IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 5, Issue 5, May 2016

Proficient and Amplified Image Revival via Visual immersion and Saliency Ingredient

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Abstract: Partial duplicate image revival plays an ample role in the real world application such as landmark search, copy protection, fake image detection. Users regularly upload images which are partially duplicate images on the domains like social site Facebook, hike and whatsapp etc. The partial image is only part of whole image, and the various kind of transformation like scale, resolution, illumination, and viewpoint. This technique is demanded by various real world applications and this has been motivated towards this research. In object based image retrieval methods we use the complete image as the query. This revival technique is similar to object based image retrieval. This technique is compare with image revival system by using the bag of visual words (BOV). Typically no any spatial information is used to retrieve image, so this approach is not execute in background noise. There is lots of background noise in the images and impossible to perform operation on the large scale database of the images.Two observations are. First, public show various objects through the images which are shared on the web, we also hope that the returned result also focus on the major parts or objects. Regions of interest are only found in salient region of the revival. The similar region in the returned result also identical to the salient region of the images. To filter out the nor-salient region from the image, which able to eliminate the background noise we introduce visual attention analysis technique. We also generate saliency region which having the expected visual contents.

Keywords: Partial duplicate image, Bags of visual words, Visual attention, Saliency feature, visually salient and rich region (VSRR) Query image, Source image, Sparse coding.

1. INTRODUCTION

In this paper, we propose a partial duplicate image revival scheme based on nearest saliency visual matching. We abstract visually salient and rich region (VSRR) from the images. We represent the VSRR using a BOV model. To achieve a lower restoration error and obtaining a sparse representation at the region level we use a group sparse coding. We also observe our result of image retrieval performance with other image database and show the effectiveness and efficiency of our approach of image revival.

A bag of visual words is nothing but the image which is stated in the state-of-the-art image retrieval systems, and this image is obtained by quantized descriptors of high-dimensional local image. From the scalable schemes of text retrieval the indexing and retrieval of image for large scale is done.To overcome challenges in partial duplicate image retrieval the visual attention analysis is carried out. The visual attention analysis also performs filtering non salient regions from an image and this filtering the unwanted noise which is produced at background of the images. For referentially allocating computational resources in examining subsequent image the non-salient region removal is important. Some other properties of partial-duplicate regions is nothing but to cover maximum visual content. This visual content which is produced by the saliency regions are not present in the old technologies. Introduced refiltering of the saliency regions is done by visual content analysis algorithm to find the regions having rich visual content.

Fig.1.1 Set of partially duplicate web image

2. ARCHITECTURE

We reprise partial duplicate image retrieval scheme based on visual attention and saliency feature. We use the group sparse coding to obtain visually salient and rich region (VSRR) in the images as retrieval units. BOV model used to express VSRR. To accelerate the process of retrieval we proposed efficient algorithms which minimize storage space and computation time. We also practice experiment on different database for partial duplicate image retrieval which shows the efficiency and effectiveness of our approach.

 DOI 10.17148/IJARCCE.2016.5592

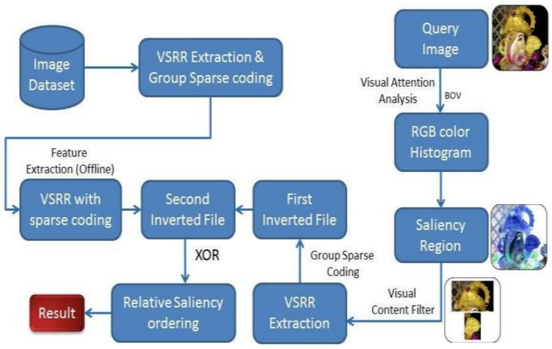

Fig. 2.1 Partial duplicate image retrieval scheme

2.1 VSRR Generation

VSRR is a particular region from image which having rich visual contents and visual saliency. The VSRR generation process is mainly divided into four different sector such as Sensitive unit construction, generation of saliency map, VSRR generation done with selection of ultimate VSRR. The resulted image decomposed into the VSRR sets.

