

Partial Duplicate Image Retrieval Using Saliency Map

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Abstract

With the rapid improvement of Internet and multimedia technology, users regularly generate partial duplicate images for picture sharing, information delivery, and so forth. Unlike in traditional image retrieval, the duplicate regions in partial duplicate images are only parts of the whole images, and the various kinds of transformations involve scale, viewpoint, illumination, and resolution. Such transformations make the retrieval task more complicated and challenging. Nevertheless, partial duplicate image retrieval is demanded by various real world applications (such as fake image detection, copy protection, and landmark search) and thus has attracted increasing research attention. The partial-duplicate image retrieval problem is similar to object-based image retrieval. Traditional object-based image retrieval methods usually use the whole image as the query and analogize text-retrieval systems by using the bag-of-visual-words (BOV) model. In our system we use different datasets to perform operation and check the performance of system like Caltech256, UKbench etc. Because of some limitations, current technologies cannot satisfactorily perform partial duplicate image retrieval, but they provide some useful insights. For example, removing the background noise from the query image and image dataset will facilitate retrieval. Ideally, noise elimination will be implemented automatically. Appropriate constraints can also improve the retrieval performance, but the constraint should not reduce the retrieval efficiency.

Keywords

Partial Duplicate Image, Image Retrieval, Bags of Visual Words (BOV), Visual Attention, Visual Saliency, Visually Salient Rich Region (VSRR), Caltech256, UKbench.

I. Introduction

In state-of-the-art image retrieval systems, an image is represented by a bag of visual words obtained by quantizing high-dimensional local image descriptors, and scalable schemes inspired by text retrieval are then applied for large scale image indexing and retrieval. Bag-of-words representations, however: 1) reduce the discriminative power of image features due to feature quantization; and 2) ignore geometric relationships among visual words. Exploiting such geometric constraints, by estimating a 2D affine transformation between a query image and each candidate image, has been shown to greatly improve retrieval precision but at high computational cost.

With the rapid improvement of Internet and multimedia technology, users regularly generate partial-duplicate images for picture sharing, information delivery, and so forth. Unlike in traditional image retrieval, the duplicate regions in partial duplicate images are only parts of the whole images, and the various kinds of transformations involve scale, viewpoint, illumination, and resolution. Such transformations make the retrieval task more complicated and challenging. Nevertheless, partial-duplicate image retrieval is demanded by various real-world applications and thus has attracted increasing research attention. Second, to improve the user experience, the similar region in the returned images must also be the salient region for the returned image maker.”

To address these challenges in partial duplicate image retrieval, we first introduce visual attention analysis [8,9] to filter out the non-salient regions from an image, which also helps to eliminate some background noises in the images. Computationally removing the non-salient regions is a useful solution for preferentially allocating computational resources in subsequent image analysis. Another characteristic of the partial-duplicate regions is they have rich visual content. Previous technologies were not able to guarantee that the saliency regions generated would contain rich visual content. To ensure regions with rich visual content, we introduce a visual content analysis algorithm to re-filter the saliency regions.

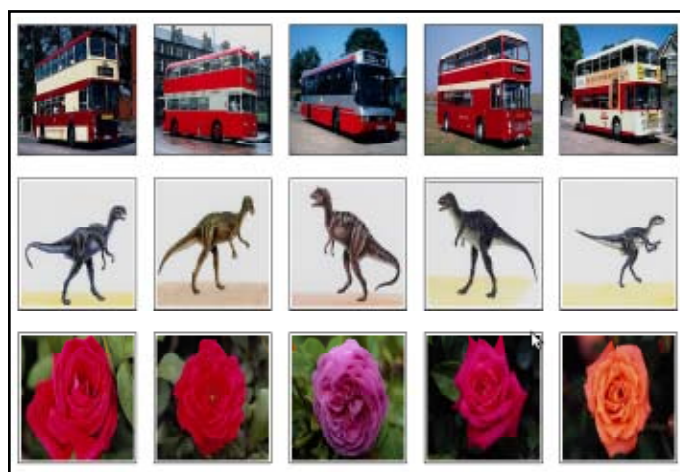


Fig. 1 : Example of Duplicate web images

In this article, we propose a novel partial duplicate image retrieval scheme based on saliency guided visual matching, and the localization of duplicates is obtained simultaneously. Figure 2 provides a flowchart of our scheme. We abstract the visually salient and rich regions (VSRR) in the images as retrieval units. We represent the VSRR using a BOV model, and we take advantage of group sparse coding to encode the visual descriptor, achieving a lower reconstruction error and obtaining a sparse representation at the region level. Furthermore, a robust relative constraint based on the saliency analysis is introduced to refine the retrieval performance, which captures the saliency-relative layout among interest points in the VSRRs. To accelerate the retrieval process, we propose an efficient algorithm to embed this constraint into the index system, which economizes both the computation time and storage spaces. Finally, experiments on five image databases for partial duplicate image retrieval show the efficiency and effectiveness of our approach.

