Content-Based Image Retrieval Using a Combination of Texture and Color Features

Hee-Hyung Bu\(^1\), Nam-Chul Kim\(^2,\)* and Sung-Ho Kim\(^1\)

Abstract
Image retrieval is headed towards the ultimate goal of achieving the performance very similar to human cognitive ability. As an attempt of such work, this paper proposes a content-based image retrieval using a combination of texture features extracted from Gabor local correlation and uniform magnitude local binary pattern in value component and color features from color autocorrelogram in hue and saturation components. The texture features have multi-resolution multi-direction characteristics. In contrast, the color features have spatial structural information for color, which is rotation-invariant. Further, the HSV color space used herein is similar to the human visual system. Especially, two-dimensional (2D) Gabor transform used to extract parts of texture features, mimics the biological visual strategy of embedding angular and spectral analysis within global spatial coordinates, as using empirical 2D receptive field profiles obtained from orientation-selective neurons in cat visual cortex as the weighting functions. Based on the experimental results, we confirm that the proposed combined method outperforms compared existing methods and the methods using partial ones stemming from the proposed features in terms of retrieval performance.

Keywords
Content-Based Image Retrieval, Gabor Local Correlation, Uniform Magnitude Local Binary Pattern, Color Autocorrelogram, HSV Color Space

1. Introduction
Currently, we are living in the age of information in which data, particularly images, exist in digital format. In industrial area, several image retrieval systems have been developed. For example, web services are utilized to ease user experience; however, methods that use keywords are limited in application because many uploaded images do not have keywords or because of different user perspectives.

Content-based image retrieval systems automatically retrieve images by image features extracted based on image content. Many image features of interest include texture, color, and shape [1–4].

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Therefore, herein, we propose a method that utilizes a combination of texture and color features. The texture features are extracted using Gabor local complex correlation and uniform magnitude local binary pattern (UMLBP). Gabor wavelets are modeled on the receptive fields of the orientation-selective simple cells [5], which is significant in the aspect of the human visual system. A set of two-dimensional (2D) Gabor wavelets proposed by Daugman [5], samples the frequency domain in a log-polar manner. The Gabor wavelets efficiently reduce image redundancy and have robustness to noise. The multi-resolution and multi-direction Gabor representations have received special attentions as receptive fields of simple cells in the primary visual cortex of mammals are oriented and have the characteristic of local spatial frequencies. In [6], the authors proposed Gabor features that provide the best pattern retrieval accuracy and distinctively describe images. Thus, the adaptive filter selection strategy is suggested to reduce image processing computations while maintaining a reasonable level of retrieval performance. Studying Gabor wavelets is important as they can significantly contribute to research areas such as texture analysis and image processing. In content-based image retrieval systems, a set of 2D Gabor wavelets is often used for extracting texture features. Joshi and Mukherjee [7] proposed the fusion technique using Gabor and scale invariant feature transform descriptors. A content-based image retrieval (CBIR) system using collective color and texture feature extraction with linear discriminant analysis was proposed by Jain and Salankar [8]. In [9], the authors proposed a CBIR using color moment and Gabor texture features. The image retrieval approach using Gabor features proposed by Manjunath and Ma [6] outperforms approaches that use pyramid-structured wavelet transform features, tree-structured wavelet transform features, and multi-resolution simultaneous autoregressive model features. Rotation-invariant and scale-invariant Gabor features for texture image retrieval have been proposed by Han and Ma [10], Rahman et al. [11], and Chen et al. [12], which use energy features but not correlation features. Although Gabor transforms implemented using Gabor wavelets are suitable for extracting texture features that thanks to Gabor wavelets responding well to edges and texture changes, they yield relatively low retrieval performance. In this paper, we propose an advanced Gabor local complex correlation feature unlike existing Gabor features with magnitude or real part. In addition, one of our goals is to select features well-matched to Gabor features and to improve the retrieval performance of the fused features. In details, we adopts the UMLBP because it is harmonized with the Gabor local complex correlation as texture features. Regarding color features, we adopts the color autocorrelogram [13]. The color autocorrelogram is extracted in HSV color space and harmonized with our texture features. Based on the result, the fused feature demonstrates high retrieval performance.

