and it lies between 2 to 20. The Daubechies-4 wavelet estimates the average and differences over 4 pixels and thus results in smoother transform. Though the computational cost and complexity of Daubechies-4 is considerably higher than the Haar, it exploits the details that are missed in Haar wavelet due to the overlap between iterations. The image is decomposed into 4 sub-bands namely LL, LH, HL and HH using Daubechies-4 wavelet and the sub-bands are representing approximation (scaling), horizontal, vertical and diagonal detail (wavelet) coefficients of the image. The image is decomposed upto to the finer level, which is determined experimentally and in our case it is 3 i.e., level 3 trade-off between discriminative power and dimension of feature descriptors. At each level of decomposition, the approximation detail image i.e. LL band is decomposed further and decomposition reduces the amount pixels by factor 2. In the proposed system, we estimated the DRLBP and DED from the detail coefficients of all levels i.e. we estimated 3 feature matrix for each level. The DRLBP and DED computed from each detail coefficients and each level are integrated to represent the image.

The scaling function coefficients h_0, h_1, h_2 and h_3 of Daubechies-4 wavelet is described as follows

$$h_0 = \frac{1+\sqrt{3}}{4*\sqrt{2}};\quad h_1 = \frac{3+\sqrt{3}}{4*\sqrt{2}};\quad h_2 = \frac{3-\sqrt{3}}{4*\sqrt{2}};\quad h_3 = \frac{1-\sqrt{3}}{4*\sqrt{2}}$$

The wavelet function coefficients g_0, g_1, g_2 and g_3 of Daubechies-4 wavelet is described as

$$g_0 = \frac{1-\sqrt{3}}{4*\sqrt{2}};\quad g_1 = \frac{-3-\sqrt{3}}{4*\sqrt{2}};\quad g_2 = \frac{3+\sqrt{3}}{4*\sqrt{2}};\quad g_3 = \frac{-1-\sqrt{3}}{4*\sqrt{2}}$$

The scaling (a_i) and wavelet (c_i) function values are estimated by taking the inner product of h_i , g_i coefficients signal s_i in each iteration and are expressed as follows

$$a_i = h_0 S_{2i} + h_1 S_{2i+1} + h_2 S_{2i+2} + h_3 S_{2i+3}$$

$$a[i] = h_0 S[2i] + h_1 S[2i+1] + h_2 S[2i+2] + h_3 S[2i+3] \tag{1}$$

$$c_i = g_0 S_{2i} + g_1 S_{2i+1} + g_2 S_{2i+2} + g_3 S_{2i+3}$$

$$c[i] = g_0 S[2i] + g_1 S[2i+1] + g_2 S[2i+2] + g_3 S[2i+3] \tag{2}$$

where i is index, incremented by 2 in each iteration. After incrementing i, new scaling and wavelet function values are estimated. The filtering structure of Daubechies-4 wavelet is illustrated as follows

$$\begin{vmatrix} h_0 & h_1 & h_2 & h_3 & 0 & 0 & 0 & 0 & & \\ g_0 & g_1 & g_2 & g_3 & 0 & 0 & 0 & 0 & & \\ 0 & 0 & h_0 & h_1 & h_2 & h_3 & 0 & 0 & & \\ 0 & 0 & g_0 & g_1 & g_2 & g_3 & 0 & 0 & & \\ 0 & 0 & 0 & 0 & h_0 & h_1 & h_2 & h_3 & & \\ 0 & 0 & 0 & 0 & g_0 & g_1 & g_2 & g_3 & & \\ 0 & 0 & 0 & 0 & 0 & 0 & h_0 & h_1 & h_2 & h_3 \\ 0 & 0 & 0 & 0 & 0 & 0 & g_0 & g_1 & g_2 & g_3 \end{vmatrix} \tag{3}$$

2.2. Dominant Rotated LBP

In an image I of M x N size, every pixel is considered as center pixel to encode local pattern among center and its neighbor's pixel. Neighbor pixels at distance or radius 1 are compared with center, depends on higher or lower value of neighbor pixel than center, a binary label is assigned for neighbors and are multiplied by corresponding weights followed by summation provides local binary pattern (LBP). The local binary map is constructed by combining LBPs of all center pixels of an image [12]. The LBP [12] is delineated as

$$LBP_{N,R} = \sum_{p=1}^{N} T(I_p - I_c) \times 2^{p-1} \tag{4}$$

where N, R, I_p and I_c signifies number of neighbors, radius around center pixel (I_c), pth neighbor pixel and center pixel respectively and T(p)=1 if $p \geq 0$ else 0.

$$H(L)\Big| LBP = \sum_{m=1}^{M} \sum_{n=1}^{N} P(LBP(m,n), L); L \in [0, (2^N - 1)] \tag{5}$$

where H (L) signifies histogram for LBP.

