Image Retrieval System Using Kirsch based Local Ternary Pattern

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Abstract. *This paper addresses the challenge imposed by the tremendous growth of digital data to retrieve relevant images. In this paper, a novel feature design methodology is proposed to represent images efficiently for Content Based Image Retrieval (CBIR). Generally, local patterns are computed directly on images and hence, directional information of the images is ignored. In the proposed feature, Kirsch operators are used to highlight eight major directional changes in the image and further, Kirsch Ternary Local Pattern (KLTP) is extracted by analysing local intensity variations in the neighbourhood. In KLTP, global color information is also incorporated to make it robust and perform well on variety of images. Experiments on natural and texture databases are done to verify the performance, as compared to the available features in the literature.*

Keywords

Corel 1k, image retrieval, pattern, texture database.

1. Introduction

With the explosion of digital images on the social media, security, biometrics, routine life and medicine, it becomes a challenge to find out the required set of images from this huge collection. Content Based Image Retrieval (CBIR) solves this problem and enables automatic matching of images and shows required set of images in a very less time [1] and [2]. Image contents, such as, color, texture, shape itself are used to extract features from images and based on these features images are compared. This helps to speed up the process of comparing. Simultaneously, it also becomes very important to extract features efficiently by covering all the contents of the images. Hence, a CBIR system has two main phases: feature extraction and comparison. A lot of research work is published with variety of hand-crafted features for this purpose. Few features along with future aspects of image retrieval are proposed in [3].

Some researchers have proposed features by taking complete image into consideration for feature extraction. This strategy is called global feature extraction, such as, global mean and histogram. On the other hand, image is partitioned into small blocks and features are computed on the small blocks by scanning the image, in local feature extraction [4]. Along with this, features are also classified based on the content considered in extraction like color and texture. To make a robust and comprehensive feature, it is preferred to use combination of suitable features. In [5], color, texture, brightness are combined for image representation. Local and global features are combined using Dual-Tree Complex Wavelet Transform and Improved Local Tetra Pattern (DTCWTILTrP) in [6]. Many features along with their short comings are discussed in [7].

Texture represents the statistics of image pixels. Hence, it contains useful information about image contents. Local Binary Pattern (LBP) is widely used and became foundation for its variants [8]. It is simple in calculation and effective as well. These characteristics make this very popular for variety of tasks, such as, face recognition, texture classification and image retrieval. It computes difference of pixel intensities in the neighbourhood and assigns binary values. Local Ternary Pattern (LTP) also computes the intensity differences, but assigns ternary values [9]. Redundant information is reduced in Center Symmetric Local Binary Pattern (CSLBP) [10] by considering only symmetric locations for LBP computation. Neighboring pixels relationship is observed in Local Neighborhood Difference Pattern (LNDP) [11]. Zernike moments and sign of differences are used in [12], for edge computation. Another way to extract features from LBP patterns is to compute co-occurrence of ternary values by Local Ternary Co-occurrence Patterns (LTCoP) [13]. Interleaving of Gaussian filtered image with the original image is used to compute Gaussian Local Ternary Co-occurrence Pattern (GLTCoP) [14]. In [15], a 3D structure is designed by arranging five Gaussian images and LTCoP is computed. Neighborhoods of different sizes are used in Local Directional Order Pattern (LDOP) [16]. Second order of Gaussian is used in jet space for Local Jet Pattern (LJP) [17]. In Local Neighborhood Intensity Pattern (LNIP) [18], along with only sign of differences, magnitude is also considered. Fractional change in the local neighborhood is evaluated in fractional LNIP [19]. LNIP is also computed on non-separable Discrete Non-separable Shearlet Transform (DNST) sub-bands [20]. Multi-Block based Local Multiple Patterns (MBLMP) enables to capture both coarse and fine details [21]. A combination of Zernike moment, curvelet transform and gradient orientation is proposed to design a robust feature in [22]. Compact statistical feature vectors are designed using trees in [23]. Amplitude and phase of Double-Density Dual-Tree Complex Wavelet Transformed (DDDTCWT) sub-bands are used in [24] to design texture features.

Both color and texture capture significant details to identify images, hence, they are also used together in literature. Color and edges are used in Local Edge Pattern for Image retrieval (LEPINV) [25]. In literature, different color spaces are also explored for feature computation. In Local Oppugnant Color Space Extrema Patterns (LOCSEP), two color spaces are used to compute Directional Local Extrema Pattern (DLEP) feature [26]. Co-occurrence of Local Extrema Pattern (LEP) values is applied in Local Extrema Co-occurrence Patterns (LECoP) [27]. LEP is also extended with the help of wavelet in Local Extrema Peak Valley Pattern (LEPVP) [28]. Color histogram is appended to add the contribution of color content. Quantized extremes on oppugnant planes are analyzed in Local Color Oppugnant Quantized Extrema Pattern (LCOQEP) [29]. In [30], multiple color channels are explored together to design Multichannel Local Ternary Pattern (MCLTP). Co-occurrence of MCLTP is computed in MCLTCoP [31]. Inter channel variation of HSV color space is used in [32] to analyze color and texture features together. Diagonally Symmetric Co-occurrence Pattern (DSCoP) is applied for texture computation. First and second order derivative responses are interleaved in [33], for directional information extraction. Two neighborhoods with radius 1 and 2, are used in Haar-like Local Ternary Co-occurrence Pattern (HLTCoP) [34].