Recently, CBIR using deep learning has become a big stream. Ahmed et al. [14] proposed a CBIR using fusion of the spatial color information with shaped extracted features and object recognition, where a bag-of-words (BoW) approach is employed when retrieving. Shakarami and Tarrah [15] proposed a combined method of deep features and handcrafted-PCA (principal component analysis) features, where deep features are extracted from improved AlexNet convolutional neural network (CNN) and handcrafted features from histogram of oriented gradients (HOG) and local binary patterns (LBP). Kan et al. [16] proposed a supervised deep feature embedding with a handcrafted feature model, which includes a new loss function combining the distance metric with the label information. Wang et al. [17] proposed enhancing a sketch-based image retrieval by CNN semantic re-ranking, which uses two CNNs of Q-Net and N-Net for classification. The obtained category information of sketches and natural images are used to re-rank initial retrieval results. Ghrabat et al. [18] proposed a greedy learning of deep Boltzmann machine’s variance and search algorithm for efficient image retrieval, which utilizes classifying an image with the optimized features by a classification algorithm. These methods using classification can be used only if the information of grouping images are already known, where in most cases low level features are functioned of vital importance.

In this paper, we concentrate on extracting low-level local features that is able to be adopted in deep learning. Its combination is able to use to CBIR directly without prior knowledge of class information. In our contribution, we suggest an excellent combination of the advanced Gabor local complex
correlation and the scale based UMLBP for texture features and the color autocorrelogram for color features. The proposed method has multi-resolution and multi-direction characteristics for texture and rotation-invariant spatial structural information for color. In the next section, we describe the proposed image retrieval system and explain the details of the feature extraction methods. The experimental processes and results are discussed in Section 3. Finally, in Section 4, we present the conclusions of the paper.

2. The Proposed Image Retrieval System

Our proposed system is achieved through the combined features extracted from the Gabor local complex correlation, UMLBP, and color autocorrelogram. The Gabor wavelets represent specific frequencies in different specific directions. Herein, we used a set of Gabor wavelets to extract texture features in this paper. The objective of this paper is to propose the method using Gabor wavelets enhanced for image retrieval performance and to combine the Gabor feature and other harmonized features. Fig. 1 represents the block diagram of our proposed content-based image retrieval system. The proposed system is conducted in the following four steps:

Step 1 converts an input RGB query image to a HSV image.

Step 2 conducts feature extraction processes. First, it performs the Gabor transform in the value (V) component and then extracts the local correlation features. Second, it extracts the UMLBP features in the V component. Finally, it extracts the color autocorrelogram features in the domain of the hue (H) and saturation (S) components.

Step 3 combines features to obtain a feature vector.

Step 4 computes the similarity of the two feature vectors, i.e., the feature vector of the query image and each of the feature vectors of test images stored in the image database, and retrieved the most similar images.

![Fig. 1. The proposed content-based image retrieval block diagram.](image)

2.1 Gabor Wavelets Transform

The 2D Gabor wavelets are Gaussian functions modulated by sine plane waves with specific frequencies and directions. They provide the local spatial frequency information. Herein, the 2D Gabor wavelet proposed by Han and Ma [10] is expressed as follows:
\[ g(x, y) = \frac{1}{2\pi \sigma_x \sigma_y} \exp \left( -\frac{1}{2} \left( \frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2} \right) - 2\pi j W x \right), \]  

where \( \sigma_x \) and \( \sigma_y \) represent the spatial variances of the Gabor wavelet. The pair of \( x \) and \( y \) denotes the spatial location of the kernel. \( j = \sqrt{-1} \) and \( W \) represents the modulation frequency of the Gaussian function. Moreover, the 2D Gabor wavelet set using \( g(x, y) \) for multiresolution and multi-direction is as follows:

\[ g_{s,n}(x, y) = a^{-2s}g(x', y'), \]  

where \( x' = a^{-s}(x\cos \theta_n + y\sin \theta_n), y' = a^{-s}(-x\sin \theta_n + y\cos \theta_n), a > 1 \), and \( \theta_n = n\pi/K \) for \( s = 0, 1, ..., S - 1 \) and \( n = 0, 1, ..., K - 1 \). The symbol \( S \) represents the number of scales and \( K \) refers to the number of directions. The symbols \( a, \sigma_x, \) and \( \sigma_y \) are as follows [10]:

\[ a = \left( \frac{U_h}{U_l} \right)^{\frac{1}{S-1}}, \quad \sigma_x = \frac{1}{2\pi u}, \quad \text{and} \quad \sigma_y = \frac{1}{2\pi v}. \]  

Spatial frequency components provide essential information, which is not gained directly from pixels. The Gabor transform is used to significantly represent the energy characteristics of the frequency of the local region, and it is unaffected by the change of the object size and illumination. The 2D Gabor transform is the convolution of the input image and 2D Gabor kernel. For the given input image \( I(x, y) \) and the 2D Gabor kernel with scale \( s \) and direction \( n \), the convolution is given as follows:

\[ J_{s,n}(x, y) = I(x, y) * g_{s,n}(x, y). \]  

where the operator * stands for the convolution and \( g_{s,n} \) is called point spread function or impulse response. The convolution outputs \( s \times n \) images whose sizes are the same as those of input image \( I \).

### 2.2 Gabor Correlation Feature Extraction

The correlation coefficient is a covariance between two random variables scaled by the product of their standard deviations. It represents the strength of the relationship between the relative movements of the two variables [19]. Given two images A and B, the mean operation for the computation of a complex correlation coefficient is expressed as

\[ \text{mean}_{t \in T}[A(p)] = \frac{1}{|T|} \sum_{t \in T} A(p - t), \]  

where the symbol \( T \) represents a \( 3 \times 3 \) window, \( p \) is a pixel position, and \( |T| \) stands for the size of \( T \). The \( \text{VAR} \) (variance) operation is also written as

\[ \text{VAR}_{t \in T}[A(p)] = \text{mean}_{t \in T}[A(p)]^2 - \text{mean}_{t \in T}[A(p)]. \]  

Using the above expression, we define the complex COR (correlation coefficient) as follows:
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\[
\begin{align*}
\text{COR}_{\text{G}(p)}(A(p), B(p)) & = \frac{\text{mean}_{t \in T}[A(p) - B^*(p)]}{\text{mean}_{t \in T}|A(p)|} - \frac{\text{mean}_{t \in T}|B^*(p)|}{T}
\end{align*}
\]

(8)

The details of the proposed correlation feature extraction are as follows.

Step 1 transforms a query image to a gray image.

Step 2 creates a Gabor kernel with scale \( s \) and direction \( \theta_n \).

Step 3 conducts a Gabor transform for the gray image resulted in Step 1.

Step 4 creates the correlation coefficient image from the complex image derived in Step 3, which can be expressed as follows:

\[
\rho_{s,n}(p) = \text{Re}\{ \text{cor}_{t \in T}[J_{s,n}(p), J_{s,n}(p - s \cdot \delta\theta_n)] \},
\]

(9)

where \( \text{Re}\{ \} \) represents the real part of the complex number. The vector \( \delta\theta_n \) represents \( \delta\theta_n = (\cos\theta_n, \sin\theta_n) \). \( J_{s,n} \) represents the Gabor transformed image by parameters of scale \( s \) and direction \( n \); \( \rho_{s,n}(p) \) is the correlation coefficient in \( T \) between a center pixel \( p \) and another centered at \( p - s \cdot \delta\theta_n \).