In [32], Mehta and Egiazarian delineated DRLBP from LBP as

$$DRLBP_{N,D} = \sum_{p=1}^{N} T(I_p - I_c) \times 2^{\mathrm{mod}(p-D,p)} \tag{6}$$

Where $2^{\mathrm{mod}(p-D,p)}$ and D signifies weight and dominant direction. The weight is depends on D. The maximum difference among center and neighbor pixels is marked as index for dominant direction [32] and is

$$D = \arg\max_{p \in (0,1,.,.,.,p-1)} \left| (I_p - I_c) \right| \tag{7}$$

The DRLBP is calculated by assigning weights from the index of dominant direction in circular mode and the run of weights remains as in LBP. In DRLBP, fixed arrangement is not followed in assigning weights and it varies depends on maximum variation among center and its neighbors [32].

2.3. Dominant Edgels Descriptor

We applied extensively studied Sobel operator [64] for edge identification. Afterwards, we estimated a novel descriptor, called DED which estimates dominant edgels (N_e), percentage (P_i), spatial homogeneity (S_i) and variance (V_i) of each dominant edgels. We define the DED as follows

$$F_e = \{D_i, P_i, S_i, V_i\} \text{ where i=1,2,.,.,., } N_e \tag{8}$$

Where D_i is i[th] dominant edgel. In DED, V_i is optional one and S_i is set to 0 as in DCD. Experimentally, we fix $N_e = 9$ because large number of D_i leads to complexity in computation and edgels that are not dominant fails to provide accurate representation of the image and it may introduce noise.

2.4. Dominant Color Descriptor

The DCD is introduced by MPEG-7 and it exploits number of dominant colors (N_c), percentage (P_i), spatial homogeneity (S_i) and variance (V_i) of each dominant color [38]. The DCD is extensively employed in CBIR because it provides compact and more effective color information and is delineated as [38]

$$F_c = \{D_i, P_i, S_i, V_i\} \text{ where i=1,2,.,.,., } N_c \tag{9}$$

Where D_i is i[th] dominant colors. In DCD, V_i is optional one and S_i is set to 0. In accordance with [38], we fixed $N_c = 8$ because large color numbers leads to complexity in computation and unimportant dominant colors in large color numbers may introduce noise, small color numbers may fails to provide accurate representation of the image.

2.5. Measure of likeness

Similarity metrics measure the divergence among input images and the images in database. Since it filtering out irrelevant images, it becomes an important component of any image retrieval system and thus it must be chosen more cautiously. It is revealed from the literature that Manhattan measure is more effective and its computational complexity is less among the other metrics. Therefore, it is employed in the proposed system [65].

Manhattan measure uses sum of absolute differences of variables [65] and also described as a measure among two points in Euclidean space with fixed Cartesian coordinate system. The Manhattan measure among two images is defined as

$$S\left(I^q, I^t\right) = \sum_{i=1}^{k}\left(I_i^q - I_i^t\right) \tag{10}$$

where, I_i^q and I_i^t - query and target image feature descriptors respectively and k- size of the combined feature descriptor. After computing divergence among all database and input images, the values obtained by Manhattan metric are sorted out in ascending manner. Accordingly, database images are displayed to user based on top n most Manhattan metric results.

2.6. Measure of Performance

We measured the performance of retrieval rate using more familiar measures precision (P) and recall (R). The accuracy of retrieval out of top k retrieved images is computed using P and accuracy with respect to total number of relevant images in the database is computed using R based on similarity value with query images. The P and R is defined as in [54, 66, 67]

$$\mathrm{Precision}(N) = \frac{I_N}{N} \tag{11}$$

$$\mathrm{Recall}(N) = \frac{I_N}{M} \tag{12}$$

where I_N, N and M are number of relevant images retrieved, total number of images retrieved and total number of relevant images in the database respectively. The average P [54, 66, 67] for a given query image (I) is defined as an average of P values of top N relevantly retrieved images and is given as

$$\mu_{P(I)} = \frac{1}{N}\sum_{i=1}^{N} P \tag{13}$$

The mAP [54, 66, 67] is defined as average P for all the input images and is expressed as follows

$$mAP = \frac{1}{N_I}\sum_{k=1}^{N_I} \mu_{P(I)} \tag{14}$$

where N_I designates total number of input images.

3. Experimental results

In this study, we aimed at high precision with low time cost and geometrically invariant system for photo, texture and histopathological images. The discriminating ability of Daubechies-4 wavelet based integrated DRLBP and DED and DCD feature vectors are verified and compared with the state-of-the-art systems for retrieval [51, 56-58] on standard texture, photo and histopathological image datasets. All the three proposed features are rotation invariant. The datasets employed in this study are Corel 1k [68], Corel 5k [68], Corel 10 k [68], Outex 10 and 12 [69], KTH-TIPS [69], KTH-TIPS ROT [70] and histopathology images of [66] and [67].