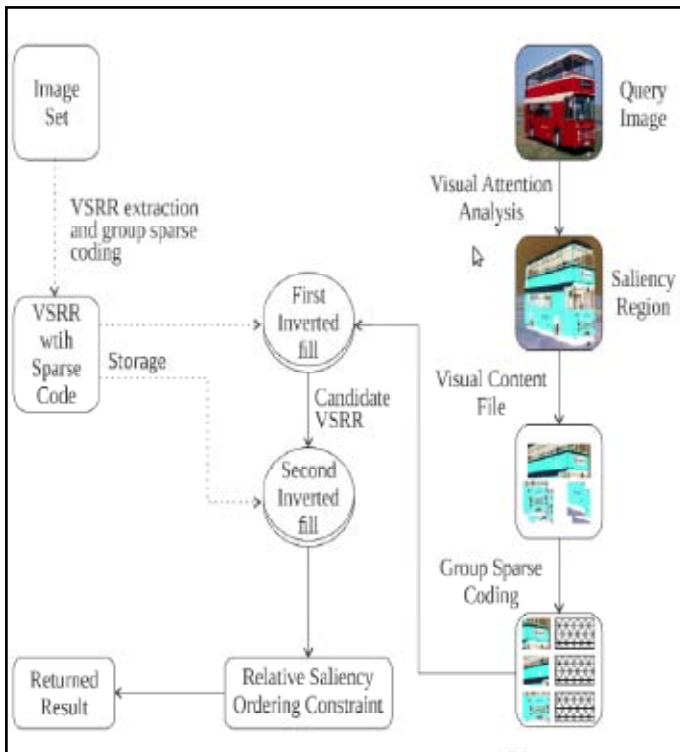


Fig.2 : Partial Duplicates Image Retrieval Schema

II. Generating VSRRs

In this work, we detect VSRRs as the retrieval unit for partial-duplicate image retrieval. We define a VSRR as an image region that has rich visual content and visual saliency. The VSRR generation procedure includes four steps: perceptive unit construction, saliency map generation, original VSRR generation, and ultimate VSRR selection. Finally, the image is decomposed into a set of VSRRs.

III. Saliency map generation

The image regions that have a strong contrast with their surroundings usually attract considerable human attention. Besides contrast, spatial relationships also play an important role in visual attention. A region that highly contrasts with its near

regions usually has a more powerful impetus for its saliency than one with a high contrast with its far regions.

Based on the perceptive units, we compute the saliency map by incorporating spatial relationship with the region contrast. This approach is the bottom-up saliency-detection strategy, and it can separate objects from their surroundings. Specifically, a color histogram for each perceptive unit is first built in the L*a*b* color space. Then, for a perceptive unit r_k , its saliency value is calculated by measuring its color contrast to all other perceptive units in the image. Meanwhile, a weight term for the spatial relationship is introduced to increase the effects of closer regions and decrease the effects of farther regions. This procedure is defined as

$$S(r_k) = \sum_{r_k \neq r_i} \exp(-D_s(r_k, r_i) / w(r_i)) D_r(r_k, r_i)$$

where \exp is the exponential function, $D_s(r_k, r_i)$ is the Euclidean spatial distance between the centroid of perceptive units r_k and r_i , and $w(r_i)$ is the number of pixels in the region r_i . Also, $\#s$ controls the scale of spatial weight; a smaller value of $\#s$ enlarges the effect of spatial weighting. $D_s(r_k, r_i)$ is the 15 color distance between r_k and r_i , which is defined as

$$D_s(r_k, r_i) = \sum_{m=1}^{N_k} \sum_{n=1}^{N_i} f(c_{k,m}) f(c_{i,n}) D(c_{k,m}, c_{i,n})$$

where $D(c_{k,m}, c_{i,n})$ is the distance between pixels $c_{k,m}$ and $c_{i,n}$, and $f(c_{k,m})$ is the probability of the m th color $c_{k,m}$ among all N_k colors in the region r_k .

IV. Relative Saliency Ordering Constraint

The ignorance of the geometric relationship limits the discriminative power of the BOV model. To address this problem, we propose a novel relative-saliency ordering constraint, which is regarded as a saliency-relative layout constraint among interest points in the VSRR. We argue that the relative order of saliency at the interest points is well-preserved in the VSRRs because duplicate VSRRs have a common visual pattern, and their saliency information distribution is similar.