Step 5 calculates the global average \( \mu_{s,n}^\rho \) and global standard deviation \( \sigma_{s,n}^\rho \) for the result derived in Step 4, and they are expressed as follows:

\[
\begin{align*}
\mu_{s,n}^\rho &= \text{mean}_{p \in P}[\rho_{s,n}(p)] \quad \text{(10)}
\end{align*}
\]

\[
\sigma_{s,n}^\rho = \text{std}_{p \in P}[\rho_{s,n}(p)] \quad \text{(11)}
\]

The superscript \( \rho \) denotes the local correlation. The operator \( \text{std} \) represents the calculated standard deviation, and \( p \) represents the pixel position.

The Gabor correlation feature vector is expressed as follows:

\[
\begin{align*}
f &= [\mu_{s,n}^\rho, \sigma_{s,n}^\rho]
\end{align*}
\]

(12)

where \( [\mu_{s,n}^\rho] \) and \( [\sigma_{s,n}^\rho] \) denote for the vectors of the global averages and the global standard deviations, respectively, for local correlation.

2.3 Uniform Magnitude Local Binary Pattern Feature Extraction

The UMLBP refers to the uniform local binary pattern (ULBP) of magnitude images, and it has rotation-invariant characteristics. The magnitude local binary pattern (MLBP) is the absolute local difference vector, which represents the image local structure well compared to the LBP [20, 21] using only a sign vector. The details of the UMLBP texture feature extraction are as follows:

Step 1 converts a query image to a gray image.

Step 2 calculates the absolute difference \( y_{r,\theta_n}(p) \) of the value of position \( p \) and the value of the position \( 2^{-1} \)-distant from \( p \) in the direction \( \theta \), where \( r \) is the resolution level.

Step 3 calculates the average \( \mu_r \) of magnitude components of \( y_{r,\theta_n}(p) \) in resolution.

Therefore, the MLBP with \( N \) directions on an image of resolution \( r \) is expressed as follows:

\[
\begin{align*}
\text{MLBP}_{N,2^{r-1}}(p) &= \sum_{n=0}^{N-1} t\left( y_{r,\theta_n}(p), \mu_r(p) \right) \cdot 2^n, \quad \text{(13)}
\end{align*}
\]

\[
\mu_r(p) = \text{mean}_{\theta_n \in \Theta}[|y_{r,\theta_n}(p)|], \quad t(x, c) = \begin{cases} 1, & x \geq c \\ 0, & x < c \end{cases}, \quad \text{(14)}
\]
where \( p \) denotes the pixel position, \( N \) denotes the total number of directions, \( |y_{\theta}(p)| \) denotes the absolute difference of the value of position \( p \) and the value of the position \( 2^{r-1} \) distant from \( p \) in the direction \( \theta \). The symbol \( r \) signifies that \( r \in \{1, 2, \cdots, M\} \), \( M \) is the total number of resolution levels, \( \theta = \frac{2\pi n}{N} \), and \( \mu_r \) is the average of magnitude components in resolution \( r \).

Step 4 evaluates the UMLBP as follows:

\[
UMLBP_{N,2^{r-1}}(p) = \sum_{n=0}^{N-1} \left[ |y_{\theta_n}(p)| - \mu_r(p) \right], \text{if } U(MLBP_{N,2^{r-1}}(p)) \leq 2, \quad N + 1, \text{ otherwise}
\]

where the operator \( U \) represents the sum of bits in the MLBP.

The UMLBP features are extracted from the normalized histogram of UMLBP in each resolution as follows:

\[
H_r(i) = \frac{1}{|P|} \sum_{p \in P} \delta(UMLBP_{N,2^{r-1}}(p) - i),
\]

where \( i \in \{0, 1, 2, \cdots, N, N + 1\} \), \( |P| \) is the image size, and \( \delta \) is the Kronecker delta.

