A Region-Based Image Retrieval System Using Salient Point Extraction and Image Segmentation

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Abstract. Although most image indexing schemes are based on global image features, they have limited capability because they cannot capture local variations of the image properly. In order to solve this problem, we propose a new region-based image retrieval system. Since objects are important for image search in a huge database, we first find the important region including an interesting object using image segmentation and salient point extraction. We then find color and texture features in each important region. We have demonstrated that the color and texture information in the important region is very useful for improving performance of the image retrieval system.

1 Introduction

In recent years, there is a rapid increase in the use of digital image collections, which motivates the research on image retrieval [1]. Early research on image retrieval has suggested manually annotated images. However, such text-based image retrieval techniques are impractical mainly because the textural annotation is usually ambiguous and very laborious to make.

An alternative approach to the manual annotation is content-based image retrieval (CBIR) [1], where images are indexed by their visual features, such as color, texture, and shape. Typically, an image index is a set of features that are extracted from the entire image. However, natural images are mainly composed of several parts of different characteristics. Therefore, it is difficult to represent these characteristics only by a few global features. The current CBIR systems, such as QBIC [2], Netra [3], VisualSEEk [4], and Blobworld [5], have focused on image retrieval based on image objects or important regions.

Our aim in this paper is to find important regions using image segmentation and salient point extraction. After salient points are extracted from an input image by the proposed method, image segmentation is performed. If the area of the selected region is large enough, we extract the important region using image segmentation. Otherwise, we use salient points to detect a region of interest (ROI) around distinct objects. We use image features, such as color and texture in the important region and salient points for similarity matching.

Y.-C. Chen, L.-W. Chang, and C.-T. Hsu (Eds.): PCM 2002, LNCS 2532, pp. 209–216, 2002.

2 Salient Point Extraction

2.1 Conventional Methods for Salient Point Extraction

Since salient points in CBIR can represent local properties of the image, they should be related to any visually interesting part of the image. In order to extract salient points from the image, we can employ conventional algorithms for object corner detection. However, they have drawbacks for image retrieval when applied to various natural images, because visual features do not need corners and which may gather in small regions [6]. Therefore, the conventional algorithms do not capture visual features properly from different parts of images.

The idea of previous algorithms for salient point extraction is to find relevant points to represent global variations by looking at wavelet coefficients at finer resolutions. Those algorithms consider the maximum value and search for the highest child. Applying this process recursively, they select a coefficient at the finer resolution. In order to select a salient point from this operation, they choose one point of the highest gradient value among all children [6].

However, they only consider wavelet coefficients of the selected children and their descendants. As a result, they may miss the situation where the coefficient of other child is larger than that of the selected child. Therefore, there are unnecessary salient points in the background.

2.2 The Proposed Method for Salient Point Extraction

In the proposed algorithm, the information is stored in three ordered lists: the list of insignificant sets (LIS), the list of insignificant salient points (LIP), and the list of significant salient points (LSP). The proposed algorithm consists of three passes: initialization, sorting pass, and update of bit planes.

2.2.1 Initialization: In the first step, we calculate the initial bit plane step n in the wavelet transform image X.

$$n = \lfloor \max_{\forall (i,j) \in X} (\log_2 |C_{i,j}|) \rfloor \tag{1}$$

In the second step, we determine entries of LIS, LIP and LSP. All coefficients in the lowest subband are used as initial LIS entries, and both LIP and LSP are set to null in this initialization pass.

2.2.2 Sorting Pass: We evaluate the significance [7] of sets in LIS. When a set in LIS is identified to be significant, we evaluate whether the set has only one entry or not. If the set has only one entry, e.g., a pixel, we determine the set as the salient point and the set is moved to LSP. Otherwise, significant evaluation of all children nodes and set partitioning [7] are performed. Each child node is partitioned to four quadrants and the set is removed from LIS. Finally, the four partitioned subsets are added to LIS. Fig. 1 shows the procedure of the LIS sorting pass.

