Performance analysis of hybrid features derived from discrete wavelet transform based XCSLDP and first-order features for image retrieval

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Abstract - In this work a simple and efficient discrete wavelet transform (DWT) based hybrid texture feature, fusing XCSLDP and first-order features texture descriptor is proposed to accurately classify the images. Primarily, DWT decomposes each image up to 3 levels using selected Daubechies (db3) wavelet as a decomposition filter. Subsequently, XCSLDP and four FOS features, namely, mean, standard deviation, skewness and kurtosis are employed to obtain substantial signatures of these images at different levels. The dwt based XCSLDP and FOS texture hybrid features, names as WXCSLDPFF, has achieved 74.68% ,86.7%, 91.33% and 75.12% on Corel1k, BrodatZ, MITVisTex and STex datasets respectively.

Key words- DWT, Wavelet transforms, XCSLDP

Introduction

Nowadays, for transferring info pictures and videos ar used wide. Visual media is capable justify, unfold and reposition. These options permit them as substantial medium for transmittal info with info technology primarily based communication devices. whether or not it's for research, rhetorical analysis or social networking, there's a growing demand for effective retrieval of digital pictures supported their visual content. Content-Based Image Retrieval (CBIR) systems ar developed to satisfy this demand. Fig. one shows the design of a typical CBIR system. for every image within the image information and its image options ar extracted and also the obtained feature house (or vector) is hold on within the feature information. . Upon request, its feature house ar attending to be compared with those among the feature information one by one and also the similar pictures with the tiniest feature distance are retrieved. the primary step extracts the low level visual options from the question and information pictures and also the second step computes similarity of the feature vectors obtained from the primary step. LBP operator has established itself as a robust texture descriptor providing glorious leads to terms of accuracy in several applications like motion detection, image retrieval, remote sensing, and medicine image analysis. LBP is one in every of the foremost common native feature-based strategies. it had been initial planned by Ojala et al. [1] as a robust methodology for describing textures. In CBIR, image descriptors describe the elemental properties, that ar basically color, text, and shape. Wavelets contain the time and frequency values, and also the options alter DWT, that is additional useful for CBIR. the importance of this approach is to observe the options of a picture that are left unobserved at one resolution level.

Related work

Texture is one in every of the foremost cogent low level options of a picture. It provides the spacing of the visual patterns presents within the pictures. numerous CBIR systems ar planned in literature supported completely different texture techniques like DWT, Gabor remodel, gray Level Co-occurrence Matrix (GLCM), LBP etc. adaptive rippling remodel texture primarily based retrieval technique was planned that provides superb texture info. Texture are often extracted from the full image or from its specific half. numerous feature extraction and classification techniques are prompt within the past for the aim of texture analysis. Initially, texture analysis was supported the primary order or second order statistics of textures [2][3][4][5][6]. Since native feature descriptors ar typically strong to look changes and occlusions, they're wide adopted in image matching , image retrieval and visual classification . several strategies are planned to extract native image options. The native binary pattern (LBP) feature has emerged as a bright side within the field of texture classification and retrieval. various researchers bestowed feature descriptors supported spacial domain. rather than finding the variations among every neighboring picture elements with center pixel, the distinction among every closet neighbor picture element with center picture element associated 2 most adjacent neighborhood pixels either at horizontal or vertical directions is computed and named as native tri-directional pattern (LTriDP) in [7]; an interval instead of single threshold worth is employed in [8] to achieve a brand new extended variation of LBP and is named native ternary pattern (LTP); like CS-LBP, CS-LTP is additionally prompt in [9] by computing the distinction among every closet picture element in center cruciform direction with neighbor picture element in horizontal or vertical direction and center picture element, and it's according that its sensitiveness to noise is a smaller amount in uniform image regions; co-occurrences of CS-LBP is bestowed in [10] that computes frequency of cooccurrence of neighboring CS-LBPs at specific spacial relationship supported distance and directions, and it attains the advantage of CS-LBP and GLCM; native spinoff pattern (LDP) derived from LBP in numerous directions is outlined by Zhang et al. in [11] for face recognition that not solely exploits initial order spinoff patterns like LBP, additionally exploits second or additional order spinoff patterns and therefore it's according as additional discriminative than LBP however it's not resilient to rotation. Completed strong native binary pattern (RLBP) is delineated mistreatment Gabour wavelets in [12] and it encompasses sign and magnitude of native patterns. Murala et al. [13–14] bestowed numerous variants of LBP patterns for content primarily based image retrieval. native characin patterns (LTrP) ar calculated by mistreatment the primary order derivatives in vertical and horizontal direction to cipher the link between the documented picture element and its neighbors. In their next work, they planned native mesh patterns (LMeP) that encodes the link among the encompassing neighbours for a given documented picture element in a picture. However, the amount of native neighbours is that the main constraint for the spatiality of feature vector mistreatment these descriptors. forest et al [15] planned XCSLBP produces a shorter bar graph than LBP, a The versions of the LBP and also the XCSLBP within the open literature cannot adequately subsume the vary of look variations that ordinarily occur in free natural pictures .Recently Akbar khan et al.[16] planned a variant of XCSLDP that is predicated on LDP and XCSLBP. The outcomes of XCSLDP includes the primary order spinoff info with relation to cruciform picture elements still as second order spinoff info considering center pixel grey level info.

