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Using Visual Constraint Matching Retrieve Efficient Duplicate images

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Abstract: Like object base image retrieval we can retrieve duplicate images using visual matching. During regular use of internet and multimedia technology user share the information and delivered the information at that time images can be duplicated. Image retrieve can be used in different real word application like fake image detection, landmark search, copy protection. By using the bag-of-visual-word(BOV) model whole image as considered as the query analogize text-retrieve system. This approach was not powerful for background noise because of spatial information was not available about the visual words in the retrieval stage.

To solve this problem local descriptors are aggregated in to more discriminative descriptions and weak geometric consistency constraint are contracted on the global image representation with the local feature and also by using user-interest region retrieval through the user interaction such as simplicity.

Keywords: Partial duplicate image, Bags of visual words (BOV), Image retrieval, Visual Attention, Saliency feature, Visually Salient and rich region (VSRR).

I. INTRODUCTION

In this paper, based on nearest saliency visual matching we are generating partial duplicate image retrieval scheme. This image retrieval scheme presents visually salient and rich region (VSRR) from the images. Using a BOV model we are representing the VSRR from the images. By using a group sparse coding lower reconstruction error and obtaining a sparse representation at the region level are achieved. As compare to other image database our image retrieval system gives effective and efficient outputs. Duplicate image retrieval system has rich visual content capability.

II. GENERATING VSRRS

In current paper we detect partial duplicate images sets using visual matching we define new algorithm base on image region called as VSRRs these images region contains high visual content. By using saliency segmentation compute new regions of images. By using the visual content analysis algorithm we refilters visual contents. In VSRR algorithm we count visual content as

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

Where n_i , N_i ,are the numbers of i visual word in the VSRR and total database respectively and k is the dictionary size and n_i reflect the repeated structure in the VSRR , $1/N_i$ captures the informativeness of visual word.

III. SALIENCY MAP GENERATION

Some images regions may have contrast with the surrounding images. By incorporating spatial relationship with the region contrast saliency map is computed. The region which contrasts with near regions has effective impetus for saliency. This approach can be used to separate objects from the other surrounding objects. The process can be defined as

$$S(r_k) = \sum_{r_k \neq r_i} \exp\left(\frac{D_S(r_k,r_i)}{\sigma_S^2}\right) w(r_i) D_r(r_k,r_i \qquad ....(1)$$

Where, $\exp\left(\frac{D_S(r_k,r_i)}{\sigma_S^2}\right)$ is the spatial weight and $\left(\frac{D_S(r_k,r_i)}{\sigma_S^2}\right)$ is the spatial distance between the centroid of perceptive unit $r_k and\ r_i$ and $w(r_i)$ is the number of pixels in the region r_i. σ_s controls the spatial weight. Values of σ_s are affects spatial weight. $(D_S(r_k, r_i))$is the color distance between $r_k and\ r_i$.

IV. ORDERING CONSTRAINT

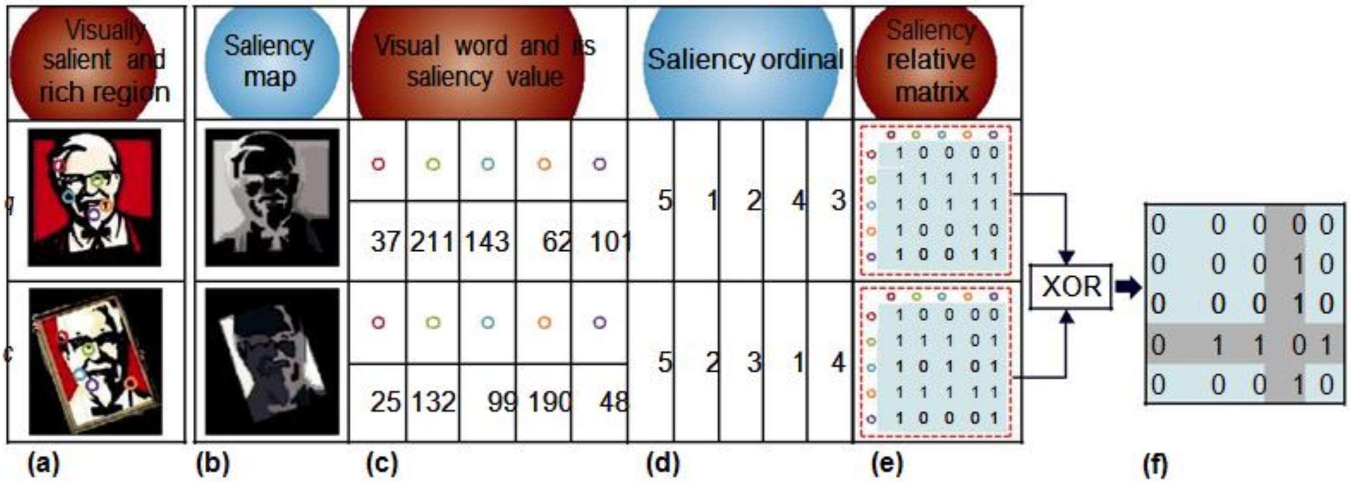

Figure 1. Relative ordering: (a) VSRR with the visual words (colored points), (b) the corresponding map with (a), (c) the saliency value at the position of visual word, (d) saliency ordinal vector of visual words in (a), (e) the saliency relative matrix (SRM) of visual words in (a), and (f) the XOR output of the two SRMs in (d).