This paper proposes a novel feature, referred as Kirsch Local Ternary Pattern (KLTP). Kirsch kernels are used to extract directional information. Further, fine local information in filtered images is analyzed through LTP patterns. Global color information is appended through hue and saturation planes of HSV color space. The key contributions of the proposed system are as follows:

- Eight Kirsch kernels are used to capture all the major directional information.
- Small neighborhood of radius 1 is applied to analyze local statistics of pixels.
- Ternary edges are used to compute gray level texture features.
- Color information is added globally through HSV color plane. This makes it a complete feature.

All these characteristics of proposed feature make it suitable to perform well on a variety of images. On two very distinct and popular natural and texture databases, proposed method has performed superior to the existing state-of-the-art features.

Rest of the paper is organised as follows: Sec. 2. gives background of basic pattern feature computation, Sec. 3. discusses about proposed methodology along with performance and distance metrics, Sec. 4. illustrates experimental details on two databases and in Sec. 5. conclusion are summarised.

2. Background

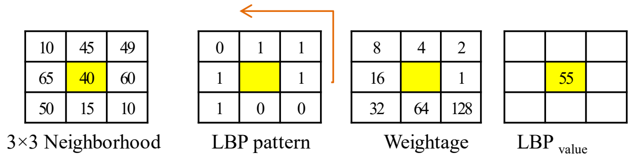

Fig. 1: LBP step wise computation.

Pattern features operate image locally for texture information extraction. Local Binary Pattern (LBP) is the first pattern, proposed by Ojala et at. [7]. It selects a neighbourhood with radius R and compares horizontal, vertical and diagonal direction pixels with

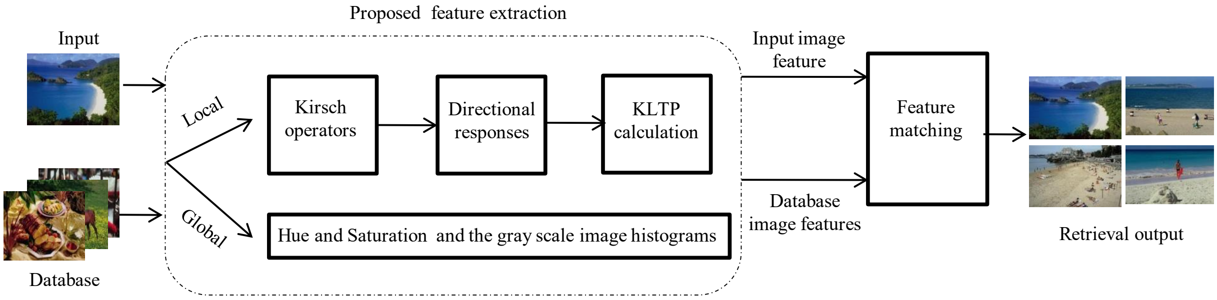

Fig. 2: Proposed retrieval system framework.

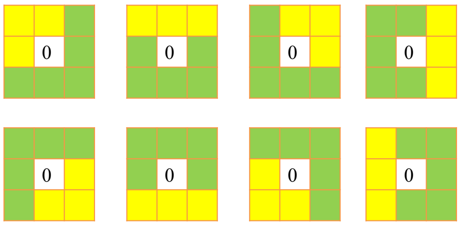

Fig. 3: Kirsch operators.

the pixel in the center. $R = 1$ creates a 3×3 neighborhood. Equation (1) shows that the center pixel I_c is compared with I_n^R where $1 \leq n \leq 8$ is representing neighboring pixels. In Fig. 1, steps of LBP calculation are shown. Arrow is drawn to show the movement of pixel comparison from LSB to MSB.

$$LBP_n^R = \begin{bmatrix} 1 & I_n^R > I_c \\ 0 & I_n^R \leq I_c \end{bmatrix}. \tag{1}$$

These 8 bit LBP patterns are converted to equivalent LBP values through Eq. (2). Likewise, each pixel of the image is considered to generate LBP image of size $X \times Y$. These LBP values are summarised in the form of a histogram using Eq. (3).

$$LBP_{\text{value}} = \sum_{n=1}^{8} 2^{n-1} \cdot LBP_n^1, \tag{2}$$

$$LBP(h) = \sum_{x=1}^{X} \sum_{y=1}^{Y} Z\left(LBP_{value}(x,y), \text{h}\right); \quad h \in \left(0, \ldots 2^8 - 1\right), \tag{3}$$

where, $Z(p,q) = \begin{bmatrix} 1 & p = q \\ 0 & else \end{bmatrix}$ and h represents the corresponding histogram bin.

