IMAGE RETRIEVAL BASED ON HISTOGRAM OF NEW FRACTAL PARAMETERS

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ABSTRACT

Image indexing and retrieval techniques are important for efficient management of visual databases. These techniques are generally developed based on the associated compression techniques. In fractal domain, the luminance offset and contrast scaling parameters are typically used as the fractal index. In this paper, we propose to use the range block mean and contrast scaling as the fractal index. The image retrieval is performed in two steps. First, a coarse search is performed using the histogram of the range block means. Subsequently, a fine search is performed using the 2-D joint histogram of the range block mean and contrast scaling parameters. Experimental results on a database of 416 texture images indicate that the proposed indices significantly improve the retrieval rate, compared to other retrieval methods.

1. INTRODUCTION

Fractal image coding [1-4] was originally developed by Barnsley et al [1]. Subsequently, Jacquin implemented a block-based fractal compression scheme by partition iterated function system, which is popularly known as fractal block coding [2]. The encoding of each range block consists of finding the "best-pair" domain block in the domain block pool. To obtain better performance, Tong et al. [6] recently substituted luminance offset for range block mean in the fractal code.

Because an image can be characterized by its fractal codes, the fractal codes can also be used as the image signature to retrieve an image from image databases. As a result, a few fractal-codes based image retrieval (FCBIR) techniques have been proposed recently.

Zhang et al. [7] have proposed an FCBIR technique where the fractal codes are used as the image index (referred to as the FC technique). Although, the FC technique provides fast retrieval, the corresponding fractal codes cannot be used to reconstruct the retrieved image.

A few researchers have employed the features extracted from fractal codes as indices. Julie et al. [9] have proposed two major attributes as the image index: mean of contrast scaling parameters and mean of the luminance offsets. Although, this technique provides a good indexing performance, the complexity is very high. Lasfar et al. [10] have proposed a retrieval technique (referred to as FDI technique) using the first decoding image (where iteration is initiated from the query image) as an image index. However, the complexity of this technique is very high, and the retrieval fails when the candidate image is a translated version of the query image.

Image histogram of gray or color pixels is known to provide a good indexing and retrieval performance while being computationally inexpensive [5]. Schouten et al. [8] extended this technique to fractal domain. The authors proposed to employ histogram of contrast scaling parameters as an image index (referred to as the HWQCS technique). Although the retrieval is very fast, this index does not provide a high retrieval rate.

In this paper, we propose 1-D histogram of range block means as a coarse image index. Furthermore, we propose a 2-D joint histogram of range block means and contrast scaling parameters as another image index. Experimental results indicate that the proposed indices provide good retrieval performance.

The remainder of the paper is organized as follows. Section II reviews a few selected fractal coding and indexing techniques. The proposed indices are provided in Section III. Experimental results are reported in Section V, which is followed by the conclusions.

2. FRACTAL CODING AND INDEXING

In the section, we first present a brief review of fractal block coding [2-4], and then introduce a selected fractal indexing technique [8].

2.1 Fractal Coding

For each range block $R = \{r_{ij}\}$, traditional fractal block coding seeks to minimize the following distortion

$$E(R,D) = \|R - sD - gU\|^2 = \sum (s * d_{ij} + g - r_{ij})^2 \qquad (1)$$

over $D = \{d_{ij}\} \in \Omega$ (domain block pool) with respect to the contrast scaling parameter s and luminance offset g.

Note that in Eq. (1), U is a matrix whose elements are all ones and $\|\cdot\|$ is the 2-norm. Given a pre-contractive domain block D, the optimal s and g (in the least square sense) can be obtained as follows [3].

$$s = \langle R - \bar{r}U, D - \bar{d}U \rangle \Big/ \left\|D - \bar{d}U\right\|^2, \; g = \bar{r} - s\bar{d} \qquad (2)$$

where $\bar{r}$ and $\bar{d}$ are the average intensities of the range blocks and the pre-contractive domain blocks, respectively. The fractal code of R is

$$(s, g, x_D, y_D) = \arg\min_{D \in \Omega} E(R, D)$$

where (x_D, y_D) is top-left corner coordinate of the "best pair" domain block. Tong et al. [6] replaced g with $\bar{r}_i - s_j\bar{d}$ (where $\bar{r}_i$ is a fractal parameter), and sought to minimize the following distortion

$$\hat{E}(R, D) = \left\|R - \bar{r}_k U - s_i(D - \bar{d}U)\right\|^2 \qquad (3)$$