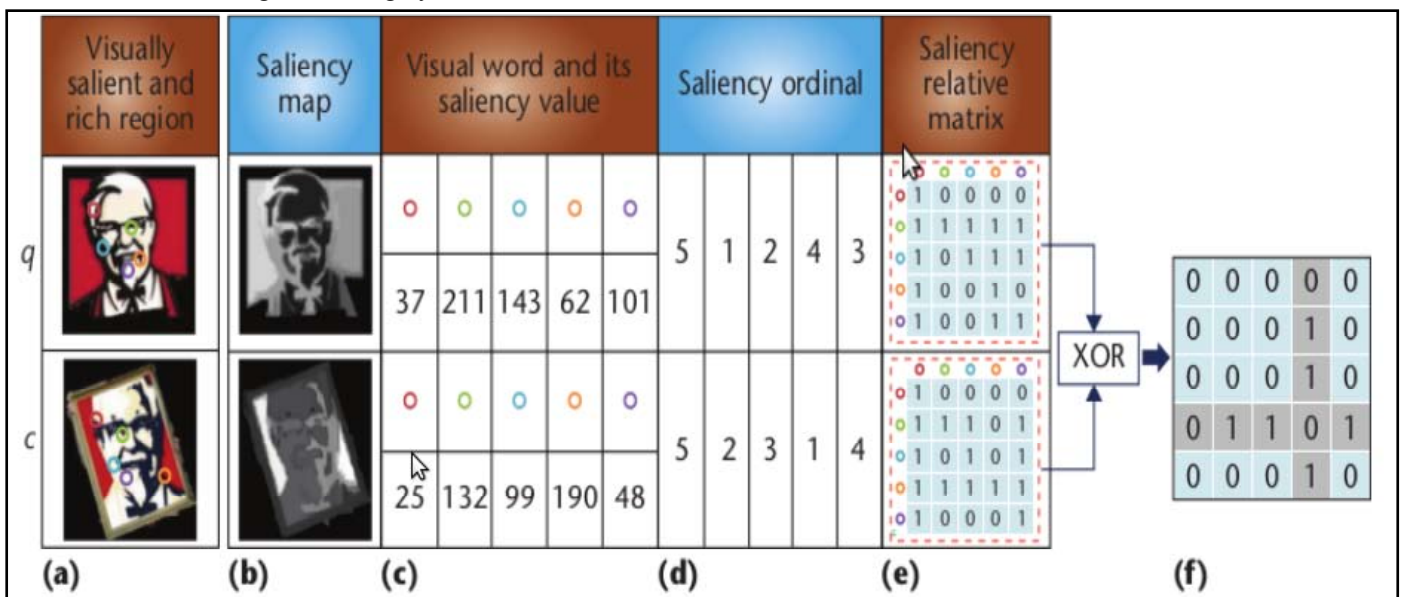


Fig.3. Relative saliency ordering: (a) VSRR with visual words (colored points), (b) the corresponding saliency map with (a), (c) the saliency value at the position of visual word, (d) saliency ordinal vector of visual words in (a), (e) the saliency relative matrix (SRM) of visual words in (a), and (f) the XOR result of the two SRMs in (d).

The first step for constraint verification is to find the matching pairs between VSRRs. Here we employ visual words with a large dictionary for efficient matching. A large dictionary can decrease the matching errors caused by the SIFT quantization. Suppose one query VSRR q and one candidate VSRR c have n matching visual words $VSRR(q) \setminus \{vq_1, \dots, vq_n\}$, and $VSRR(c) \setminus \{vc_1, \dots, vc_n\}$ —and vq_i and vc_i are the i th matching visual word. $S(q) \setminus \{\#q_1, \dots, \#q_n\}$ and $S(c) \setminus \{\#c_1, \dots, \#c_n\}$ represent the saliency values for the corresponding visual words in q and c , respectively. We construct a saliency-relative matrix (SRM) for each VSRR:

$$SRM = \begin{bmatrix} 1 & r_{12} & \dots & r_{1n} \\ r_{21} & 1 & \dots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \dots & 1 \end{bmatrix} \quad SRM^+ = \begin{bmatrix} 1 & 1 & \dots & 1 \\ 0 & 1 & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix}$$

$$r_{ij} = \begin{cases} 0 & \alpha_i > \alpha_j \\ 1 & \text{otherwise} \end{cases}$$

Where SRM is defined by comparing Saliency values α_i , α_j and Visual words v_i , v_j

V. Application

1. Fake Image Detection: Over the years, history greatest painters, sculptors, and craftsman have toiled to create the iconic pieces of art we all become familiar with. While many of those masterpieces remain safely tucked away in museums or private collections, others have not been so lucky. so we can detect those similar images from the large database or from the Internet and able to maintain the copyright of the valuable images.
2. Geometric image searching: If we want to search a particular land image we can easily map the dataset images with the query images and gets the expected result through this application.
3. Crime detection : To solve the crime cases and detect the criminal this application is very useful. We can able to detect the criminal by matching the criminal faces or sketch drawn by the artist. We can search the person from large database and easily solve the criminal cases.