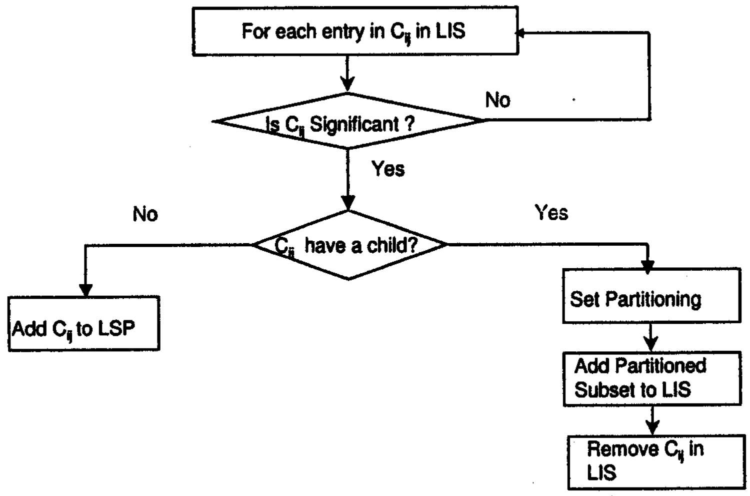
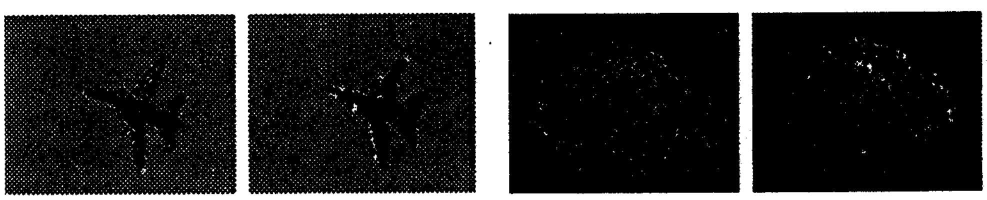


Fig. 1. Procedure for LIS

2.2.3 Update of Bit Planes: After we decrease the bit plane step n by one, we repeat the searching from the sorting pass.



(a) Previous (b) Proposed (c) Previous (d)Proposed

Fig. 2. Comparison of Salient Point Extraction

Fig. 2 shows test results obtained by a conventional method [6] and our proposed algorithm, where the number of salient points is 100. We search for significance of all children using the dispersion principle in the wavelet transform. As shown in Fig. 2, the proposed algorithm can reduce the number of salient points needed to extract the background compared the conventional method. We can obtain extracted results quicker than the conventional recursive method.

3 A Region-Based Image Retrieval System

3.1 Overview of the Proposed System

In this paper, we propose a region-based image retrieval system. Fig. 3 shows the architecture of the proposed system. We can divide it into two parts: database generation and image retrieval.