Additional recently strategies supported multi-resolution or multi-channel analysis like Gabor filters and rippling remodel have received a great deal of attention. Srivastava et al. [17] planned a dance orchestra feature-based multi resolution exploration strategy for the retrieval of a picture via the merging of texture and form options. This approach combined Legendre Moments and native binary patterns at numerous resolutions of rippling disintegration. The performance was measured through recall and exactness, and also the analysis showed the planned approach outperformed alternative out there methodologies. However, low retrieval accuracy occurred once mistreatment larges datasets, and results validity may well be any increased by mistreatment LDP and LTP. Cui et al. [18] delineated a novel merging methodology supported text and visual relevancy learning that collieries matter appropriateness from image labels, then integrates each visual and matter relevancy for CBIR. The labeling/tagging completion is enforced to impart the absent tags and corrects datasets pictures with clamorous labels. The results verified the utility of the planned approach, however, the authors will improve the machine power for labeling of compressed sensing and matrix completion, giving a possible resolution for the illustration schemes of linguistics modeling from connected labels.

It is ascertained from said literature that numerous feature extraction schemes ar out there in CBIR systems. However, it's necessary to boost the retrieval performance with effective and economical feature illustration. Hybrid options are developed by mistreatment DWT by dynamic a number of its attributes however it's solely the mix of DWT and GLCM within the planned technique that produces a good hybrid texture descriptor. Two improved versions of native Binary descriptor (LBP) with rippling remodel are used for texture classification [20].The used techniques ar specified by rippling domain native applied mathematics binary pattern (WLSBP) and directional rippling domain native applied mathematics binary pattern (dWLSBP). Again, LBP suffers from some drawbacks associated an economical retrieval system can't be designed. A texture feature extraction technique specified by native amount edge binary pattern (LQEBP) is enforced in HSV color house. These amount patterns ar used for the extraction of native info [21]. The conception of extraction of spectral textural options has been according by Joydeb kumar et al. [22]. Here law remodel (PLT) has been used for identical. a picture retrieval system supported revolved rippling remodel (RWT), distinct rippling remodel (DWT), twintree complicated rippling remodel (DT-CWT) and at last Dual tree revolved complicated rippling filter (DT- RCWF) and their completely different combos are planned by Das et al. [19]. Huang et al. bestowed the survey relating to the LBP technique regarding its applications and analysis within the domain of image process [23]. SVM primarily based hybrid CBIR system was designed during which color, texture and edge options ar extracted from Corel information. The DWT has been used here thanks to its multi resolution capability for analyzing pictures at completely different frequencies for many levels of resolutions [24]. equally multi level LBP options ar coalesced with multi level Tamura options and applied for retrieval in [25]. Akbar Khan et al. [26] planned coalesced multiresolution XCSLDP and Tamura options for cbir system, whose performance improved for texture pictures.