VI. Feature Scope

For future work we believe that investigating more sophisticated techniques for image abstraction, including robust color or structure distance measures, will be beneficial. Moreover, our proposed filter-based formulation is sufficiently general to serve as an extend able framework. We also try apply new techniques to improve the result of image retrieval. In the future, we plan to research both visual attention analysis and visual content analysis and introduce a partial-duplicate image retrieval system. As we develop this application in Java, We also try to develop it for android operating system by which any person who use android device can use this application on large scale.

VII. Conclusion

In the future, we plan to research both visual attention analysis and

visual content analysis and introduce a practical partial-duplicate image retrieval system.

References

- [1] Z. Wu et al., "Adding Affine Invariant Geometric Constraint for Partial-Duplicate Image Retrieval," *Proc. 20th IEEE Conf. Pattern Recognition (ICPR), IEEE CS, 2010*, pp. 842-845.
- [2] J. Sivic and A. Zisserman, "Video Google: A Text Retrieval Approach to Object Matching in Videos," *Proc. 2003 IEEE Conf. Computer Vision (ICCV), vol. 2, IEEE CS, 2003*, pp. 1470-1477.
- [3] Jorge E. Camargo, Juan C. Caicedo, Fabio A. Gonzalez, A kernel-based framework for image collection exploration, *Journal of Visual Languages Computing, Volume 24, Issue 1, February 2013, 53-57. ISSN 10-45-926X. http://dx.doi.org/10.1016/j.jvlc.2012.10.008*
- [4] Treisman, A. M.; G. Gelade (1980). "A feature-integration theory of attention". *Cognitive psychology* 12 (1): 97136. doi:10.1016/0010-0285(80)90005-5. PMID 7351125. Retrieved 2012-11-19.
- [5] Liang Li and Shuqiang Jiang, Zheng-Jun Zha, Zhipeng Wu, Qingming Huang Partial Duplicate Image Retrieval via Saliency Guided Visual Matching, *Proc. 2013 IEEE Computer Society, July-Sept.2013*, pp. 13-23.
- [6] X. Wang et al., Contextual Weighting for Vocabulary Tree Based Image Retrieval, *Proc. 2011 IEEE Conf. Computer Vision (ICCV), IEEE CS, 2011*, pp. 209-216.
- [7] S. Bengio, Pereira, F.; Singer, Y; and Strelow, D. Group Sparse Coding, *NIPS, 2009*.
- [8] D.G. Lowe, Distinctive Image Features from Scale Invariant Keypoints, *Intl J. Computer Vision, vol. 60, no. 2, 2004*, pp. 91-110.
- [9] C. Rother, V. Kolmogorov, and A. Blake, Grabcut: Interactive Foreground Extraction Using Iterated Graph Cuts, *ACM Trans. Graphics, vol. 23, no. 3, 2004*, pp.309-314.
- [10] H. Wu et al., Resizing by Symmetry-Summarization, *ACM Trans. Graphics, vol. 29, no. 6, 2010*, article no. 159.
- [11] M. Chen et al., Global Contrast Based Salient Region Detection, *Proc. 2011 IEEE Conf. Computer Vision and Pattern Recognition (CVPR), IEEE CS, 2011*, pp.409416.
- [12] W. Zhou et al., Spatial Coding for Large Scale Partial-Duplicate Web Image Search, *Proc. Intl Conf. Multimedia, ACM, 2010*, pp. 510-520.
- [13] F. Perronnin et al., Large-Scale Image Retrieval with Compressed Fisher Vectors, *Proc. 2010 IEEE Conf. Computer Vision and Pattern Recognition (CVPR), IEEE CS, 2010*, pp. 3384-3391.
- [14] H. Jegou et al., Aggregating Local Descriptors into a Compact Image Representation, *Proc. 2010 IEEE Conf. Computer Vision and Pattern Recognition (CVPR), IEEE CS, 2010*, pp. 3304-3331.
- [15] D. Nistr and H. Stewnius. Scalable recognition with a vocabulary tree. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR), volume 2, pages 2161-2168, June 2006*.
- [16] Griffin, Gregory and Holub, Alex and Perona, Pietro (2007) Caltech-256 Object Category Dataset. California Institute of Technology. <http://resolver.caltech.edu/CaltechAUTHORS:CNS-TR-2007-001>