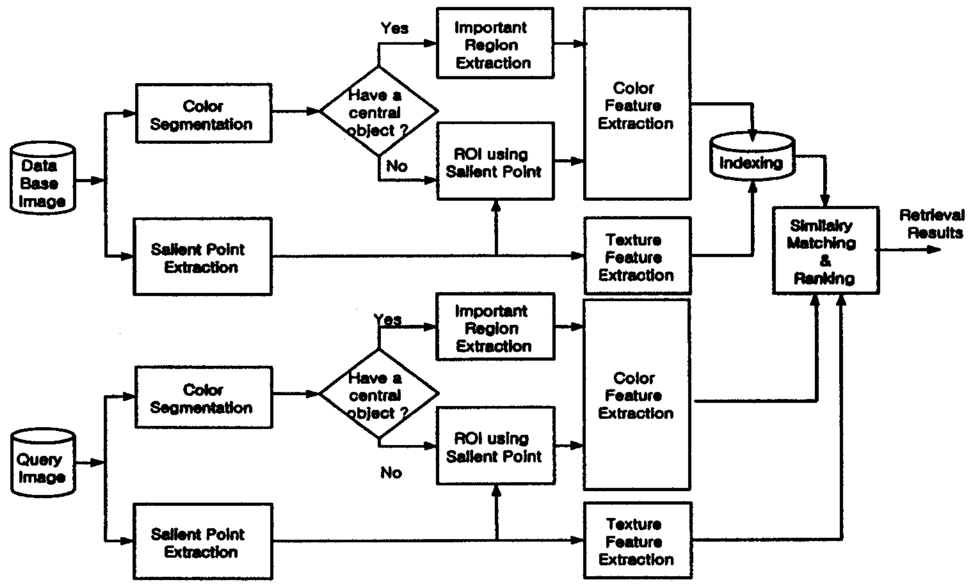


Fig. 3. A Region-based Image Retrieval System

Once salient points are extracted from an input image, they are used to obtain texture features or to form ROI. We then perform image segmentation of two levels [8]. In the first level, we segment an image using three types of adaptive circular filters based on the amount of texture information. In the second level, small patches of the image can be merged into adjacent similar regions by a region merging and labeling method. After image segmentation, we determine important regions or ROI and their important scores.

3.2 Important Region Extraction

Although an image is composed of several regions, all those regions are not equally important for image retrieval. For successful retrieval, we need to find important regions in the image.

In this paper, we propose a new method to search for important regions and extract visually significant features. In general, main objects are located near the center of the scene. Fig. 4(a) shows some examples. We can exploit this property to find important regions by allocating priority levels among different regions. Fig. 5 explains the overall procedure for region extraction.

After image segmentation, we calculate the boundary length and the area of each region. We count the number of pixels that contact with the borders of the image. Then, we check the following condition.

$$\frac{BCL_j}{BL_j} \times 100 \leq Threshold \tag{2}$$

(a) Query Image (b) Segmented Image (c) Important Region

Fig. 4. Results of Region Segmentation

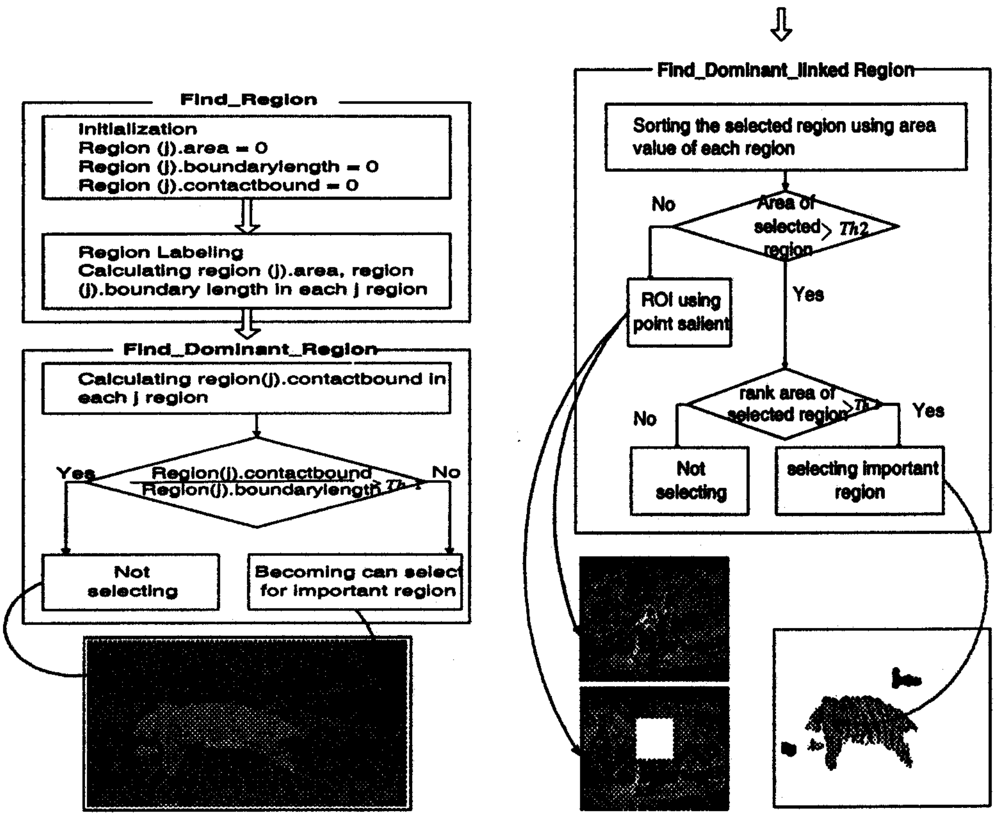


Fig. 5. Procedure of Important Region Extraction

where BCL_j is the number of pixels contacted with the border, BL_j is the boundary length of each region, and j is the index of the region in the image. *Threshold* is experimentally set to 15%.