2.2 Sensitive Unit Construction

Sensitive unit is representing as image patch that corresponds to the center of field which willing to accept new fields around it. So that we introduce graph related segmentation algorithm which merges smaller size patches with similar appearances and small minimum spanning tree weight.

2.3 Generation of Saliency map

The particular region of the image which having strong contrast with their surrounding attracts human attention. This spatial relationship gives an important role in visual attention. The region having high attraction which is highly contrasted with its near region than the high contrast with its far region. We compute saliency map on the basis of spatial relationship 1 with the contrast region. This technique is used to separate the Object from their surroundings.th its near region than the high contrast with its far region.

On the computation of L*a*b color space the color histogram is built, and then the sensitive unit, its saliency value is calculated by calculating color contrast of other perceptive units in the image. The weight of spatial relationship is defined as raise the effect of closer region and decline the effect of farther region

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

Where, (Exp ($D_s(r_k,r_i)$)) is the spatial weight and ($w(r_i)D_r(r_k,r_i)$) is the spatial distance between the centroid of perceptive unit and $w(r_i)$) is the number of pixels in the region .Controls the spatial weight. $D_r(r_k,r_i)$ is the color distance between (r_k,r_i). Color distance between rk and ri is calculated as follows

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

Where(Ck,m) is the probability of mth color and (Ci,n) is probability of the nth color.D(ck,m,cin,n) is the distance between the pixel ck,m,cin,n.

2.4 Generation of VSRR

Once the saliency map was produced the next step is to compute the saliency region by saliency segmentation and then we got the original VSRR by filtering the saliency. After filtering we select the VSRR that contains large numbers of visual content. With binaries the saliency map using threshold we divide saliency map into background and initial saliency region. On the early saliency region we apply grabcut. Grabcut is an interactive tool for foreground segmentation in fixed images using iterated graph cuts. Finally a group of region is obtained which is called as original VSRR. The total count of visual content in the VSRR is measured as

$$Score = \sum_{i=1}^{K} \frac{1}{N} \times ni$$

Where K is the volum of dictionary and N and ni,are the numbers of visual word I in this database and VSRR respectively. 1/N defines the informative ness of the visual word and ni represents the repeated structure in the VSRR. After obtaining the VSRR, the popular image representation in image retrieval is nearest neighbor vector quantization (VQ) which is depend on the BOV model. To improve the discriminative power of traditional BOV model we apply Group Sparse Coding (GSC) algorithm. This method gives us to improve our result as compare to traditional BOV model such as lower reconstruction error, lower storage space etc.

2.5 Relative Saliency Order Constraints

If we ignore geometric relationship it limits the discrimination power of the BOV model. To propose a relative saliency ordering constraints we have to first find the matching pairs between VSSRs. Suppose query VSRR q and candidate VSRR chave n numbers of matching visual words. VSRR(q) = $\{V_{q1},\ldots,V_{qn}\}$, and VSRR(c) = $\{V_{c1},\ldots,V_{c\,n}\}$ and $V_{qi}$and $V_{ci}$are the visual matching words. So S(q) = $\{\alpha_{q1}\ldots\alpha_{qn}\}$ and S(c) = $\{\alpha_{c1}\ldots \alpha_{cn}\}$ represents the saliency value in q and c respectively. We construct the relative matrix called saliency relative matrix (SRM)

$$SRM = \begin{bmatrix} 1 & r_{12} & \cdots & r_{1n} \\ r_{21} & 1 & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & 1 \end{bmatrix}$$

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

IJARCCE

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r_{ij} is defined by comparing the saliency values a_i and a_j of v_i and v_j In VSRR. Each visual word is compared with other visual words. The inconsistency of query SRM and the candidate SRM is measured by hamming distance.

$D_{is}= \left| SRM_q \Theta SRM_c \right|_0$ ………… Where I_0 is total number of non-zero element.