The modified fractal code of range block R is

$$(s, \bar{r}, x_D, y_D) = \arg\min_{D \in \Omega} \hat{E}(R, D)$$

2.2 Fractal Indexing

Schouten et al. [8] have proposed HWQCS technique where the histogram of weighted quad-tree contrast scaling parameter s is used as the image index. If L refers to the depth of quad-tree partition and J refers to the number of the quantized s, the normalized histogram of the quantized s corresponding to the level l is denoted by $\{v_{lj}\}_{j=1}^{J}$ $(1 \le l \le L)$ and w_l is the weighting factor corresponding to level l, then the image index used in [8] is $h_{lj} = w_l v_{lj}$. Although, the HWQCS technique is fast, the retrieval rate is low.

3. THE PROPOSED INDEXING TECHNIQUE

It has been demonstrated that image histogram provides a good indexing and retrieval performance while being computationally inexpensive [5]. However, histogram is still a coarse statistical feature, and visually different texture images may have similar image histogram. In this section, we propose the histograms of range block mean and contrast scaling parameters as image indices. The indices are detailed in the following.

3.1 Indices

Index-1

The range block mean is an important fractal parameter. From $\{\bar{r}_i\}_{i=1}^{I}$ (where I is the number of possible quantized $\bar{r}$), we count the normalized histogram of range block means $\{p(\bar{r}_i)\}_{i=1}^{I}$, which is used as Index-1. Note that Index-1 is a coarse scale representation of the image histogram, and is expected to provide a good performance. Index-1 is invariant under translation and rotation.

Index-1+HWQCS

Theorem 1: s and $\bar{r}$ are independent.

Proof: Since $D - \bar{d}U$ and U are orthogonal, from Eq. (2) we obtain:

$$s = \frac{\langle R - \bar{r}U, D - \bar{d}U \rangle}{\left\|D - \bar{d}U\right\|^2} = \frac{\langle R, D - \bar{d}U \rangle - \langle \bar{r}U, D - \bar{d}U \rangle}{\left\|D - \bar{d}U\right\|^2}$$
$$= \frac{\langle R, D - \bar{d}U \rangle}{\left\|D - \bar{d}U\right\|^2}$$

In other words, $P(s) = P(s|\bar{r})$ (or $P(\bar{r}, s) = P(\bar{r})P(s)$), and hence s and $\bar{r}$ are independent. ■

Theorem 1 shows that in mathematical sense, $\bar{r}$ and s is better feature representation than g and s for the range block. Hence we choose $\bar{r}$ and s, rather than g and s.

Histogram of contrast scaling parameters (s) has been proposed as an image index [8]. The complexity of this technique is very small. However, the index does not provide a high retrieval rate. Since $\bar{r}$ and s are independent, in order to enhance the retrieval rate, we propose to combine this index and Index-1 as follows:

$$w\{p(\bar{r}_i)\}_{i=1}^{I} + (1 - w)\{v_{1j}\}_{j=1}^{J} \qquad (4)$$

where w and (1-w) are the weights of the histograms of $\bar{r}$ and s, respectively.

The Index-1+HWQCS takes advantage of the statistical information from both $\bar{r}$ and s. Therefore, it is expected to provide a superior performance compared to the histogram of s only. Index-1+HWQCS is also invariant under translation and rotation, and has a low complexity. However, Index-1+HWQCS depends on the weight coefficient w, hence w should be chosen carefully to obtain a good retrieval performance.

Index-2

Index-1+HWQCS provides a good performance. However, it is based on the individual histograms, and does not exploit the joint statistics of these two parameters. Note that the affine transform from the domain block to the range block is determined by both $\bar{r}$ and s. Hence, the 2-D joint histogram of $\bar{r}$ and s would capture the statistical feature of affine transforms more efficiently. Hence we propose to employ the 2-D joint normalized histogram of $\bar{r}$ and s for retrieval and is expressed as

$$\{q(\bar{r}_i, s_j)\} \quad (i = 1, \cdots, I;\ j = 1, \cdots, J).$$

The 2-D joint histogram provides detailed texture information than individual histograms of $\bar{r}$ or s. As a result, Index-2 can be employed as a fine image index. Index-2 is also invariant under translation and rotation.