When this condition is satisfied, the region becomes a candidate for the important region. We assume that all images in the database have one or more important regions. However, some images, such as landscape, cannot be analyzed because there is no common and central object. If pixels in the selected region are more than *Th2*, 2.5% of the total number of pixels, we adopt the sorted regions that rank top *Th3*, 80% of the selected regions. Otherwise, we form a rectangular ROI box around the object by searching the maximum and minimum values among all extracted salient points. Fig. 4 shows result of important region extraction.

3.3 Feature Extraction

We extract color information from the important regions or ROI and texture features from salient points.

In the first step, we use the salient points to extract directional texture information. After selecting top 50% of the salient points, we examine the texture information of pixels in a neighborhood of 3 × 3 pixels around each salient point. After the first-step wavelet transform, high frequency sub-images (LH_1, HL_1, HH_1) are upsampled back to the full size. From the full-sized high-frequency images, we calculate X, Y and XY directional magnitude (X_d, Y_d, XY_d) of each salient point. The distance in texture $(d^T_{Q,T})$ between the query image Q and the database image T is computed by

$$d^T_{Q,T} = |\frac{Yd_Q}{Xd_Q} - \frac{Yd_T}{Xd_T}| + |\frac{XYd_Q}{XYd_Q} - \frac{XYd_T}{XYd_T}| \quad (3)$$

In the second step, we make a color histogram in the extracted important region. The image distance is evaluated by

$$Score = w_1 \cdot H_d + w_2 \cdot D \quad (4)$$

where w_1 and w_2 are weighting factors, set to 0.75 and 0.25 ,respectively. H_d indicates the color histogram distance and D is the directional distance in the texture information.

4 Experimental Results

In order to evaluate performance of the proposed retrieval system, we use the precision factor defined by

$$precision = \frac{detect \ - \ falsealarm}{detect} \quad (5)$$

detect means the number of image which is retrieved images and *false alarm* is the number of image which is not related retrieved image with query images. Our database contains 3000 images from COREL (http://corel.digitlriver.com). We have classified the test set into eight groups: Tiger, Bird, Car, Sun, Flower, Lion, Horse, and Sign. Fig. 6 shows Eagle image query from the Bird group and its retrieval results. Matching quality is decreased from the top left to the bottom right.

Fig. 7 compares precision value of different schemes for each query group. While the global color scheme uses only the color histogram, the global moment