3. Proposed System Framework

The structure of the proposed system is shown in Fig. 2. It is a combination of three major building blocks arranged sequentially. First of all, global and local features of the image are extracted. These features are given as input to the matching block. It performs comparison between input image and database images features. In the last block, images with maximum similarity with the input image are retrieved from the database. Number of retrieved images can be changed by the user. Images having maximum matching with the input image will be listed first. In Fig. 2, an image is taken from beaches category of Corel 1k database and images are retrieved using proposed system.

3.1. Feature Computation

Firstly, the gray scaled images are passed through a set of Kirsch operators shown in Fig. 3. These are 3×3 kernels with center pixel having zero intensity value. Yellow and green pixels represent 5 and -3 intensity values, respectively [35]. These filters highlight major eight direction information present in the image. Let k_m represents eight directional Kirsch Kernels where $m \in [1, \ldots, 8]$ and $I(x,y)$ represents the input gray image of size $M \times N$, such that, $1 \leq x \leq M, 1 \leq y \leq N$. These kernels are convolved with the image to get the eight filtered images $F_m(x,y)$, using following equation. Here, '*' is representing convolution operation.

$$F_m(x,y) = k_m^* I(x,y). \tag{4}$$

In the next step, a small square neighborhood of radius, $R = 1$ and 3×3 size is taken into consideration to obtain texture features. Pixel in the center is compared with the surrounding eight pixels. Sign of the intensity differences (positive, negative and equal) are encoded into three patterns by using following Eq. (5):

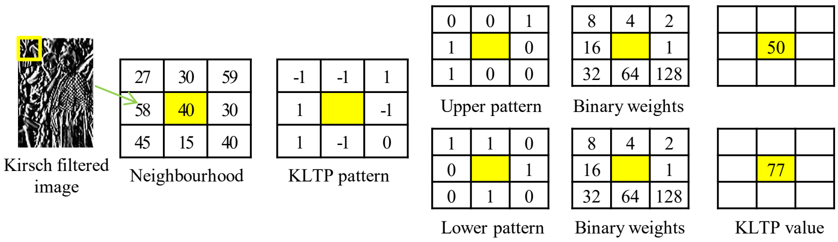

Fig. 4: KLTP computation.

$$KLTP_n^n = \begin{bmatrix} 1 & F_m^n > F_m^c \\ 0 & F_m^n = F_m^c \\ -1 & F_m^n < F_m^c \end{bmatrix}, \tag{5}$$

where F_m^c represents center pixel of the m^{th} filtered image and F_m^n represents n^{th} surrounding pixel of filtered image. If the surrounding pixels are having larger intensities as compared to the center pixel, then those pixels are assigned to generate upper pattern '1' and if surrounding pixels are having smaller intensities as compared to the center pixel, then those pixels are assigned to lower pattern '-1'. 8-bit upper and lower patterns are converted to KLTP values ranging from 0–255. Finally, KLTP feature vector is created in term of upper and lower histograms by observing frequency of KLTP values. Hence, $8 \times 2 \times 256$ length of feature is obtained. Figure 4 shows the computation of KLTP features for a sample neighborhood on the Kirsch filtered image.

KLTP gives a gray level local feature of the image. It is analyzed from the literature that global and color information both are equally important to understand the image. Hence, this information is appended in the KLTP from the histograms of gray scale image, hue and saturation channels. It makes the KLTP feature more robust for image variations.

3.2. Image Matching and Performance Measures

The local and global features are concatenated and they are used to calculate image matching index. For the input image I and database image D, d_1 distance is computed as follows:

$$d_1^{I,D} = \sum_{l=1}^{L} \frac{|F_D(l) - F_I(l)|}{1 + F_D(l) + F_I(l)}. \tag{6}$$

where $F_D(l)$, $F_I(l)$ are the lth feature component of database image D and input image I, respectively. L is the length of feature.

Manhattan distance or L_1 is computed as follows:

$$d_M^{I,D} = \sum_{l=1}^{L} |F_D(l) - F_I(l)|. \tag{7}$$

Euclidean distance is computed as follows:

$$d_E^{I,D} = \sqrt{\sum_{l=1}^{L} (F_D(l) - F_I(l))^2}. \tag{8}$$

Canberra distance is computed as follows:

$$d_C^{I,D} = \sum_{l=1}^{L} \frac{|F_D(l) - F_I(l)|}{|F_D(l)| + |F_I(l)|}. \tag{9}$$

Out of many available similarity measures, d_1 distance metric is being preferred due to its high retrieval performance [36]. Similarity index is inversely proportional to distance measure value. All the database images are ranked based on the similarity index. The maximum similar images will be displayed first. Count of retrieved images can be selected by the user.