Table.1 Accuracy of proposed and existing systems on Photo image datasets

Databases	Proposed	Soumya et al. [57]	Sukhiaa et al. [58]	Mary et al. [56]	Srivastava et al. [51]
Corel 1k	92.34	89.89	85.10	82.45	82.11
Corel 5k	92.01	89.10	84.98	82.00	79.90
Corel 10k	91.11	88.23	83.01	81.12	78.96

Table.2 Accuracy of proposed and existing systems on Texture image datasets

Databases	Proposed	Mary et al. [56]	Sukhiaa et al. [58]	Srivastava et al. [51]	Soumya et al. [57]
Outex 10	89.22	83.88	83.01	82.09	78.90
Outex 12	89.12	82.90	82.71	81.97	78.01
KTH-TIPS	89.10	84.06	83.78	81.78	77.88
KTH-TIPS ROT	89.04	82.10	81.90	80.09	76.10

Table.3 Accuracy of proposed and existing systems on Histology image datasets

Databases	Proposed	Sukhiaa et al. [58]	Mary et al. [56]	Srivastava et al. [51]	Soumya et al. [57]
Histology	78.45.	75.32	72.49	71.89	69.30

Table.4 Accuracy of proposed and existing systems on Photo image datasets in which images are rotated to random degree

Databases	Proposed	Sukhiaa et al. [58]	Mary et al. [56]	Srivastava et al. [51]	Soumya et al. [57]
Corel 1k	91.21	77.19	76.25	78.21	85.19
Corel 5k	91.01	76.03	76.03	77.80	84.90
Corel 10k	90.00	75.21	75.22	76.86	83.13

Table.5 Accuracy of proposed and existing systems on Histology image datasets in which images are rotated to random degree

Databases	Proposed	Soumya et al. [57]	Sukhiaa et al. [58]	Mary et al. [56]	Srivastava et al. [51]
Histology	78.00.	66.20	68.02	65.11	67.88