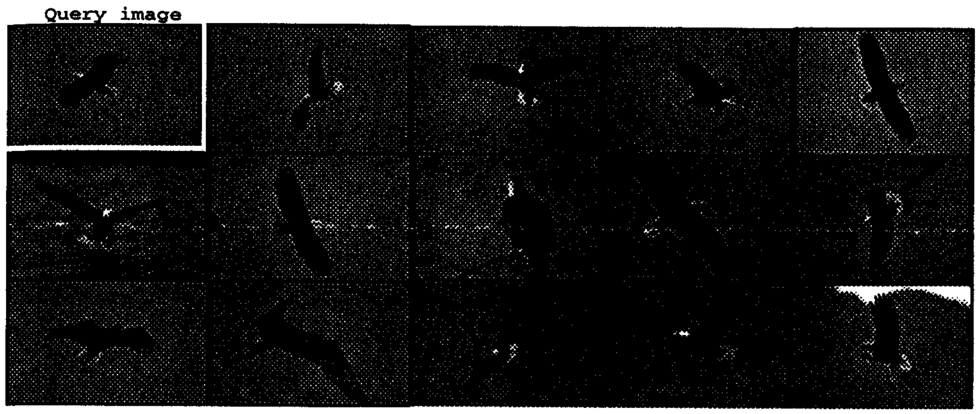


Fig. 6. Retrieved Images from A Query

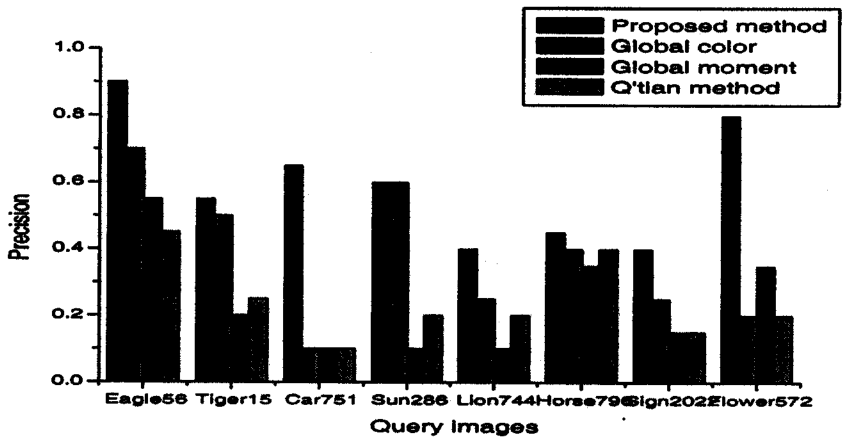


Fig. 7. Performance Comparison

scheme includes the first, second and third moments about the luminance component of the image. Q'tian method [6] is local color indexing using salient point extraction.

When the background of the image is simple, the global color and the global moment schemes perform reasonably well; however, if the image background is complex as in Car and Flower, they do not work well. If the background is complex on the other hand, the proposed algorithm can capture the important region containing a distinct object automatically and correctly. Because the proposed method uses color and texture information in the extracted important region and salient points, we can obtain improved performance compared to other global methods.

5 Conclusions

In this paper, we have proposed a region-based image retrieval system using salient points and important regions. We can find salient points efficiently by removing unnecessary feature points in the background. We extract an important region by capturing the significant object using image segmentation and salient point. Once the important region is determined, we calculate color and texture features and retrieve images by similarity matching. Color and texture features in the important region and salient points enhance retrieval performance significantly, compared to global feature extraction.

Acknowledgement. This work was supported in part by the Korea Science and Engineering Foundation (KOSEF) through the Ultra-Fast Fiber-Optic Networks (UFON) Research Center at Kwangju Institute of Science and Technology (K-JIST), and in part by the Ministry of Education (MOE) through the Brain Korea 21 (BK21) project.

References

1. Chang, S., Smith, J., Beigi, M., and Benitez, A.: Visual Information Retrieval from Large Distributed Online Repositories. Communications of ACM, Vol. 12 (1997) 12–20
2. Flicker, M., Sawhney, H., Niblack, W., Ashley, J. and Yanker, P.: Query by Image and Video Content: The QBIC System. IEEE Computer Special Issue on Content Based Picture Retrieval System, Vol. 28, No. 9 (1995) 23–32
3. Ma, W.Y. and Manjunath, B.S.: Netra: A Tool-box for Navigating Large Image Database. IEEE Conf. on Image Processing, Vol. 1 (1997) 568–571
4. Smith, J. and Chang, S.: VisualSEEk: A Fully Automated Content-Based Image Query System. ACM Multimedia (1996) 87–98
5. Carson, C., Thomas, M., Belongie, S., Hellerstein, J.M. and Malik, J.: Blobworld: A System for Region-based Image Indexing and Retrieval. Int. Conf. Visual Inf. Sys. Vol. 3 (1999) 509–516
6. Tian, Q., Sebe, N., Lew, M.S., Loupias, E. and Huang, T.S.: Image Retrieval using Wavelet-based Salient Points. Journal of Electronic Imaging, Special Issue on Storage, Processing and Retrieval of Digital Media, Vol. 10, No. 4 (2001) 3–11
7. Said, A. and Pearlman, W.A.: A New, Fast, and Efficient Image Codec Based on Set Partitioning in Hierarchical Trees. IEEE Trans. on Circuit and Systems for Video Tech., Vol. 6, No 3 (1996) 243-250
8. Ko, B.C., Lee, H.S. and Byun, H.R.: Region-based Image Retrieval System using Efficient Feature Description. Int. Conf. Pattern Recognition. Vol. 4 (2000) 284–286