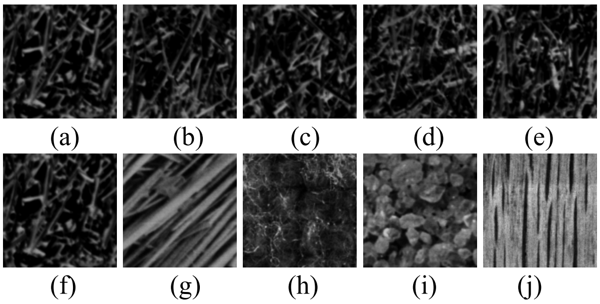
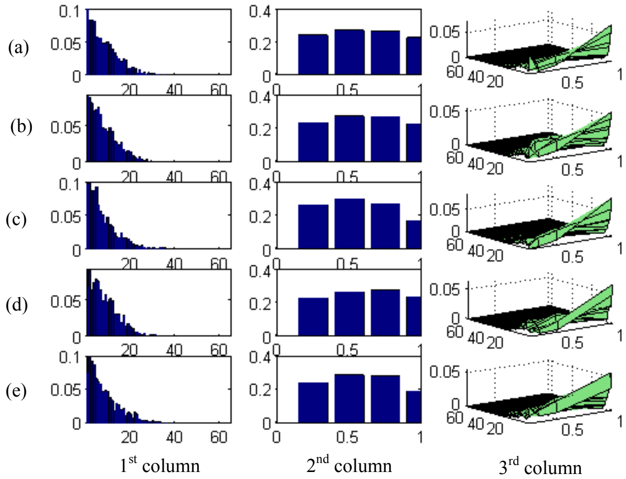
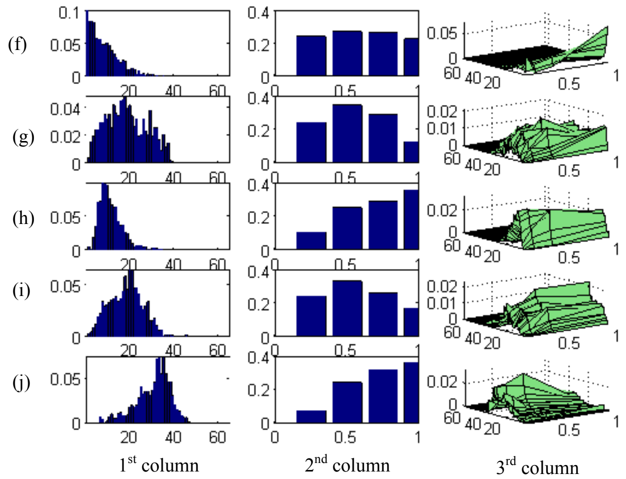


Figure 1: Examples of 128x128 texture images. (a)-(e) Five similar images, (f)-(j) Five different texture images.



(i) Five similar texture images



(ii)Five different texture images

Figure 2: Histogram of fractal parameters corresponding to five similar and different texture images shown in Fig. 1. The 1st column shows Index-1, the 2nd column shows histogram of contrast scaling parameters, and the 3rd column shows Index-2. $\bar{r}$ and s are quantized to 6 and 2 bits, respectively.

Fig. 1 shows five similar and five different texture images. Index-1 (i.e., histogram of $\bar{r}$), histogram of contrast scaling parameters, and Index-2 (the joint histogram of $\bar{r}$ or s) corresponding to these images are plotted in Fig 2. In most cases, the corresponding indices are close for similar texture images, and different for the different texture images.

3.2 Multi-step Retrieval

In the last section, we have presented two indices with different complexities. The Index-1 has a lower complexity than Index-2. In order to achieve a superior performance, a hierarchical retrieval can be employed. The retrieval process can thus be implemented in two steps:

Step 1: Select a short list of candidate images by matching Index-1 or Index-1+HWQCS (satisfying a given threshold).

Step 2: Retrieve the top μ "closest" images from the short-listed images by matching Index-2.