Thus, the dimensions of features are \( M(N + 2) \).

### 2.4 Color Autocorrelogram Feature Extraction in 2D of H and S Components

The HSV color model, similar to the human visual system, is often used for separating chrominance components from luminance components, as a cause of the robustness to a variant of illumination. The HSV color space comprises chrominance components of \( H \) and \( S \) and the luminance components of \( V \). The color autocorrelogram [13] expresses the spatial correlation of colors using distance, unlike histograms using statistics. It has characteristics of robustly tolerating substantial appearance change by a variant of positions viewing, and camera zooming. The used color autocorrelogram features in this paper are extracted in the 2D domain after quantizing vectors of \( H \) and \( S \) components. The components of the 2D domain can be expressed as follows:

\[
I_{QHS}(p) = I_{QH}(p) \times \text{SaturationLevel} + I_{QS}(p),
\]

where the subscript \( QHS \) denotes the quantized image composed of \( H \) and \( S \) components. Further, our experiment uses eight levels for hue and saturation components. The quantization is conducted of uniformly spaced between minimum and maximum values. The color autocorrelogram computes the probability of center pixel having neighbor of pixels of the same color with distance \( k \) as follows:

\[
a_c^{(k)}(I_{QHS}) = Pr[I_{QHS}(p) = I_{QHS}(p')] = c \mid |p - p'| = k \text{ for } p, p' \in P.
\]

where \( c \) denotes the pixel value on the image \( I_{QHS} \). \( p \) is a pixel position.

### 3. Experimental Results

The method proposed in this paper is the combined method of the Gabor local complex correlation, UMLBP, and color autocorrelogram. The retrieval performance of the proposed method is compared with those of the existing methods. The compared methods include methods that use partial features of our proposed method and the existing methods, such as color histogram, color structure descriptor (CSD), scalable color descriptor (SCD), ULBP, CLBP, color autocorrelogram, and UMLBP. Some of these features are extracted from the RGB space. In our experiment, Corel [22], VisTex [23], and Corel-1K [24] databases are used. Corel database has 990 color images of 192×128 of most artificial
objects, which comprises 11 groups with 90 images in each group such as cars, flowers, airplanes, houses, etc. VisTex database has 1,200 color images of 128×128 with most homogeneous patterns. It contains 75 groups with 16 images in each group, such as bark, fabric, tile, water, etc. Corel-1K database has 1,000 color images of 384×256 or 256×384. It includes 10 groups which consist of 100 images in each group, such as Africans, beaches, buildings, etc.

The feature vector of our proposed method has 136 dimensions composed of 32 dimensions of Gabor correlation, 40 dimensions of UMLBP, and 64 dimensions of color autocorrelogram. The existing methods used herein include color histogram, CLBP, SCD, and CSD of MPEG-7, and ULBP which has often referenced recently in image processing research areas. Table 1 shows the dimensions and color spaces of the methods used in our experiments.