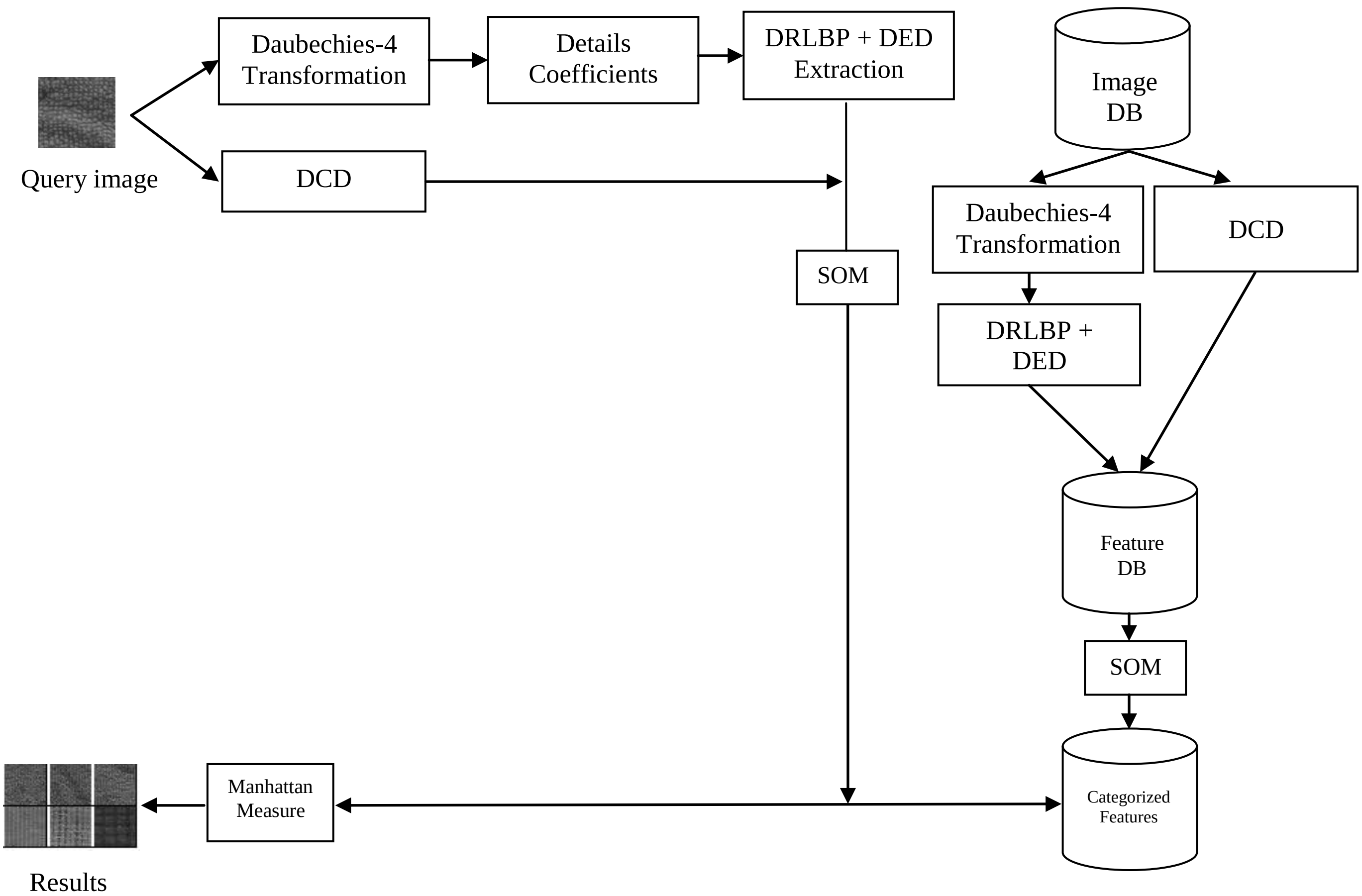

Figure1. Framework of proposed retrieval system

Table.6 Accuracy of proposed and existing systems on Photo image datasets in which images are scaled to random sizes

Databases	Proposed	Soumya et al. [57]	Sukhiaa et al. [58]	Mary et al. [56]	Srivastava et al. [51]
Corel 1k	92.34	89.89	85.10	82.45	82.11
Corel 5k	92.01	89.10	84.98	82.00	79.90
Corel 10k	91.11	88.23	83.01	81.12	78.96

Table.7 Accuracy of proposed and existing systems on Texture image datasets in which images are scaled to random sizes

Databases	Proposed	Mary et al. [56]	Sukhiaa et al. [58]	Srivastava et al. [51]	Soumya et al. [57]
Outex 10	89.00	82.98	82.91	81.99	78.00
Outex 12	88.92	82.20	82.01	81.07	77.91
KTH-TIPS	88.99	83.96	83.08	81.00	77.02
KTH-TIPS ROT	88.84	81.90	81.00	79.89	75.89

Table.8 Accuracy of proposed and existing systems on Histology image datasets in which images are scaled to random sizes

Databases	Proposed	Sukhiaa et al. [58]	Mary et al. [56]	Srivastava et al. [51]	Soumya et al. [57]
Histology	78.05.	66.00	67.92	65.00	67.07

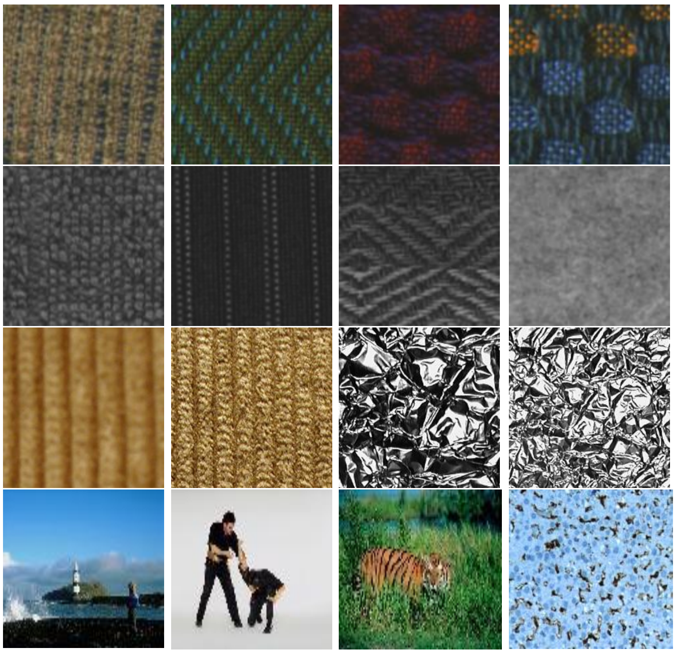

Figure 2.Example images from experimental texture, photo and histological dataset

For instance, we have shown few images from experimental databases in Figure 2. In offline, we computed the feature descriptors of proposed and state-of-the-art systems [51, 56-58] and are stored in database, named as feature vector database. In online, the feature vector of query is computed then the comparison shall be carry out on the likeness between query image features and the features in feature vector database and then the result is given back to the user in the decreasing order of similarities. Experiments are performed with all the images in each database as query. The comparative studies considered in this work are

1. Gray level co-occurrence matrix, estimated from 8 orientations is integrated with color moments and geometric shape features for photo image retrieval in Mary et al. [56].
2. Srivastava et al. [51] combined DWT based LBP with Legendre moments exploited from LBP for image retrieval.
3. Color moments, texture features from ranklet transformed image and Hu moment invariants are merged in Soumya et al. [57] for image retrieval
4. Multi-scale and multi-channel decoder based LTP is used in [58] for the retrieval of histopathological images.

