Image Retrieval By Local Contrast Patterns and Color Histogram

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Abstract—

Despite simplicity of the Local binary patterns (LBP) or local edge patterns (LEP) for texture description, they do not always convey complex pattern information. Hence we propose a new descriptor called Local Contrast Patterns(LCP), which encode the joint difference distribution of patterns (edges, points, blobs) attributed by multi-order image derivatives. While a suitable derivative appears sufficient for texture representation, we proposed two simple algorithms that combines nine dirrectional derivatives through local bit frequency and contrast-ratio maximization. Global RGB color histogram is then combined with the proposed LCP for color-texture retrieval. Experiments with the grayscale (Brodatz album) and color-texture (MIT VisTex) databases show very impressive outcomes by the proposed approach.

Index Terms—**Retrieval, local contrast patterns, texture , color histogram.**

I. Local Contrast Pattern

Local binary patterns(LBP) is one way of representing local patterns in images. But they are noise sensitive. However, according to Taylor series expansion, local surface is better described by mulple higher order derivatives. We thus propose a new local contrast patterns (LCP), which can be obtained by convolving image function with various order directional Gaussian derivatives $G_i^{\theta_j}$, where i, j are order and orientation parameters, respectively. Fortunately, we have a nice scale space theory that uses unique Gaussian kernel, given by

$$G(x, y; \sigma) = \frac{1}{2\pi\sigma^2} exp\left(-\frac{x^2+y^2}{2\sigma^2}\right). \quad (1)$$

While the number and order of the Gaussian derivatives are many, we used a minimal basis set: G_1^0,G_1^{90},G_2^0,G_2^{60},G_2^{120},G_3^0, G_3^{45}, G_3^{90}, and G_3^{135} from the rotation invariant perspective.

$$G_i^{\theta_j}, i = 1, 2, 3; \theta_j = j\pi/(i+1), j = 0, 1, ..., i. \quad (2)$$

Note that we have omitted using σ for the sake of simplicity. The response of an image patch I centered at (x_0, y_0) to a particular basis filter $G_i^{\theta_j}$ can be obtained by convolving it with the filter:

$$r_{i,j}(x_0, y_0) = \int\int G_i^{\theta_j}(x_0 - x, y_0 - y) I(x, y) \partial x \partial y \quad (3)$$

These responses $r_{i,j}(x_0, y_0)$ can be extended to multiscale representation by $r_{i,j,s}(x_0, y_0)$, where $s = s_{min}, ..., s_{max}$. Note also that the Y-component of the YIQ transformation is used for LCP computation. LCP therefore integrates various responses by

$$LCP_{i,j}(x, y) = \sum_{(k,l)\in I or R} bw(k, l) \times u(r_{i,j}(k+x, l+y) - r_{i,j}(x, y)), \quad (4)$$

$$u(z) = \begin{cases} 1 & (z \geq 0) \\ 0 & (z < 0) \end{cases}$$

and

$$bw(k, l) = \begin{pmatrix} 1 & 2 & 4 \\ 8 & 0 & 16 \\ 32 & 64 & 128 \end{pmatrix}$$

Here $r_{i,j}(x, y)$ is a 3×3 block from each of derivative responses, and $bw(k, l)$ is the binary weight mask. Note that the LCP value ranges between 0 and 255. Color histogram is obtained by partitioning RGB color space into 64 disjoint regions. Fig. 1 shows how LCP histograms represent various patterns at 0^o, 90^o, 120^o, and 45^o orientations for an example image.

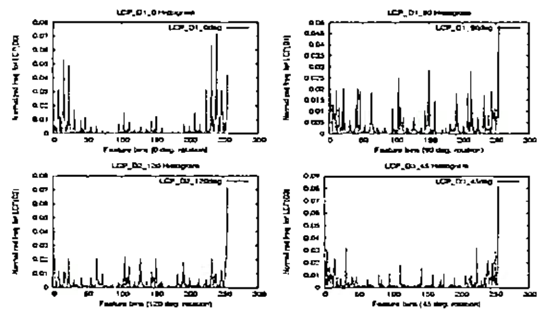

Fig. 1. LCP Histograms. LCP histograms with (a) first derivative with 0^o, (b) first derivative with 90^o, (c) second derivative with 120^o, and (d) third derivative with 45^o.

A. *LCP by local bit-frequency maximization(LCP1)*

1. Compute nine directional responses by using Gaussian derivative filters as mentioned.
2. Select a small 3×3 block from each of the nine responses and compute LCP patterns.
3. For each bit position, count the number of '1' and '0' bits as $sum1$ and $sum0$. If $sum1 > sum0$, assign '1' for that position. Assign '0' otherwise. This will create a new pattern, called LCP1.

B. *LCP by contrast ratio maximization (LCP2)*

1. Compute nine directional responses by using Gaussian derivative filters as mentioned.

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2. Select a small 3×3 block from each of the nine responses $r(x, y)$ and compute contrast-ratio (CR) for the block, where $CR(x,y) = \frac{SAD(x,y)}{AOS(x,y)}$. Here $SAD(x,y) = \sum_{(k,l)\in R} |r(k+x, l+x) - r(x,y)|$ and $AOS(x,y) = |\sum_{(x,y)\in R} r(x,y)|$ and (x, y) is the block center.
3. Select the response that maximizes nine contrast-ratio, (CR).
4. Compute LCP, which is the LCP2 for that block.