3.3. Performance Evaluation

Experiments are performed using MATLAB 2017a on a system with Intel Core i5 processor, 8GB RAM and 500 GB hard drive. The average retrieval performance of the system is measured in terms of average precision and average recall values. For every image, precision and recall values are calculated as follows. Let image I is considered for evaluation.

$$Precision_1 = \frac{\#Relevant\,images\,retrieved}{Retrieved\,images}, \tag{10}$$

$$Recall_1 = \frac{\#Relevant\,images\,retrieved}{Retrieved\,images\,in\,the\,database}. \tag{11}$$

After computing these values for all of the database images, average is computed as follows:

$$Avg_P = \frac{1}{DB} \sum_{i=1}^{DB} Precision_i, \tag{12}$$

$$Avg_R = \frac{1}{DB} \sum_{i=1}^{DB} Recall_i, \tag{13}$$

where DB is the number of images presents in a particular image database.

4. Experiments

It is the desired condition for any feature to perform well on publicly available databases. Hence, for this purpose, two distinct databases have been selected to evaluate performance, namely, Corel 1k [37] and STex [38]. Table 1 shows the summary of these databases. Description of images in these databases and CBIR system performance on them are discussed in the following section.

Tab. 1: Database summary.

Database	Image size	# Category	# Total images
Corel 1k	256 × 384 or 384 × 256	100	1000
STex	128 × 128	416	7616

4.1. Corel 1k Natural Database

Corel 1k is a repository of professional photographs of natural scenes [37]. It is very popular and freely available for the research purposes. There are 10 different groups of images, namely, buses, beaches, flowers, elephants, people, buildings, dinosaurs, food, mountains, and horses. Every group has 100 images in JPG format of 256 × 384 or 384 × 256 sizes. Few images from this database are shown in Fig. 5 for visualization. Figure 6 shows the precision of each group of the database while 10 images are retrieved. Buses and buildings images are retrieved relatively with high precision. Figure 7 shows the effect of d_1, Manhattan, Euclidean and Canberra distances on the average precision for various numbers of retrieved images. It is observed that results of d_1 distance are better than Manhattan, Euclidean and Canberra for all the instances of retrieved imaged from 10 to 100. Hence, further results on this database are calculated for d_1 distance only.

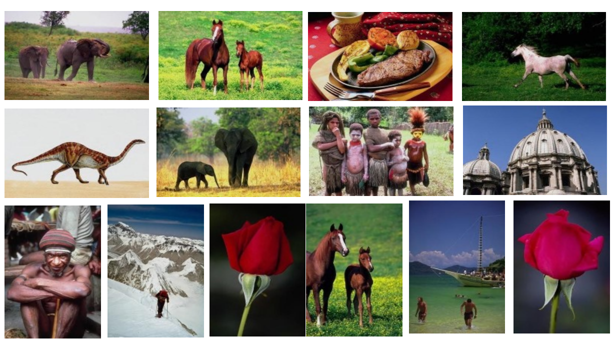

Fig. 5: Images from Corel 1k database.

Number of retrieved images is varied and trend of average precision and recall values are computed using Eq. (12) and Eq. (13). Output results are plotted in Fig. 8 and Fig. 9, respectively. These results are compared with other contemporary methods, such as, GLTCoP, MCLTP, DSCoP and MCLTCoP. It is observed that proposed method is giving higher values of average precision and recall for all the instances, if the retrieved images are changed from 10 to 100. Average precision and average recall values of the proposed method are 85.5 % and 58.3 % for 10 and 100 retrieved images, respectively. Average precision value decreases by increasing the number of retrieved images. On the other hand, average recall value increases by increasing the number of retrieved images.

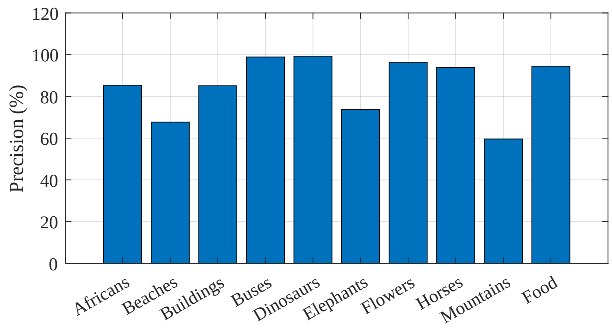

Fig. 6: Group precision of Corel 1k database (10 Retrieved image).