Table 1. Dimensions and color spaces of the methods used in the experiments

<table>
<thead>
<tr>
<th>Methods</th>
<th>Dimension</th>
<th>Color space</th>
<th>Remark</th>
</tr>
</thead>
<tbody>
<tr>
<td>Color histogram</td>
<td>128</td>
<td>RGB</td>
<td></td>
</tr>
<tr>
<td>SCD</td>
<td>128</td>
<td>HSV</td>
<td></td>
</tr>
<tr>
<td>CSD</td>
<td>128</td>
<td>HMMDD</td>
<td></td>
</tr>
<tr>
<td>ULBP</td>
<td>40</td>
<td>V</td>
<td></td>
</tr>
<tr>
<td>Color autocorrelogram_HS</td>
<td>64</td>
<td>HS</td>
<td>8:8</td>
</tr>
<tr>
<td>Color autocorrelogram_RGB</td>
<td>216</td>
<td>RGB</td>
<td>6:6:6</td>
</tr>
<tr>
<td>UMLBP</td>
<td>40</td>
<td>V</td>
<td>Scale 1–4</td>
</tr>
<tr>
<td>CLBP_RGB</td>
<td>186</td>
<td>RGB</td>
<td></td>
</tr>
<tr>
<td>CLBP_RGB + Color autocorrelogram_RGB</td>
<td>250(186, 64)</td>
<td>RGB</td>
<td></td>
</tr>
<tr>
<td>Gabor correlation</td>
<td>32</td>
<td>V</td>
<td>Scale 1–4, Directions 8</td>
</tr>
<tr>
<td>UMLBP + Color autocorrelogram_HS</td>
<td>104(40, 64)</td>
<td>V, HS</td>
<td></td>
</tr>
<tr>
<td>UMLBP + Gabor correlation</td>
<td>72(40, 32)</td>
<td>V</td>
<td></td>
</tr>
<tr>
<td>Gabor correlation + Color autocorrelogram_HS</td>
<td>96(32, 64)</td>
<td>V, HS</td>
<td></td>
</tr>
<tr>
<td>Proposed</td>
<td>136</td>
<td>HSV</td>
<td></td>
</tr>
</tbody>
</table>

The similarity between one of the feature vectors of the target images and a query feature vector is measured by Mahalanobis distance [25] defined as follows:

$$D(f^d, f^q) = \left( \sum_{i=1}^{n} \frac{|f^d_i - f^q_i|^{2M}}{\sigma_i} \right)^{\frac{1}{M}},$$  \hspace{1cm} (19)

where $\cdot$ represents the absolutes, $f^d_i$ is the $i$-th component feature of $f^q$ feature vector extracted from query image $q$, $f^d_i$ is the $i$-th component feature of $f^d$ feature vector extracted from database images and stored in feature database, $M$ denotes the metric order, $n$ represents the feature vector dimension, and $\sigma_i$ is the standard deviation of the $i$-th component features of feature vectors in the entire feature database which is already built.

The generally used measurement for retrieval performance [26] is as follows:

$$\text{precision} = \frac{|A(q) \cap R(q)|}{A(q)},$$  \hspace{1cm} (20)

$$\text{recall} = \frac{|A(q) \cap R(q)|}{R(q)},$$  \hspace{1cm} (21)

where $\cdot$ denotes the size of the set, $q$ is a query image, $A(q)$ represents the retrieved image set for the query image, and $R(q)$ is the relevant image set for the query image.

The proposed Gabor local complex correlation method shows better retrieval performance than one
using absolute as shown in Fig. 2, where the difference shows approximately 6.6% when retrieving 10 images in Corel database.

![Fig. 2. Precision against recall for Gabor correlations using complex and absolute, respectively in Corel database.](image)

Tables 2–4 show the average gains for precision and recall. The average gains of the proposed method is 29.43% and 16.39% for accuracy and recall, respectively, in Corel database and those of 34.2% and 22.58% in VisTex database over the methods using one of our partial features. Moreover, over the methods using pairs of our partial features, the average gains are 5.75% and 3.31% for precision and recall, respectively, in Corel database and 4.26% and 3.07% in VisTex database. However, over the existing methods, the average gains are 21.81% and 12.21% for precision and recall, respectively, in Corel database and 7.07% and 5.15% in VisTex database.

### Table 2. Average gains (%) for precision and recall of the methods using one of our partial features

<table>
<thead>
<tr>
<th></th>
<th>Corel database</th>
<th>VisTex database</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Precision</td>
<td>Recall</td>
</tr>
<tr>
<td>Gabor correlation</td>
<td>18.14</td>
<td>10.16</td>
</tr>
<tr>
<td>UMLBP</td>
<td>55.76</td>
<td>30.80</td>
</tr>
<tr>
<td>Color autocorrelogram̃</td>
<td>14.38</td>
<td>8.20</td>
</tr>
</tbody>
</table>