In the experiments highest and lowest performer for photo image retrieval are proposed one and Mary et al [56] and the system presented in [51] is moderate and the systems [57] and [58] are above moderated and the accuracy attained by all the retrieval systems are depicted in Table.1. Whereas, the lowest performer for texture datasets is Soumya et al., [57], moderate performers are [51], [56] and [58] and the proposed system attains highest accuracy, and the results are illustrated in Table.2. In the case of histolopatological image datasets, Marry et al., [56] and Srivastava et al. [51] systems attains moderate accuracy rate, [57], [58] and proposed system are poor, above moderate and superior performer, and the results are depicted in Table. 3. By examining the values in Table 1, 2 and 3, we can observe that proposed system is superior in performance and its accuracy is constant even the images are geometrically vary.

We next carry out the experiments for the accuracy rate under in-plane rotation of the images of Corel and histopathological datasets. The accuracy rates for the rotated datasets are shown in Table 4 and 5. In Corel and histopathological datasets, angle of rotation for an image is selected randomly between 0° and 360°. It is seen from Table 1 and 4, and 3 and 5 that the accuracy rates on all the rotated datasets are extremely close to their non-rotated values for the proposed system. Overall, decrease in accuracy rate is too less and is less than 1% for the proposed system. The Mary et al., [56] and Multi-scale and multi-channel decoder based LTP [58] approach results in worst on rotated image datasets and the maximum decrease in accuracy rate is achieved by Mary et al., [56] and is 8.40% and 7.26% pertains to the Corel and histopathological datasets. These results evident the robustness of proposed system on rotation. Since the texture databases consist of rotated images, we have not conducted experiments separately for it.

Later, we performed experiments for verifying the ability of proposed and state-of-the-art systems on scaled datasets which are obtained by scaling the images in each datasets with the randomly selected factors 0.25, 0.50, 0.75, 1.00, 1.50, 2.00 respectively. The results for the scaling datasets are shown in Table 6, 7 and 8 respectively for photo, texture and histological datasets. It is clearly observed that all the accuracy rates on the scaled datasets are very close to the accuracy rates on the normal datasets for the proposed one. This evidence the robustness of proposed system to scale. i.e., the discriminative ability of proposed feature descriptors and their fusion are very effective and efficient in providing as high accuracy rates as under the normal condition.

4. Conclusion

In this study, we introduce an effective novel shape descriptor, named DED and is integrated with DRLBP and DCD. All the proposed features are geometrically invariant and are integrated to represent the image in the proposed system. The DCD is computed from RGB color image. The DRLBP and proposed DED features are exploited from the details coefficients of Daubechies-4 wavelet transformed image. The finer level of decomposition is determined experimentally and is 3 in the proposed study.

Detailed experimental analysis has been performed on photo, texture and histological databases and proves that the proposed integrated feature descriptor is very effective descriptor which gives better accuracy rates than the state-of-the-art systems for non-rotated, rotated and scaled image databases.

References

[1] Stricker, M., Orengo, M., Similarity of color images, in: Proc. SPIE Storage and Retrieval for Image and Video Databases, San Jose, (1995) pp. 381–392.

[2] Qing-Fang Zheng, Constructing visual phrases for effective and efficient object-based image retrieval, ACM Transactions on Multimedia Computing, Communications, and Applications (TOMCCAP), (2008),Vol 5(1).

[3] R. M. Haralick, K. Shangmugam, Textural feature for image classification, IEEE Trans. Syst. Man Cybern. SMC-3 (6) (1973) 610–621.

[4] M. M. Galloway, “Texture analysis using gray level run lengths,” Comput. Graphics Image Process., vol. 4, pp. 172–179, June (1975).

[5] M. Kamarasan, S.Sathiamoorthy, A Novel Approach for Image Retrieval using BDIP and BVLC, International Journal of Innovative Research in Computer and Communication Engineering, (2014), 2(9):5897-5902.

[6] S.Sathiamoorthy, Image Retrieval Using Texture and its Spatial Information, International Journal of Innovative Research in Science, Engineering and Technology, (2014), 3(10):17066-17075.

[7] Meng Zhao, Huaxiang Zhang, Jiande Sun, A novel image retrieval method based on multi-trend structure descriptor , J. Vis. Commun. Image R., (2016), 38: 73–81.

[8] Sathiamoorthy, S., Natarajan, M. An efficient content based image retrieval using enhanced multi-trend structure descriptor. SN Appl. Sci. 2, 217 (2020) doi:10.1007/s42452-020-1941-y

[9] Hossein Nezamabadi-pour, Ehsanollah Kabir, Concept learning by fuzzy k-NN classification and relevance feedback for efficient image retrieval, Expert Systems with Applications. (2009) 36: 5948–5954.