3.2. Discrete Wavelet Transform

Distinct rippling remodel is superior to the fourier remodel because it is capable to research the parts of a non stationary signal. It permits the decomposition of difficult and complicated info relating to, patterns, images, speech etc to elementary forms at completely different scales and positions then reconstruct the signal with high accuracy. These transforms are stand on tiny waves referred to as wavelets. These transforms will represent the pictures at completely different resolutions looking on the chosen frequencies [27]. thanks to this ability some vital options that are usually neglected in numerous resolutions ar taken into thought. For extracting the feel options from DWT the constant distribution of the mother rippling is calculated. This wavelet Ψ (t) once translated by b and scaled by a is given in Equation 1. These sets give the main points of 4 components like horizontal, diagonal, vertical and approximation and thus it will give the fine details of the image [28].

$$\Psi_{a,b}(t)=\frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right) \qquad (1)$$

The low frequency parts are the approximation half whereas alternative 3 are the parts of high frequencies. With the appliance of this method a picture is split into four sub-bands and one sub-sampled band that is clearly shown in Figure 1. During this sub band LHA, HHA, HLA describes the best details of coefficients of the rippling whereas the coefficients of the coarse level are diagrammatic by sub-band LLA which implies associate approximate plan of a picture. The sub-band LLA is any divided for obtaining the opposite level of rippling coefficients. This is often additionally shown in Figure 1. the method remains in continuation till the ultimate scale is obtained. These each worth of approximation and of careful pictures are terribly helpful and vital for the extraction of the feel options and supply a high value of exactness once image is taken at completely different resolutions.

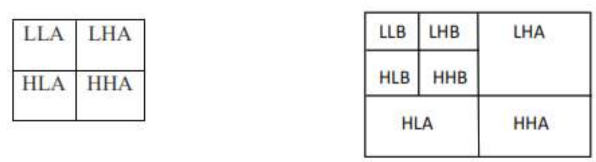

Figure 1: DWT showing its sub-band.

First-order Features (FoF)

The first-order applied math moments of the grey level bar chart of pictures, particularly mean, variance, asymmetry and kurtosis square {measure} used for feature extraction [29]: Mean is that the measure of average intensity of pixels in a picture. the quality deviation refers to the live of distinction in a picture. The asymmetry (3rd moment) may be a live of symmetry; that deals with the degree of bar chart spatial property round the mean. The kurtosis (4th moment) may be a live of relative flatness conjointly referred to as fourth moment, a descriptor of the form of a likelihood distribution. The mathematical expression of the higher than descriptors is obtainable in [29].

Extended Center Symmetric Local Derivative Pattern (XCSLDP) :

LBP encodes the binary pattern of the first-order spinoff among native neighbors by considering an easy mathematical function, that is ineffectual to explain additional elaborate information. during this paper, we've projected a replacement native pattern, Extended Centre symmetrical local derivative pattern to gather the feel statistics from the input image. It attracts out the directional data of all three x three patterns of the given input image by hard 2 native second order variations between the centre constituent and its rhombohedral native neighbors (defined in equivalent weight. 2). completely different from LBP secret writing the binary spinoff gradient directions, CSLDP encodes the modification of the neighborhood spinoff directions, that represents the second-order pattern data within the native region. additionally to spinoff directional data, the magnitude distinction second orders spinoff term is calculated. After that, the centre Center Symmetrical Local Derivative Pattern on 0^0 , 45^0 , 90^0 , 135^0 directions are obtained as follows:

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

where the parameters Ic, Ii , Ii+(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 in equ 3:

$$f1(x1; x2) = \begin{cases} 0 \text{ if } x1 * x2 > 0 \\ 1 \text{ if } x1 * x2 \leq 0 \end{cases} \quad (3)$$

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

After calculation of XCSLDP, the whole image is represented by building a histogram supported by Eq. (4).

$$XCSLDP\ (l)= \sum_{k=1}^{N2} \sum_{j=1}^{N1} f2(XCSLDP(j,k), l) \quad l \in [0, 255] \quad (4)$$

where the size of input image is N1 × N2.