### Table 3. Average gains (%) for precision and recall of the methods using pairs of our partial features

<table>
<thead>
<tr>
<th></th>
<th>Corel database</th>
<th>VisTex database</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Precision</td>
<td>Recall</td>
</tr>
<tr>
<td>Gabor correlation + RMLBP</td>
<td>11.24</td>
<td>6.52</td>
</tr>
<tr>
<td>UMLBP + Color autocorrelogram̃</td>
<td>5.20</td>
<td>3.12</td>
</tr>
<tr>
<td>Gabor correlation + Color autocorrelogram̃</td>
<td>0.82</td>
<td>0.28</td>
</tr>
</tbody>
</table>

### Table 4. Average gains (%) for precision and recall of the existing methods

<table>
<thead>
<tr>
<th></th>
<th>Corel database</th>
<th>VisTex database</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Precision</td>
<td>Recall</td>
</tr>
<tr>
<td>Color histogram</td>
<td>33.98</td>
<td>19.38</td>
</tr>
<tr>
<td>SCD</td>
<td>11.98</td>
<td>6.44</td>
</tr>
</tbody>
</table>
Figs. 3–5 show graphs for precision against the recall. The apparent points are 10, 30, 50, 70, and 89, corresponding to the number of retrieved images in Corel database and 5, 10, and 15 in VisTex database. In Fig. 3(a) and 3(b), the 2D color autocorrelogram produces 64.44% and 67.33% average precisions in Corel and VisTex databases, respectively, which is found to be the best color feature in the experiments. In Fig. 4(a) and 4(b), as a result of the methods using a pair of our partial features, “Gabor correlation + UMLBP” produces 67.58% and 83.47% average precisions in Corel and VisTex databases, respectively, which is the best harmony for texture features. “UMLBP + Color autocorrelogram\_HS” provides 73.62% and 81.3% average precisions, and “Gabor correlation + Color autocorrelogram\_HS” provides 78% and 83.87% average precisions in Corel and VisTex databases, respectively.

Fig. 5(a) and 5(b) show the retrieval performance of the proposed method against the existing methods. As shown in these figures, the combination of CLBP\_RGB and Color autocorrelogram\_RGB using RGB color space yields relatively high retrieval performance, which is 62.98% and 83.53% average precisions in Corel and VisTex databases, respectively; however, our method using HSV color space outperformed these earlier methods. Furthermore, we confirmed that our method is superior by 3.27% in Corel-1K database against the performance of the method of demonstrated in a recent research [27]. Fig. 6(a) and 6(b) show the top five retrieved images using Corel and ViTex databases accordingly. Based on the result, we confirmed that all result images are similar.

**Fig. 3.** Precision against recall for ones of our partial features in (a) Corel and (b) VisTex databases.
Fig. 4. Precision against recall for pairs of our partial features in (a) Corel and (b) VisTex databases.

Fig. 5. Precision against recall for the proposed method and the existing methods in (a) Corel and (b) VisTex databases.
Fig. 6. Examples of query images and their top-five retrieved images in (a) Corel and (b) VisTex databases.

4. Conclusion

In this paper, we proposed a content-based image retrieval method using combined features extracted from the Gabor local complex correlation, UMLBP, and color autocorrelogram. The Gabor local complex correlation and UMLBP features were used as texture features, and color autocorrelogram features were used as color features. As results of the experiments, the proposed method demonstrates excellent retrieval performance over the compared methods, which include the methods using our proposed partial features and the existing methods. It can be explained by major factors of using Gabor wavelets and the harmony of the combined features.

In a future research, we hope to develop advanced methods with less complexity and improved retrieval performance by adding shape features and adopting recent popular deep learning and bag of word of semantic technologies. It also applies to image databases with different types of contents.

Author’s Contributions

Hee-Hyung Bu wrote the manuscript. All the authors have reviewed the manuscript.

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None.

Competing Interests

The authors declare that they have no competing interests.

References