3. INDEXING AND RETRIEVAL

To retrieve images from large scale image database retrieval system is a critical factor. We introduced inverted file index scheme to retrieve the result we have to first find candidate VSRRs from the dataset and to refine the output by relative saliency ordering constraint. For efficiency we use index structure with a bilayer inverted file. There are two types of inverted files, first preserves the VSRR information and second stores the saliency order of visual words in each VSSR. By executing the first file we get the ID of candidate VSRR and image which is direct input to the second inverted file

3.1 First inverted file structure

Figure 3.1 shows first inverted file structure. For each visual word in the dictionary D. this structure contain the list of VRSS which having visual word occurs and its term weight. In figure "VW freq." is the sum of weight of visual word i which is calculated by the code of the visual word i by GSC for one VSRR. This file utilizes sparseness to index images and allows fast searching of candidate VSRRs.

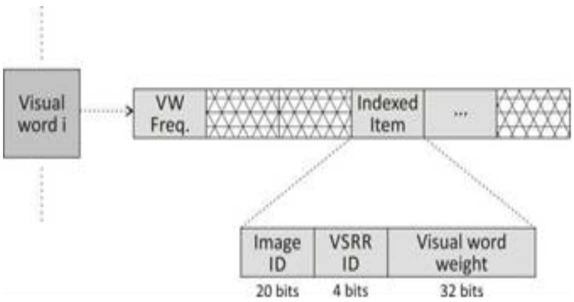

Fig. 3.1 first inverted file structure

3.2 Second inverted file structure

Figure 3.2 shows second inverted file structure. This structure stores the information of each VSRR. "VSRR area" gives total number of pixel. "Vw count" gives total number of visual words in VSRR. "VWi" is ID of the visual word I. These visual words are sorted according to their saliency value in ascending order.

Dictionary D is different in first and second inverted file. Dictionary D is calculated by a hierarchical K means clustering.

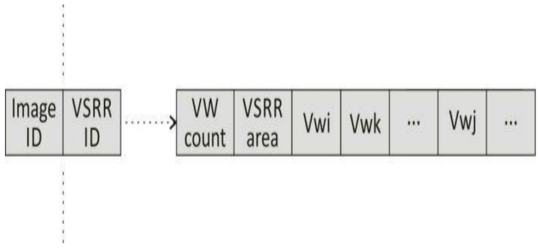

Fig. 3.2 Second inverted file structure

3.3. RETRIEVAL SCHEME

In retrieval scheme we find the candidate VSRR. The process is similar like voting scheme. The score of all VSRR in the database is first initialized to 0, then for every visual word j, we retrieve the list of VSRR from first inverted file. The VSRR count is increase by the weight of visual word score L

(i)=Weight of visual word j/VW j Freq………………..

Likewise we have to process all the visual word the final score of VSRR i is product between the vectors of VSRR i and the query q. then we have to calculate the SRM inconsistency between the query and Candidate VSSR

We define the total matching score M(q,c)

$$M(q,c)=M_v(q,c) + \lambda M_r(q,c)$$

Where Mv(q,c) is a visual Similarity and Mr(q,c) is the consistency relative saliency constrant which is equal to 1-(Inconsistancy(SRM(q,c))). λ is a weight parameter.after obtaining similarity we define similarity between query image Iq and candidate image Im as

Sim(Iq,Im)=ΣqiεIq 2*sqrt(Rarea(qi)) /1+Rarea(qi) *M(qi,mi)……..

Where qi is the i^{th} VSSR of Image Iq

4. EXPERIMENTAL APPROACH

To evaluate our system, we compared our method with the state-of-the-art approaches on five image datasets:

- The Public Internet Partial-Duplicate (PDID) image dataset consists of 10 image collections and 30,000 distractors. 1 each collection has 200 images.
- The Large-Scale Partial-Duplicate (PDID1M) image dataset consists of the PDID dataset and 1 million distracter images from Flickr. The UKbench dataset consists of 2,550 groups of four images each.
- The Mobile dataset includes images of 300 objects, and it indexes 300 images of the digital copies Downloaded from the Internet, blended by the 10,200 images from the UKbench as distracters.
- The Caltech256 (50) dataset is a subset of Caltech256 that consists of 50 classical object categories with 4,988 images.