Feature Extraction:

In our approach, we tend to mix Daubechies riffle remodel with XCSLDP to get multi resolution illustration. rotten a picture with the primary level of decomposition can turn out four sub bands (see Figure 1(a)). Throughout feature extraction the grayscale pictures ar rotten by DWT upto 3 levels victimization Daubechies db3 riffle family as decomposition filter. The decomposition method is as follows: grayscale image is rotten into four identical quarter-size subimages, viz., approximation (LL1), horizontal (LH1), vertical (HL1) and diagonal (HH1) parts at the first level of decomposition. The approximation (LL1) part is afterwards rotten into four quarter-size subimages, LL2, LH2, HL2 and HH2 of identical size to provide ordinal level of decomposition. The sub band LL represents a coarser approximation to the first image.

The sub bands hectoliter and gonadotropin represent, severally, the changes of the image on the horizontal and also the vertical directions. The sub band HH records the higher-frequency part of the image [26]. Similarly, approximation constant of every level is once more metameric into four subimages of equal-size to get next higher level of decomposition. At every level of decomposition XCSLDP options ar derived from approximate sub band image .Further, four first-order applied math (FOS) options, viz., mean, variance, asymmetry and kurtosis ar calculated from every of those subimages in every level of decomposition. Moreover, these texture feature vectors containing varied vary of values ar normalized within the vary of zero to one, by victimization equivalent weight. (1), and these normalized feature vectors ar concatenated. The hybrid feature derived here is called as WXCSLDPFOF.

The normalized hybrid feature vector is used as in input CBIR system with completely different classifier on customary datasets COREL 1k, STex, Brodatz and MITVIstex. The retrieval performance of this hybrid feature is studied and compared with different options. The diagram of the CBIR system with options extraction is shown within the figure 2.

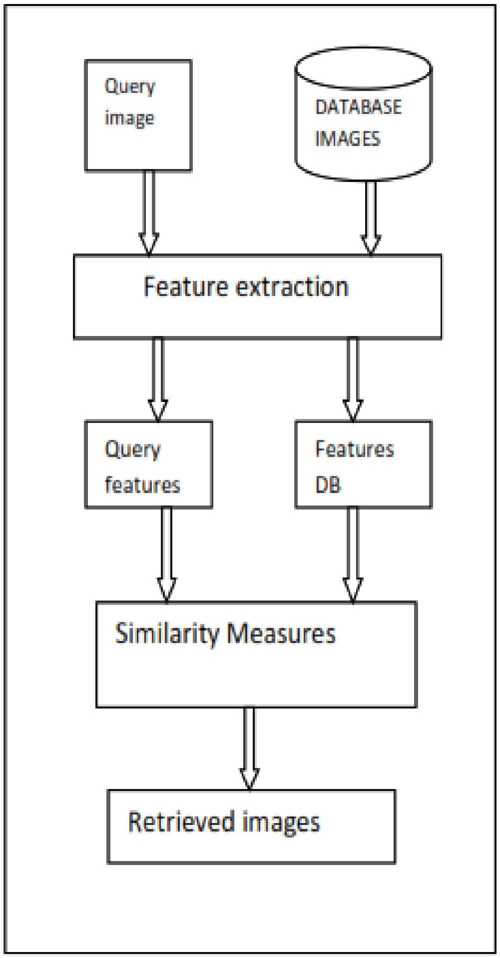

Figure2. CBIR SYSTEM

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:

Precision: P(Iq)= $\frac{\text{Number of relevant images retrieved}}{\text{Total Number of images retrieved}}$ (5)

Average Retrieval Precision: ARP= 1 |DB| ∑ P DB i=1 (Ii) (6)

Recall: R(Iq)= $\frac{\text{Number of relevant images retrieved}}{\text{Total Number of relevant images in the database}}$ (7)

Average Retrieval Rate: ARR = 1 |DB| ∑ R DB i=1 (Ii) (8)

4. Experiments, Results and Analysis

Three regular Corel 1K, 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 First order features using the db3 dwt technique. Furthermore, precision, recall, average precision rate and average recall rate parameters are tested using a distance of d1 and compared to that of the SVM classifier.