[10] P.W. Huang, S.K. Dai, Design of a two-stage content-based image retrieval system using texture similarity, Information Processing & Management, Volume 40, Issue 1, (2004), Pages 81-96, ISSN 0306-4573,https://doi.org/10.1016/S0306-4573(02)00097-3.

[11] Guang-Hai Liu, Jing-Yu Yang, Image retrieval based on the texton co-occurrence matrix, Pattern Recognition, Volume 41, Issue 12, (2008), Pages 3521-3527, ISSN 0031-3203, https://doi.org/10.1016/j.patcog.2008.06.010.

[12] T. Ojala, M. Pietikäinen, D. Harwood, A comparative study of texture measures with classification based on featured distributions, Pattern Recognit. 29 (1996) 51–59.

[13] Z. Guo, L. Zhang, and D. Zhang, ―A completed modeling of local binary pattern operator for texture classification,‖ IEEE Trans. On Image Processing, vol. 19, no. 6, pp. 1657-1663, (2010).

[14] Manisha Verma, Balasubramanian Raman, Center symmetric local binary co-occurrence pattern for texture, face and bio-medical image retrieval, Journal of Visual Communication and Image Representation, Volume 32, October 2015, Pages 224-236.

[15] Xue, G., Sun, J., and Song, L. (2010). Dynamic background subtraction based on spatial extended center-symmetric local binary pattern. In IEEE Int. Conf. on Multimedia and Expo, pages 1050– 1054.

[16] Manisha Verma, Balasubramanian Raman, Local tri-directional patterns: A new texture feature descriptor for image retrieval, Digital Signal Processing, Volume 51, 2016, Pages 62-72, ISSN 1051-2004, https://doi.org/10.1016/j.dsp.2016.02.002.

[17] X. Tan and B. Triggs, Enhanced local texture feature sets for face recognition under difficultlighting conditions, IEEE Transactions on Image Processing 19 (6) (2010) 1635–1650.

[18] Subrahmanyam Murala, Q.M. Jonathan Wu, (2013). Local ternary co-occurrence patterns: A new feature descriptor for MRI and CT image retrieval, Neurocomputing, 119: 399–412.

[19] Manisha Verma, Balasubramanian Raman, Center symmetric local binary co-occurrence pattern for texture, face and bio-medical image retrieval, Journal of Visual Communication and Image Representation, Volume 32, October 2015, Pages 224-236.

[20] Baochang Zhang, Yongsheng Gao, Sanqiang Zhao and Jianzhuang Liu, "Local Derivative Pattern Versus Local Binary Pattern: Face Recognition With High-Order Local Pattern Descriptor," in IEEE Transactions on Image Processing, vol. 19, no. 2, pp. 533-544, Feb. 2010.doi: 10.1109/TIP.2009.2035882.

[21] Yang Zhao , Wei Jia , Rong-Xiang Hu , Hai Min, Completed robust local binary pattern for texture classification, Neurocomputing 106 (2013) 68–76.

[22] S. Murala, R. P. Maheshwari, and R. Balasubramanian, “Local tetra patterns: A new feature descriptor for content-based image retrieval,” IEEE Trans. Image Process., vol. 21, no. 5, pp. 2874–2886, May 2012.

[23] Srivastava, P., Binh, N.T. & Khare, A. Content-Based Image Retrieval Using Moments of Local Ternary Pattern. Mobile Netw Appl 19, 618–625 (2014). https://doi.org/10.1007/s11036-014-0526-7.

[24] Subrahmanyam Murala, Q.M. Jonathan Wu, Local ternary co-occurrence patterns: A new feature descriptor for MRI and CT image retrieval, Neurocomputing, Volume 119, 2013, Pages 399-412,ISSN 0925-2312,https://doi.org/10.1016/j.neucom.2013.03.018.

[25] T. H. Rassem, M. F. Mohammed, B. E. Khoo and N. M. Makbol, "Performance evaluation of Completed Local Ternary Patterns (CLTP) for medical, scene and event image categorisation," 2015 4th International Conference on Software Engineering and Computer Systems (ICSECS), Kuantan, 2015, pp. 33-38. doi: 10.1109/ICSECS.2015.7333119.

[26] Gupta, R., Patil, H., Mittal, A.: Robust Order-based Methods for Feature Description. In: CVPR, pp. 334–341 (2010).

[27] Wu X., Sun J. (2011) An Extended Center-Symmetric Local Ternary Patterns for Image Retrieval. In: Lin S., Huang X. (eds) Advances in Computer Science, Environment, Ecoinformatics, and Education. CSEE 2011. Communications in Computer and Information Science, vol 214. Springer, Berlin, Heidelberg.

[28] K. Fan and T. Hung, "A Novel Local Pattern Descriptor—Local Vector Pattern in High-Order Derivative Space for Face Recognition," in IEEE Transactions on Image Processing, vol. 23, no. 7, pp. 2877-2891, July 2014. doi: 10.1109/TIP.2014.2321495.