C. Similarity measurement and Performance evaluation

In our study, we used histogram intersection technique to measure the degree of matching between two texture regions on the basis of the distributions.

If SMc and SM_t are the similarity measures for color and texture, the overall similarity can be obtained by

$$SM = w_{color} \times SM_c + w_{contrast} \times SM_t. \quad (5)$$

Currently, we set equal weights (i.e.,1.0) for w_{color} and $w_{contrast}$. Performance evaluation in this study is done by using two well-known metrics, namely rank ratio (RR), precision (P) and recall (R).

II. Experimental results

A. Image databases

We used two data sets, one for grayscale iamges (Brodatz album) and the other for color images (MIT VisTex). Grayscale set consists of 1000 images from 40 different texture categories, while color set consists of 512 images from 32 categories. Each of the images has 128×128 size.

B. Results and Comparison

Fig. 2 shows an example retrieval result of the proposed LCP2+RGB feature. Results for other features are not shown for space problem. Clearly LCP2 feature is able to retrieve almost all 16 related color images. Fig. 3 shows the impressive results (average precision and recall rates) of a preliminary experiment over five queries for gray and color images.

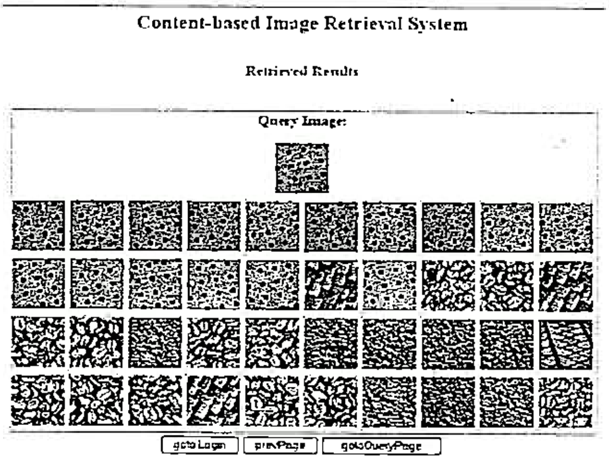

Fig. 2. Retrieved results . Results are due to our proposed LCP2+RGB. A single Gaussian scale ($\sigma = 0.5$) is used with (7×7) filter kernel.

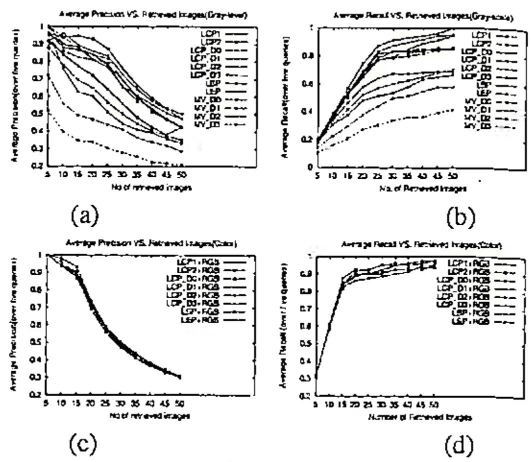

Fig. 3. Performance analysis for gray and color image retrieval. Average (over 5 query images) plots for (a)(c) $P^{(T)}$, (b)(d) $R^{(T)}$, at 5 interval, i.e., $T = 5, 10, ..., 50$. Note that a single scale ($\sigma = 0.85$ for gray, $\sigma = 0.5$ for color) is used with (7×7) filter kernel.

TABLE I

COMPARISON OF OUR LCP(+RGB) FEATURES WITH LBP(+RGB), AND LEP(+RGB) IN AVERAGE RETRIEVAL PERFORMANCE. AVERAGE IS DONE OVER 40 QUERIES FOR GRAYSCALE, 32 QUERIES FOR COLOR DATABASES.

Features	Retrieval Performance			
	Greyscale		Color	
	$R^{(25)}$	RR	$R^{(25)}$	RR
LCP1	74.9	3.307	91.4	1.610
LCP2	76.9	**2.789**	92.7	**1.482**
LCP(D0)	75.1	3.886	93.1	1.454
LCP(D1)	**78.4**	2.938	**93.5**	1.489
LCP(D2)	72.7	3.424	91.9	1.521
LCP(D3)	68.2	3.660	93.3	1.490
LBP	70.4	3.528	92.1	1.605
LEP	76.3	2.889	91.6	1.766

Table I shows a detail comparative performance of the proposed and conventional features. For grayscale database, the average (over 40 queries) retrieval performance by LCP2 is increased by 6.5% and 0.6% compared to LBP, and LEP features. LCP(D1) shows a bit better performance (8% from LBP, 2.1% from LEP) but the lowest (2.789 for gray, 1.482 for color) RR is achieved by our LCP2. For the color database, a minor improvement (0.6% to LBP, 1.1% to LEP) but similar trend is observed compared to LBP+RGB and LEP+RGB. Findings are quite commensurate with the priliminery results in Fig. 3. Note that in both experiments, LCP(D1), LCP(D2), and LCP(D3) are computed for 0^o orientation.

III. Conclusion

We have proposed a new texture extraction approach called local contrast patterns(LCPs) and combined it with the global RGB histogram for color-texture retrieval. Results show very impressive outcomes though future extension is needed for object-based retrieval.