4.1 Experiment #1

WANG customary color info images[30] that are a part of the Corel 1K info and freely accessible to researchers. the fundamental info includes one thousand pictures in JPEG format that ar separated into ten teams (Elephants, Flowers, Buses, Foods, Horses, Mountains, African folks, Beach, Buildings, and Dinosaurs). Every cluster has a hundred pictures in (256x384) and (384 x 256) formats. The top 10,20,30...100 pictures are recovered by taking every image from the whole info as a question image. Precision and recall curves are tested employing a distance of d1 and seen in Figure 3.

4.2 Experiment #2

The Brodatz texture[31] info, that consists of thirteen separate categories of images, like bark, stone, grass, raffia, etc. with a scale of 512 x 512, is turned within the 1st experiment and every category consists of seven pictures with orientations (0^0, 30^0, 60^0, 90^0, 120^0, 150^0, 200^0). Each image is divided into sixteen smaller pictures and also the additive archive presently consists of 1456 pictures, every 128 x 128 in resolution. The top 25, 35, 45, 55, sixty five pictures are recovered by taking every image from the whole info as a query image. Graphs (Figure 4) are obtained from the projected exactitude and recall operate victimization d1 distance, that indicates that the performance of the projected structure is way superior to different texture techniques like WXCSLDPTF and WXCSLDPFF.

4.3 Experiment #3

MIT VisTex[32] database was employed in the third experiment within which forty completely different texture pictures of 512 x 512 sizes were picked. After this, every image was divided into sixteen bits, every 128 x 128 in size, and also the final archive contains 640 pictures. Like in the 1st experiment, all the photos are taken because the question image and also the pictures ar recovered at the highest sixteen, 32, 48, 64 and 80. the mixture of the XCSLDP dependent riffle and also the first order features operate is evaluated. As seen within the graphs obtained, the results of the projected approach use d1 distance similarity and shown in Figure5. Any SVM classifier conjointly offer the most effective results compared to the others during this dataset as mentioned in Table1.

Experiment #4

We have evaluated the performance of the projected method on our fourth dataset the Salzburg texture (STex) dataset[33]. The set consists of 7616 pictures. This includes 476 classes with sixteen pictures in every class. For STex dataset, we've retrieved sixteen pictures to live the exactitude and recall performance. To supply an in depth study, we've retrieved some additional pictures that is reportable with the assistance of exactitude and recall curves in Fig. 6.

Table 1 Retrieval Results in terms of Average Precision Rate(APR)

Descriptor Name	Corel 1K	BrodatZ	MITVisTex	STex
LBP	67.9	73.47	89.8	66.9
XCSLDP	70.5	84.6	90.05	70.7
WXCSLDPTF	71.02	84.5	86.84	65.8
WXCSLDPFF	74.18	86.7	91.33	75.12
WXCSLDPFF +SVM	84.44	99.45	92.73	84.8

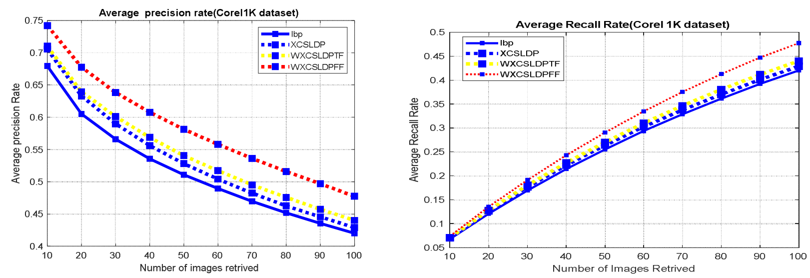

Figure 3. Avg. Precision Rate (left) and Avg. Recall Rate(right) vs. number of retrieved images