3.3 Similarity Measurement

To measure the similarity between the query image and the candidate images, the proposed indices must be matched using a distance criterion. In this paper, we choose L_p-norm as the distance metric. If $f_Q(\cdot)$ and $f_C(\cdot)$ are the histograms of the query image and candidate image, respectively, the distance of the two images is calculated as follows.

$$d_{L_p}(Q,C) = \sqrt[p]{\frac{1}{V}\left\| f_Q(\cdot) - f_C(\cdot) \right\|^p}$$

where V is the length of feature vector.

4. PERFORMANCE EVALUATION

In this section, we present the performance of the proposed indices and compare it with other retrieval methods.

We have used twenty-six 512x512 gray-scale Brodatz texture images. Each of the 512x512 image is divided into sixteen 128x128 non-overlapping subimages to create a test database of Z=416 texture images. Each subimage is fractal encoded using adaptive search [6] with $T_0 = 3$ and $T_1 = std(R)/8$. $\bar{r}$ is quantized to 6 bits, and s is quantized to 2 bits or 3 bits. In retrieval experiments, a query image is selected randomly from the test database. Sixteen images are then retrieved based on the smallest distance criterion. Ideally, all sixteen images, corresponding to a selected test image, should be retrieved in each test. However, it does not generally happen in practice. We evaluate the performance of the proposed and other retrieval methods using the average retrieval rate that is defined as follows [11]. Let the number of ideally retrieved images be denoted by F (in this case F=16), and the number of correctly retrieved images at z-th test be denoted by m_z. The average retrieval rate is then calculated as

$$\text{Average retrieval rate}=\sum_{z=1}^{Z} m_z \Big/ (F \times Z)$$

In order to compare the proposed techniques with existing FCBIR techniques, we have implemented three FCBIR techniques: HWQCS [8], FC [7], and FDI [10].

The average retrieval rates of various techniques are shown in Table 1. The average retrieval rates of both FC and FDI are 21.4%. Note that the feature vectors used in these indexing techniques do not reflect statistical information of the texture images, and hence the retrieval rates are very low. Generally, these indexing techniques correctly retrieve candidate images that are almost identical to the query image. Another limitation of these techniques is the very high computational complexity. For the FC and FDI techniques, the lengths of feature vectors are 4*(M/B)*(N/B) and MxN, respectively. The image size (MxN) is typically very large, and hence it is impossible to employ these techniques in real-time retrieval systems.

Table 1. Average Retrieval Rate (ARR) of different retrieval methods. L_1 metric has been used to calculate the distance. MxN is the size of image, BxB is the size of range block.

Retrieval Method	Length of the feature vector	ARR (%)
IH	256	55.5
FDI [10]	MxN	21.4
FC [7]	4*(M/B)*(N/B)	21.4
GGD-KLD [11]	18	69.9
HWQCS [8] (L=1)	4 8	42.6 44.5
Index-1	64	51.7
Index-1+HWQCS	68	66.1
Index-2	256	71

The performance of the proposed indices is shown in Table 1. It is observed that Index-1 provides a performance close to that provided by the image histogram (IH) of gray values. This is expected because Index-1 is a coarse scale representation of the image histogram. Note that Index-1 provides a performance superior to all other fractal techniques mentioned in Table 1. The only technique that provides a performance better than Index-1 is the GGD-KLD [11] technique that is based on wavelet (and NOT fractal) features.

As mentioned in Section III, Index-1+HWQCS provides a performance superior to the HWQCS [8]. However, in order to achieve a good performance, the weight w should be selected carefully. The retrieval rate peaks around w=0.9 for the test database, and the corresponding retrieval rate is 66.1% (see Table 1).

It is observed in Table 1 that Index-2 provides the best performance compared to all other existing techniques. The Index-2 provides a performance comparable to GGD-KLD technique that employs wavelet-based features [11]. Although the length of feature vector of the proposed indexing technique is larger than that of GGD-KLD, the multi-step retrieval can be employed to reduce the overall search time.

5. CONCLUSIONS

In this paper, we have proposed two indices: Index-1 and Index-2. Then two indices are employed for two-step image retrieval. Although our discussion is focused on the single level fractal block coding, we can extend the proposed indexing technique into multilevel fractal block coding by multilevel histogram indexing.

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