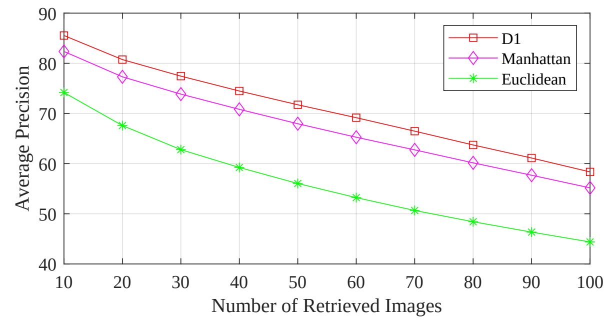

Fig. 7: Distance metric effect on the retrieval results of Corel 1k database.

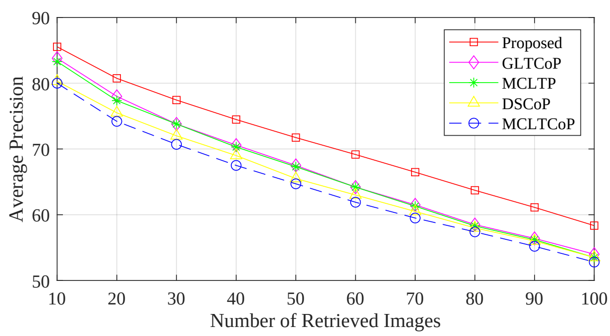

Fig. 8: Average precision for Corel 1k.

Retrieval result of input image number '352' is shown in Fig. 10. This query image belongs to 'bus" category. It is visible that retrieved images belong to 'bus' category (301 to 400 image numbers are from the ‘bus’ category).

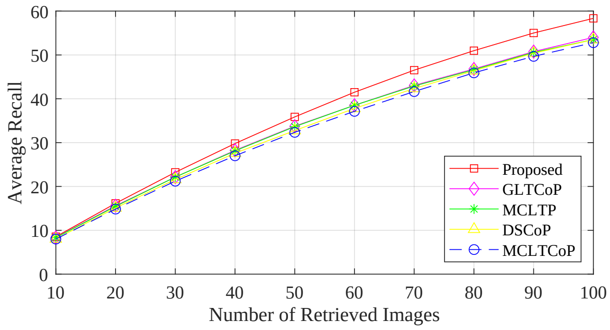

Fig. 9: Average recall for Corel 1k.

Fig. 10: Retrieval result for the input image number ‘352’.

4.2. STex Texture Database

To validate the performance of the proposed system, in the second experiment, a collection of completely different set of texture images is considered. STex database has 7616 images from 476 different groups [38]. Some images are shown in Fig. 11 to have a glimpse of the database images. Images are in JPG format of 128 × 128 size. Figure 12 shows the effect of various distance metrics on the average precision. Manhattan and d_1 distances are performing almost similar for STex database but it is observed that d_1 distance is giving the best results out of d_1, Manhattan, Euclidean and Canberra distance metrics. Using Eq. (12) and Eq. (13), average precision and recall are computed for 16 to 112 retrieved images. Figure 13 and Fig. 14 show the comparison with the state-of-the-art methods, such as, LEPVP, DLEP, LNIP, CSLBP, DTCWTILTrP and DDDTCWT. It is evident that for all the different number of retrieved images, proposed method is performing the best among others. If 16 images are retrieved, then average precision is 73.5 % by using the proposed method.

Fig. 11: Images from STex database.

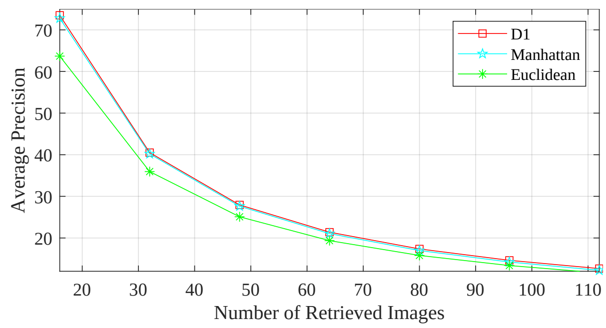

Fig. 12: Distance metric effect on the retrieval results of STex database.

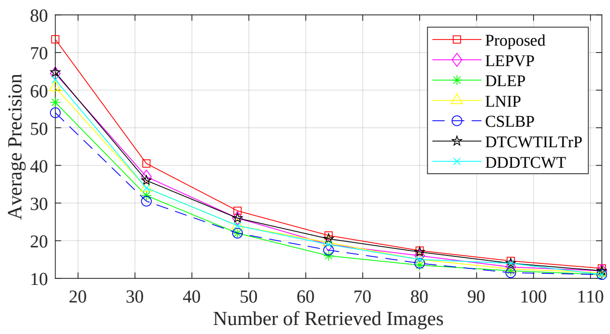

Fig. 13: Average precision for STex.