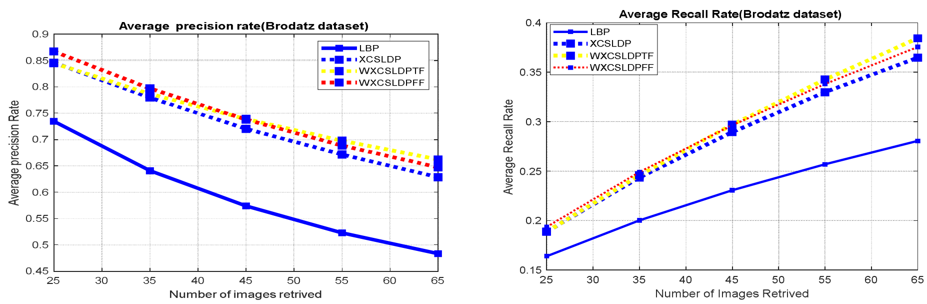

Figure 4. Avg. Precision Rate (left) and Avg. Recall Rate(right) vs. number of retrieved images

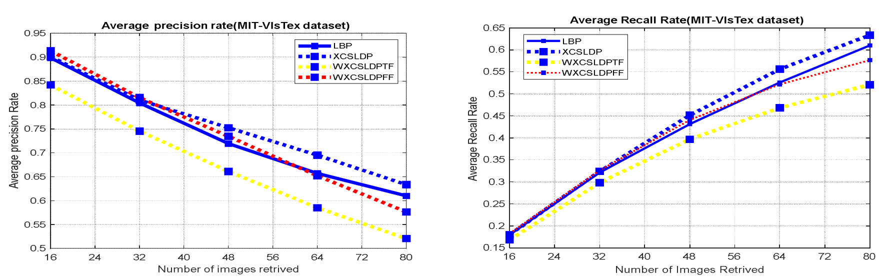

Figure 5. Avg. Precision Rate (left) and Avg. Recall Rate(right) vs. number of retrieved images

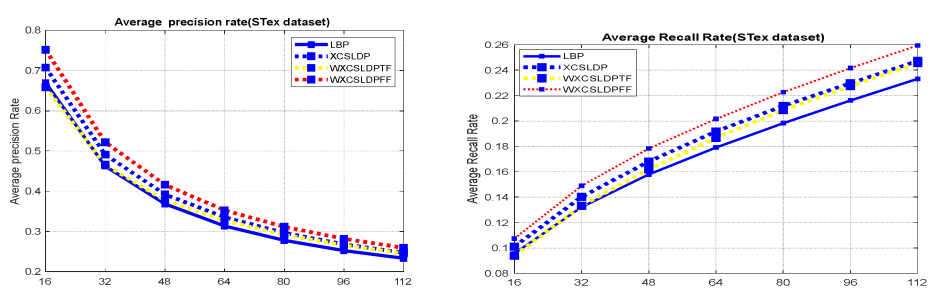

Figure 6. Avg. Precision Rate (left) and Avg. Recall Rate(right) vs. number of retrieved images

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 Corel 1k ,MiTVistex ,STex and BrodatZ datasets. It is observed that hybrid features perform with First order features out perform other features results. The CBIR system with hybrid features XCSLDP and First order features perform well with d1 distance similarity classification and SVM classifier. 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 APR,ARR and the individual features of the classified methods and other existing ones.

References

[1]. T. Ojala, M. Pietikainen and D. Harwood, “A comparative study of Texture Measures with Classification based on Featured Distribution”, Pattern Recognition, Vol. 29, No. 1, pp. 51 - 59, 1996.

[2]. Haralick, R.M., Shanmugam, K., Dinstein, I., . Texture features for image classification. IEEE Trans. System Man Cybernat. 8 (6), 610–621,1973

[3]. Weszka, J.S., Dyer, C.R., Rosenfeld, A.,. A comparative study of texture measures for terrain classification. IEEE Trans. System Man Cybernat. SMC-6 (4), 269–286,1976.

[4]. Davis, L.S., Johns, S.A., Aggarwal, J.K., 1979. Texture analysis using generalized co-occurrence matrices. IEEE Trans. Pattern Anal. Machine Intell. PAMI-1, 251– 259

[5]. Faugeras, O.D., Pratt, W.K., 1980. Decorrelation methods of texture feature extraction. IEEE Trans. Pattern Anal. Machine Intell. PAMI-1, 323–332.

[6]. Chen, P.C., Pavlidis, T., 1983. Segmentation by texture using correlation. IEEE Trans. Pattern Anal. Machine Intell. PAMI-5, 64–69.

[7] 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,

[8] 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.