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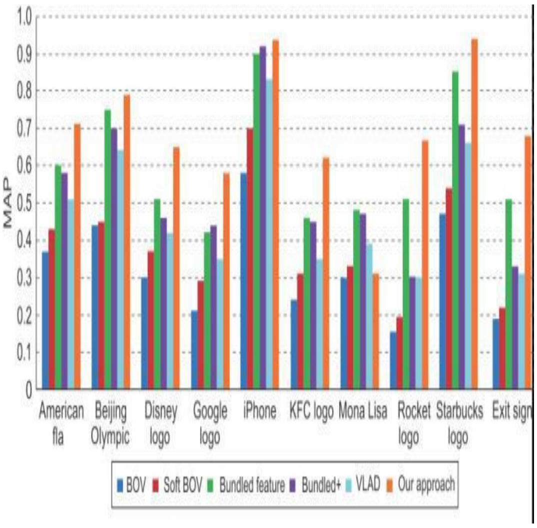

Figure 4.1: Comparison of five approaches with the mean average precision (MAP) for partial-duplicate Image retrieval

We use the evaluation metric this metric is the mean average precision (MAP) which is used to evaluate the PDID, PDID1M, and Caltech256 datasets which we used in our scheme. We calculate the average precision (AP) of our query image. If we compare the performance measurement of the UKbench dataset and Mobile dataset then there is difference. In UKbench dataset we consider top-four retrieved images among the queries and in Mobile dataset top-ten hit rates.

5. MATHEMATICAL MODEL

Let Q be the set of Query images that are going to submit the queries for visual attention analysis.

Query Images Q = {C_xQ1, C_xQ2, C_xQ3,C_xQ4,…C_xQn}

Let S be the set of images who provides number of images from various resources

Source Image S = {C_xS1, C_xS2, C_xS3,C_xS4,…C_xSn}

Let VS be the set of VSRR images with sparse code Source Images

VS = {C_xVS1, C_xVS2, C_xVS3,C_xVS4,…C_xVSn}

Let QS be the set of contents of query images with sparse code

Query Images QS = {C_xQS1, C_xQS2, C_xQS3,C_xQS4,…C_xQSn}

Query images (C_xQ) : it is an image which provide by the user for matching and retrieval purpose which is then analyses and the contents will be separated on the basis of saliency region.

Source Image (C_xS) : it is the set of source images from various sources may be online or offline image source which is then gets extracted as VSRR and group of sparse coding.

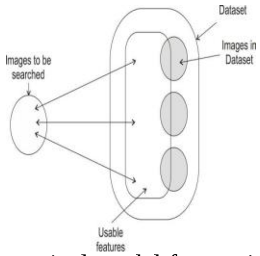

Fig. 5.1 Mathematical model for partial image retrieval

VSRR with sparse code (C_xVS): is a set of extracted image with sparse code in it which is provided to first inverted file and second inverted file. Query images with sparse code (C_xQS) :is a set of query images with sparse code in it which is provided to first inverted fill and second inverted file. The saliency map can be generated by applying set of rules on the available datasets. Saliency map obtained by the union of saliency algorithm and Sparse coding algorithm.

SM=(SA U LSSD U SC)

Track 1: Computer Graphics and Visualization

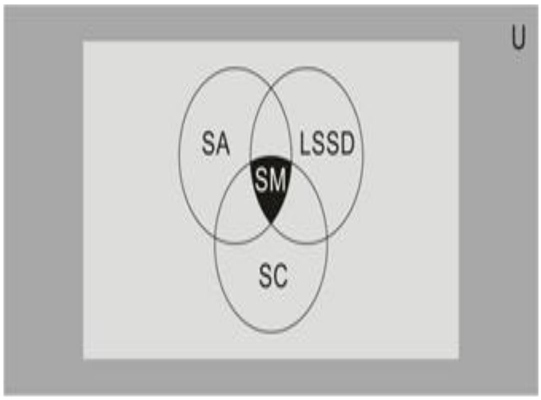

Fig. 5.2.Product set SM

6. CONCLUSION

We presented Saliency Filters, a method for saliency computation based on an image abstraction into structural representative component and contrast-based saliency measures, which can be consistently formulated as high dimensional Gaussian filters. Our filter-based formulation allows for efficient computation and produces per-pixel saliency maps, with the available best performance in a ground truth comparison to various state-of-the-art works.