Figure 15 shows the retrieval result for the input query image number ‘417’. Out of 7616 images, image numbers 417 to 432 are from input image’s group. Total 16 images are shown to the user. It is observed that out of 16 images, 12 images are from the same group as of the query image. Rest 4 images are from other categories.

Table 2 summarises average precision results of various distance measures, d_1, Manhattan, Euclidean and Canberra, on both the databases and it is concluded that d_1 distance is giving the best performance. Although Manhattan and d_1 distances are performing almost similar for STex database but there is significantly better performance of d_1 distance on Corel 1k database.

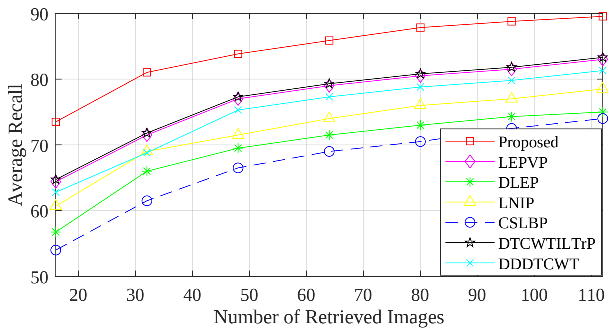

Fig. 14: Average recall for STex.

Fig. 15: Retrieval result for the input image number '417'.

Tab. 2: Database summary.

Database	d_1	Manhattan	Euclidean	Canberra
Corel 1k	85.5 %	82.36 %	74.18 %	83.26 %
STex	73.5 %	72.77 %	63.68 %	70.75 %

5. Conclusion

A new feature, KLTP is proposed in this paper, for image retrieval. Unlike other pattern features existing in the literature, KLTP extracts information in eight major directions using Kirsch operators. Hence, all the sharp changes in those directions are stored which help to represent the content of the image efficiently. Further, these filtered images are passed for LTP computation. In this computation, small local neighbourhoods are used to observe intensity variations. Global color information of images is also appended by hue and saturation histograms. Results are also verified for various similarity metrics. Overall performance on two distinct databases shows better results of the proposed method as compared to the state-of-the-art methods and has proved it to be a robust feature for real-time applications.

Author Contributions

M.A. has conceptualized the idea, arranged the data, implemented methodology, validated results and written the manuscript.

References

[1] LIU, Y., D. ZHANG, G. LU and W.-Y. MA. A survey of content-based image retrieval with high-level semantics. *Pattern Recognition*. 2007, vol. 40, iss. 1, pp. 262–282. ISSN 0031-3203. DOI: 10.1016/j.patcog.2006.04.045.

[2] MULLER, H., N. MICHOUX, D. BANDON and A. GEISSBUHLER. A review of content-based image retrieval systems in medical applications—clinical benefits and future directions. *International Journal of Medical Informatics*. 2004, vol. 73, iss. 1, pp. 1–23. ISSN 1386-5056. DOI: 10.1016/j.ijmedinf.2003.11.024.

[3] ROUT, N. K., M. ATULKAR and M. K. AHIRWAL. A review on content-based image retrieval system: present trends and future challenges. *International Journal of Computational Vision and Robotics*. 2021, vol. 11, iss. 5, pp. 461–485. ISSN 1752-914X. DOI: 10.1504/IJCVR.2021.117578.

[4] SINGH, N., K. SINGH and A. K. SINHA. A Novel Approach for Content Based Image Retrieval. *Procedia Technology*. 2012, vol. 4, iss. 1, pp. 245–250. ISSN 2212-0173. DOI: 10.1016/j.protcy.2012.05.037.

[5] THEETCHENYA, S., S. RAMASUBBAREDDY, S. SANKAR and S. M. BASHA. Hybrid approach for content-based image retrieval. *International Journal of Data Science*. 2021,

vol. 6, iss. 1, pp. 1–13. ISSN 2053-082X. DOI: 10.1504/IJDS.2021.10040767.

[6] WANG, H., H. QU, J. XU, J. WANG, Y. WEI and Z. ZHANG. Texture image retrieval based on fusion of local and global features. *Multimedia Tools and Applications*. 2022, vol. 81, iss. 10, pp. 14081–14104. ISSN 1573-7721. DOI: 10.1007/s11042-022-12449-3.

[7] OJALA, T., M. PIETIKAINEN and D. HARWOOD. A comparative study of texture measures with classification based on featured distributions. *Pattern Recognition*. 1996, vol. 29, iss. 1, pp. 51–59. ISSN 0031-3203. DOI: 10.1016/0031-3203(95)00067-4.

[8] TAN, X. and B. TRIGGS. Enhanced Local Texture Feature Sets for Face Recognition Under Difficult Lighting Conditions. *IEEE Transactions on Image Processing*. 2010, vol. 19, iss. 6, pp. 1635–1650. ISSN 1941-0042. DOI: 10.1109/TIP.2010.2042645.