[29] Subrahmanyam Murala, Q.M. Jonathan Wu, Local ternary co-occurrence patterns: A new feature descriptor for MRI and CT image retrieval, Neurocomputing, Volume 119, 2013, Pages 399-412, ISSN 0925-2312, https://doi.org/10.1016/j.neucom.2013.03.018.

[30] S.-Z. Su, S.-Y. Chen, S.-Z. Li, S.-A. Li, and D.-J. Duh, "Structuredlocal binary Haar pattern for pixel-based graphics retrieval,"Electron.Lett., vol. 46, no. 14, pp. 996–998, Jul. 2010.

[31] Murala, S., Maheshwari, R.P. & Balasubramanian, R. Directional Binary Wavelet Patterns for Biomedical Image Indexing and Retrieval. J Med Syst 36, 2865–2879 (2012). https://doi.org/10.1007/s10916-011-9764-4.

[32] Rakesh Mehta, Karen Egiazarian, Dominant Rotated Local Binary Patterns (DRLBP) for Texture Classification, Pattern Recognition Letters (2015), doi:10.1016/j.patrec.2015.11.019.

[33] S. Sivakumar and S. Sathiamoorthy, "Image Retrieval Using Fuzzy k-NN on Dominant Rotated Local Binary Patterns, (2019) International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India, (2019), pp. 806-812. doi: 10.1109/ICSSIT46314.2019.8987898.

[34] S.Sivakumar, S.Sathiamoorthy, Dominant Feature Descriptors With Self Organising Map for Image Retrieval, 2nd International Conference on Computer Networks, Big Data and IoT [ICCBI 2019], 9-20, December 2019, Vaigai College of Engineering, Madurai, India.

[35] Swain, M.J., and Ballard, D.H., 1991, Color indexing, Int. J. Comput. Vis., 7(1):11–32.

[36] Rickman, R. and Stonham, J., 1996. Content-based image retrieval using colour tuple histograms, in Proc. SPIE Storage and Retrieval for Image and Video Databases.

[37] Cinque, L., Ciocca, G., Levialdi, S., Pellicano, A., Schettini, R., 2001. Color-based image retrieval using spatial-chromatic histograms. Image Vision Comput.19, 976–986.

[38] Cieplinski, L., Kim, M., Ohm, J.-R., Pickering, M., Yamada, A. (Editors), 2001. Text of ISO/IEC 15938-3/FCD Information Technology -Multimedia Content Description Interface-Part 3: Visual. Final Committee Draft, ISO/IEC/JTC1/SC29/WG11 (MPEG), document no. N4062.

[39] Huang, J., Kumar, S. R., Mitra, M., Zhu, W. J. and Zabih, R., 1997. Image indexing using color correlogram, in Proc. 16th IEEE Conf. on Computer Vision and Pattern Recognition, pp. 762–768.

[40] K. Seetharaman, S. Sathiamoorthy, Color image retrieval using statistical model and radial basis function neural network, Egyptian Informatics Journal, Volume 15, Issue 1, 2014, Pages 59-68.

[41] K. Seetharaman, S. Sathiamoorthy, A unified learning framework for content based medical image retrieval using a statistical model, Journal of King Saud University - Computer and Information Sciences, Volume 28, Issue 1, 2016, Pages 110-124.

[42] Sathiamoorthy, 2014, Color Image Retrieval Using Color, Texture and its Spatial Information, International Journal of Innovative Research in Computer and Communication Engineering, 2(11):7106-7114.

[43] K.Seetharaman, S.Sathiamoorthy, "A framework for color image retrieval using full range Gaussian Morkov random field model and multi-class SVM learning approach.", International Journal of Innovative Research in Advanced engineering, Vol. 1, No. 7, Aug 2014, pp. 53-63. 2014.

[44] Tao, Yi., Grosky, W.I., 2001. Spatial Color Indexing Using Rotation, Translation, and Scale Invariant Anglograms, Multimedia tools and applications, 15(3):247-268.

[45] Belongie, S., Malik, J., Puzicha, J., 2002. Shape matching and object recognition using shape contexts, IEEE Transactions on Pattern Analysis and Machine Intelligence. 24 (4): 509–522.

[46] Mokhtarian, F., Mackworth, A., 1986. Scale-based description and recognition of planar curves and two-dimensional shapes, IEEE Pattern Analysis Machine. Intelligence. 8(1) :34–43.

[47] Otterloo, P.J. V, 1991. A Contour-Oriented Approach to Shape Analysis, Prentice-Hall International (UK) Ltd, Englewood Cliffs, NJ, pp. 90–108.

[48] Xin Shu, Xiao-Jun Wu, A novel contour descriptor for 2D shape matching and its application to image retrieval, Image and Vision Computing (2010), doi: 10.1016/j.imavis.2010.11.00.