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

[10] 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.

[11] 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.

[13] 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.

[14] Subrahmanyam Murala, Q.M. Jonathan Wu, Local ternary co-occurrence patterns: A new feature descriptor for MRI and CT image retrieval, Neuro computing, Volume 119, 2013, Pages 399-412

[15]. Silva, Caroline; Bouwmans, Thierry; Frelicot, Carl. "An eXtended Center-Symmetric Local Binary Pattern for Background Modeling and Subtraction in Videos". The 10th International Joint Conference on Computer Vision, Imaging and Computer Graphics

Theory and Applications (VISAPP), Berlin, Germany (oral presentation), March, 2015.

[16]. Akbar Khan B. L. Deekshatulu and L. Pratap Reddy,"XCSLDP: Extended Centre Symmetric Local Derivative Pattern for image retrieval" DRSRJournal, Vol-10 Issue-08 No.08 August 2020.

[17] Srivastava, P.; Khare, A. "Integration of wavelet transform, local binary patterns and moments for content-based image retrieval. "J. Vis. Commun. Image Represent. 2017, 42, 78–103.

[18] Cui, C.; Lin, P.; Nie, X.; Yin, Y.; Zhu, Q. "Hybrid. textual-visual relevance learning for content-based image retrieval." J. Vis. Commun. Image Represent. 2017, 48, 367–374

[19] Das, R., Dash, J.K. and Mukhopadhyay, S. "Rotation invariant textural feature extraction for image retrieval using eigen value analysis of intensity gradients and multi-resolution analysis." Pattern Recognition 46: pp. 3256–3267,2013

[20] Nadu, T. ""Two Improved Extension of Local Binary Pattern Descriptors using Wavelet Transform for Texture Classification" IET Image Processing Repository 12(11): pp. 2–13,2018

[21] Sucharitha, G. and Senapati, R.K. "Local quantized edge binary patterns for colour texture image retrieval. Journal of Theoretical and Applied Information Technology" 96(2): pp. 291-303,2018

[22] Sana, J.K. "PLT-based spectral features for texture image retrieval." IET Image Processing 12(11): pp. 2065– 2074. 2018

[23]. Huang, D., Member, S., Shan, C., & Ardabilian, M. "Local Binary Patterns and Its Application to Facial Image Analysis: A Survey," (November),2011

[24]. Shefali Dhingra and Poonam Bansal ,"An Intelligent Multi-Resolutional and Rotational Invariant Texture Descriptor for Image Retrieval Systems", ADCAIJ: Advances in Distributed Computing and Artificial Intelligence Journal Regular Issue, Vol. 8 N. 2 ,(2019), 33-49.

[25]. Akbar khan,B. L. Deekshatulu and L. Pratap Reddy .,"A novel texture descriptor using fused multi resolution LBP and Tamura features for image retrieval system", DRR journal, Vol-10 Issue-11 No. 03 November 2020

[26]. Akbar khan, B. L. Deekshatulu and L. Pratap Reddy ,"Content-Based Image Retrieval Using Multiresolution XCSLDP and Tamura Features", JXAT, Volume XII, Issue XII, 2020.

[27]. Alaei, F., Alaei, A., Pal, U., & Blumenstein, M. (2018). AC PT US CR. Expert Systems With Applications.

[28].Karthikeyan, T., & Manikandaprabhu, P. (2014). A Study on Discrete Wavelet Transform based Texture Feature Extraction for Image Mining, 5(5), 1805-1811.

[29] Gonzalez RC, Woods RE. Digital image processing. 3rd, Pearson Prentice Hall, 2002.

[30]. Corel-10000 image database. http://www.ci.gxnu.edu.cn/cbir/ Dataset.aspx

[31]. MIT Vision and Modelling Group, Cambridge, "Vision texture", Available online: http://vismod.media.mit.edu/pub/.

[32]. Brodatz Texture (CBT) database available on (http://pages.usherbrooke.ca/asafia/mbt/).

[33].R.Kwitt,P.Meerwald, Salzburg TextureImageDatabase,September2012, Available online: ⟨http://www.wavelab.at/sources/STex/⟩