[9] HEIKKILA, M., M. PIETIKAINEN and C. SCHMID. Description of interest regions with center-symmetric local binary patterns. In: *Proceedings of the 5th Indian conference on Computer Vision, Graphics and Image Processing*. Madurai: Springer, 2006, pp. 58–69. ISBN 978-3-540-68301-8. DOI: 10.1007/11949619_6.

[10] DUBEY, S. R. Face retrieval using frequency decoded local descriptor. *Multimedia Tools and Applications*. 2019, vol. 78, iss. 12, pp. 16411–16431. ISSN 1573-7721. DOI: 10.1007/s11042-018-7028-8.

[11] VERMA, M. and B. RAMAN. Local neighborhood difference pattern: A new feature descriptor for natural and texture image retrieval. *Multimedia Tools and Applications*. 2018, vol. 77, iss. 10, pp. 11843–11866. ISSN 1573-7721. DOI: 10.1007/s11042-017-4834-3.

[12] SUCHARITHA, G. and R. K. SENAPATI. Biomedical image retrieval by using local directional edge binary patterns and Zernike moments. *Multimedia Tools and Applications*. 2020, vol. 79, iss. 3, pp. 1847–1864. ISSN 1573-7721. DOI: 10.1007/s11042-019-08215-7.

[13] MURALA, S. and Q. M. J. WU. Local ternary co-occurrence patterns: A new feature descriptor for MRI and CT image retrieval. *Neurocomputing*. 2013, vol. 119, iss. 1, pp. 399–412. ISSN 0925-2312. DOI: 10.1016/j.neucom.2013.03.018.

[14] SARAN, V. H. and R. K. MISRA. *Advances in Systems Engineering: Select Proceedings of NSC 2019*. 1st ed. Singapore: Springer, 2021. ISBN 978-981-15-8025-3.

[15] AGARWAL, M., A. SINGHAL and B. LALL. 3D local ternary co-occurrence patterns for natural, texture, face and bio medical image retrieval. *Neurocomputing*. 2018, vol. 313, iss. 1, pp. 333–345. ISSN 0925-2312. DOI: 10.1016/j.neucom.2018.06.027.

[16] DUBEY, S. R. and S. MUKHERJEE. LDOP: local directional order pattern for robust face retrieval. *Multimedia Tools and Applications*. 2020, vol. 79, iss. 9, pp. 6363–6382. ISSN 1573-7721. DOI: 10.1007/s11042-019-08370-x.

[17] ROY, S. K., B. CHANDA, B. B. CHAUDHURI, D. K. GHOSH and S. R. DUBEY. Local jet pattern: a robust descriptor for texture classification. *Multimedia Tools and Applications*. 2020, vol. 79, iss. 7, pp. 4783–4809. ISSN 1573-7721. DOI: 10.1007/s11042-018-6559-3.

[18] BANERJEE, P., A. K. BHUNIA, A. BHATTACHARYYA, P. P. ROY and S. MURALA. Local Neighborhood Intensity Pattern–A new texture feature descriptor for image retrieval. *Expert Systems with Applications*. 2018, vol. 113, iss. 1, pp. 100–115. ISSN 0957-4174. DOI: 10.1016/j.eswa.2018.06.044.

[19] GHOSE, S., A. DAS, A. K. BHUNIA and P. P. ROY. Fractional Local Neighborhood Intensity Pattern for Image Retrieval using Genetic Algorithm. *Multimedia Tools and Applications*. 2020, vol. 79, iss. 25, pp. 18527–18552. ISSN 1573-7721. DOI: 10.1007/s11042-020-08752-6.

[20] WANG, X., H. YANG, S. GAO and P. NIU. Texture image retrieval using DNST domain local neighborhood intensity pattern. *Multimedia Tools and Applications*. 2022, vol. 81, iss. 20, pp. 29525–29554. ISSN 1573-7721. DOI: 10.1007/s11042-022-12819-x.

[21] YANG, W., X. ZHANG and J. LI. A local multiple patterns feature descriptor for face recognition. *Neurocomputing*. 2020, vol. 373, iss. 1, pp. 109–122. ISSN 0925-2312. DOI: 10.1016/j.neucom.2019.09.102.

[22] DAS, P. and A. NEELIMA. A Robust Feature Descriptor for Biomedical Image Retrieval. *IRBM*. 2021, vol. 42, iss. 4, pp. 245–257. ISSN 1959-0318. DOI: 10.1016/j.irbm.2020.06.007.

[23] PALWE, S. A. and D. MISHRA. Statistical tree-based feature vector for content-based image retrieval. *International Journal of Computational Science and Engineering*. 2020, vol. 21, iss. 4, pp. 556–563. ISSN 1742-7193. DOI: 10.1504/IJCSE.2020.106868.