[49] Glauco V. Pedrosa, Marcos A. Batista, Celia A.Z. Barcelos, Image feature descriptor based on shape salience points,Neurocomputing, Volume 120, 2013, Pages 156-163, ISSN 0925-2312, https://doi.org/10.1016/j.neucom.2012.07.055.
[50] K. Seetharaman and S. Sathiamoorthy, "An Improved Edge Direction Histogram and Edge Orientation Auto corrlogram for an Efficient Color Image Retrieval," 2013 International Conference on Advanced Computing and Communication Systems, Coimbatore, 2013, pp. 1-4.doi: 10.1109/ICACCS.2013.6938725.
[51] Prashant Srivastava, Ashish Khare, Integration of wavelet transform, Local Binary Patterns and moments for content-based image retrieval, Journal of Visual Communication and Image Representation, Volume 42, 2017, Pages 78-103, ISSN 1047-3203, https://doi.org/10.1016/j.jvcir.2016.11.008.
[52] X. Fu, Y. Li, R. Harrison, S. Belkasim, Content-based image retrieval using gabor zernike features, in: 18th International Conference on Pattern Recognition, 2, 2006, pp. 417-420.
[53] Ehsan Yousefi, Yasser Baleghi, Sayed Mahmoud Sakhaei, Rotation invariant wavelet descriptors, a new set of features to enhance plant leaves classification, Computers and Electronics in Agriculture 140 (2017) 70–76.
[54] A.Saravanan, S.Sathiamoorthy, Image Retrieval using Autocorrelation Based Chordiogram Image Descriptor and Support Vector Machine, International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-8 Issue-3, pp. 6019-6023, September 2019.
[55] Ashutosh Aggarwal, Suchita Sharma, Karamjeet Singha, Harpreet Singhc, Sunil Kumar, A new approach for effective retrieval and indexing of medical images, Biomedical Signal Processing and Control 50 (2019) 10–34.
[56] Mary I Thusnavis Bella, A. Vasuki, An efficient image retrieval framework using fused information feature, Computers & Electrical Engineering, Volume 75, 2019, Pages 46-60, ISSN 0045-7906, https://doi.org/10.1016/j.compeleceng.2019.01.022.
[57] Soumya Prakash Rana, Maitreyee Dey, Patrick Siarry, Boosting content based image retrieval performance through integration of parametric & nonparametric approaches, Journal of Visual Communication and Image Representation, Volume 58, 2019, Pages 205-219, ISSN 1047-3203, https://doi.org/10.1016/j.jvcir.2018.11.015.
[58] K.N. Sukhiaa, M.M. Riaz, A. Ghafoor, S.S. Ali, N. Iltaf, Content-based histopathological image retrieval using multi-scale and multichannel decoder based LTP, Biomedical Signal Processing and Control 54 (2019) 101582.
[59] Jiang J, Wang R, Zhang P (2008) Texture description based on multiresolution moments of image histogram. Optical Eng 47(3):037005. doi:10.1117/1.2894149.
[60] Reddy PVN, Satya Prasad K (2011) Multiwavelet based texture feature for content based image retrieval. Int J Comput Appl 17(1):39–44.
[61] Sai NST, Patil R (2011) Dual-Tree complex wavelet Transform on Row mean and Column mean of images for CBIR. Int J Comput Sci Technol 2(1).
[62] Daubechies I (1990), The wavelet Transform, time-frequency localization and signal analysis. IEEE Trans Inf Theory 36(5):961–1005.
[63] Seetharaman, K., Kamarasan, M. Statistical framework for image retrieval based on multiresolution features and similarity method. Multimed Tools Appl 73, 1943–1962 (2014). https://doi.org/10.1007/s11042-013-1637-z.
[64] R. Gonzalez and R. Woods Digital Image Processing, Addison Wesley, 1992, pp 414 - 428.
[65] A. Saravanan , M. Natarajan and S. Sathiamoorthy, A Novel Hybrid Framework for Medical Image Retrieval, Asian Journal of Engineering and Applied Technology, Vol. 7 No.1 Jan-June 2018 pp 37-41.
[66] M. Natarajan, S. Sathiamoorthy, Multi-Trend Structure Descriptor At Micro-Level For Histological Image Retrieval, International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-8 Issue-3, pp. 7539-7543, September 2019.
[67] M.Natarajan, S. Sathiamoorthy, Heterogeneous Medical Image Retrieval using Multi-Trend Structure Descriptor and Fuzzy SVM Classifier, International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-8 Issue-3, pp.3958-3963, September 2019.
[68] D. Tao, X. Li, and S. J. Maybank, “Negative Samples Analysis in Relevance Feedback,” IEEE Tras. on Knowledge and Data Engineering, vol. 19, no. 4, pp. 568-580, April 2007.
[69] http://lagis-vi.univ-lille1.fr/datasets/outex.html
[70] https://www.nada.kth.se/cvap/databases/kth-tips/

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