[24] NIU, P.-P., J. TIAN, Q.-C. WU, C. ZHANG and X.-Y. WANG. Statistical texture image retrieval in DD-DTCWT domain using magnitudes and relative phases. *Multimedia Tools and Applications*. 2021, vol. 80, iss. 19, pp. 29893–29913. ISSN 1573-7721. DOI: 10.1007/s11042-021-11124-3.

[25] YAO, C.-H. and S.-Y. CHEN. Retrieval of translated, rotated and scaled color textures. *Pattern Recognition*. 2003, vol. 36, iss. 4, pp. 913–929. ISSN 0031-3203. DOI: 10.1016/S0031-3203(02)00124-3.

[26] REDDY, A. H. and N. S. CHANDRA. Local oppugnant color space extrema patterns for content based natural and texture image retrieval. *AEU - International Journal of Electronics and Communications*. 2015, vol. 69, iss. 1, pp. 290–298. ISSN 1434-8411. DOI: 10.1016/j.aeue.2014.09.015.

[27] VERMA, M., B. RAMAN and S. MURALA. Local extrema co-occurrence pattern for color and texture image retrieval. *Neurocomputing*. 2015, vol. 165, iss. 1, pp. 255–269. ISSN 0925-2312. DOI: 10.1016/j.neucom.2015.03.015.

[28] DEY, M., B. RAMAN and M. VERMA. A novel colour- and texture-based image retrieval technique using multi-resolution local extrema peak valley pattern and RGB colour histogram. *Pattern Analysis and Applications*. 2016, vol. 19, iss. 4, pp. 1159–1179. ISSN 1433-755X. DOI: 10.1007/s10044-015-0522-y.

[29] RAO, L. K., P. ROHINI and L. P. REDDY. Local color oppugnant quantized extrema patterns for image retrieval. *Multidimensional Systems and Signal Processing*. 2019, vol. 30, iss. 3, pp. 1413–1435. ISSN 1573-0824. DOI: 10.1007/s11045-018-0609-x.

[30] AGARWAL, M., A. SINGHAL and B. LALL. Multi-channel local ternary pattern for content-based image retrieval. *Pattern Analysis and Applications*. 2019, vol. 22, iss. 4, pp. 1585–1596. ISSN 1433-755X. DOI: 10.1007/s10044-019-00787-2.

[31] AGARWAL, M. and R. P. MAHESHWARI. Multichannel Local Ternary Co-occurrence Pattern for Content-Based Image Retrieval. *Iranian Journal of Science and Technology, Transactions of Electrical Engineering*. 2020, vol. 44, iss. 1, pp. 495–504. ISSN 2364-1827. DOI: 10.1007/s40998-019-00219-1.

[32] BHUNIA, A. K., A. BHATTACHARYYA, P. BANERJEE, P. P. ROY and S. MURALA. A novel feature descriptor for image retrieval by combining modified color histogram and diagonally symmetric co-occurrence texture pattern. *Pattern Analysis and Applications*. 2020, vol. 23, iss. 2, pp. 703–723. ISSN 1433-755X. DOI: 10.1007/s10044-019-00827-x.

[33] SINGHAL, A., M. AGARWAL and R. B. PACHORI. Directional local ternary co-occurrence pattern for natural image retrieval. *Multimedia Tools and Applications*. 2021, vol. 80, iss. 10, pp. 15901–15920. ISSN 1573-7721. DOI: 10.1007/s11042-020-10319-4.

[34] AGARWAL, M. and A. SINGHAL. Directional local co-occurrence patterns based on Haar-like filters. *Multimedia Tools and Applications*. 2022, vol. 81, iss. 1, pp. 1109–1123. ISSN 1573-7721. DOI: 10.1007/s11042-021-11361-6.

[35] KIRSCH, R. A. Computer determination of the constituent structure of biological images. *Computers and Biomedical Research*. 1971, vol. 4, iss. 3, pp. 315–328. ISSN 0010-4809. DOI: 10.1016/0010-4809(71)90034-6.

[36] BEECKS, C., M. S. UYSAL and T. SEIDL. A comparative study of similarity measures for content-based multimedia retrieval. In: *2010 IEEE International Conference on Multimedia and Expo*. Singapore: IEEE, 2010, pp. 1552–1557. ISBN 978-1-4244-7491-2. DOI: 10.1109/ICME.2010.5582949.

[37] WANG, J. Z., J. LI and G. WIEDERHOLD. SIMPLIcity: semantics-sensitive integrated matching for picture libraries. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 2001, vol. 23, iss. 9, pp. 947–963. ISSN 0162-8828. DOI: 10.1109/34.955109.

[38] KWITT, R. and P. MEERWALD. Salzburg Texture Image Database (STex). In: *WaveLab* [online]. Available at: `https://www.wavelab.at/sources/STex/`.

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