In BOV model restrict the discrimination power if we give less attention to geometric relationship. To solve these problem we generate new constraint called as ordering constraint. Ordering constraint was used to find out matching pairs in the VSRR algorithm. For effective matching large dictionary can be used to employ visual words. Using ordering constraint matching error can be reduced with the help of this dictionary. Suppose query VSRR *q* and candidate VSRR *c* has n numbers of matching visual words.

VSRR(q) = $\{V_{q1}, ..., V_{qn}\}$, and VSRR(c) = $\{V_{c1}, ..., V_{c\,n}\}$ and V_{qi} and V_{ci} are the visual matching words. So $S(q) = \{\alpha_{q1} \ldots \alpha_{qn}\}$ and $S(c) = \{\alpha_{c1} \ldots \alpha_{cn}\}$ shows the saliency value in q and c respectively. We developed new the relative matrix called saliency relative matrix (SRM)

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

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

$r_{ij}$is defined by comparing the saliency values $\alpha_i\ and\ \alpha_j$ of $v_i and\ v_j$ in VSRR. Each and every visual word is compared with other words Figure 1e show the SRM of VSRRs . The inconsistency of query SRM and the candidate SRM is measure by the Hamming distance

$$Dis = \left|SRM_q \oplus SRM_c\right|_o \quad ....(2)$$

Where $|.|_0$ (I_0 norm) is the total number of nonzero elements.

Ordering constraint can be expanding in to large scale retrieval depending upon offline inverted file index.

V. RETRIEVAL SCHEME

Suppose in VSRRs given query is q and candidate c has to find out then this can be achieve with the help of voting scheme In the VSRRs database the scores should be initialize to zero during first step. With the help of first inverted file we retrieve list of VSRRs these VSRRs contains visual words. By weights of visual words we are increment the score for each and every VSRRs i in the list as: (i)=(weight of visual words j)/(VW j Freq.) final score of VSRRs i is dot produce between vector i and query q. for ranking cosine similarities is obtain finally. In VSRRs query q and candidate c SRM inconsistency is calculated only after finding the candidate VSRRs. With the help of following formula we are calculating total matching score.

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

Where $M_v(q,c)$ is a visual similarity, and $M_r(q,c)$ is the consistency relative saliency constraint, which is equal to $1 - \left(inconsistency\left(SRM(q,c)\right)\right).\lambda$ is a weight parameter. After getting similarity we define similarity between query image I_q and the candidate image I_m as

$$Sim\left(I_q, I_m\right) = \sum_{qi \in I_q} \frac{2 \times sqrt(R_{area}(q_i))}{1 + R_{area}(q_i)} \times M(q_i, m_i) \quad ....(3)$$

Where q_i is the i^{th} VSRR of image I_q.

VI. DATASETS OF DIFFERENT IMAGES

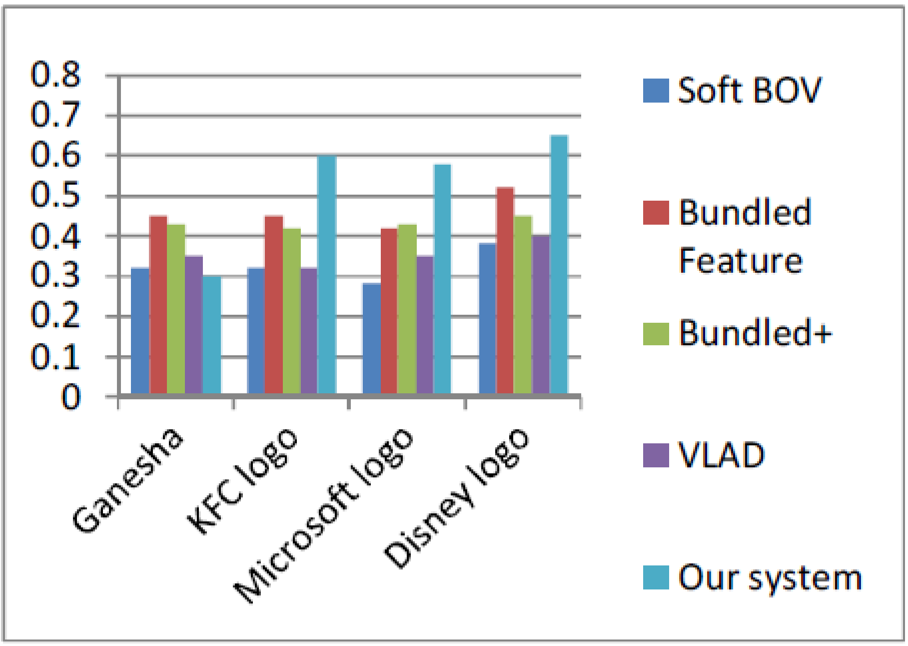

Figure 2 For image retrieval comparison with mean average precision (MAP).

Encoding of very VSRRs with GSC, where many visual word is learn through algorithm. Figure 2 illustrate the experimental observations. The MAP of Bundled+, VLAD, Bundled feature approaches are less as compared to our system approach. The CW method is best working as making comparisons with our approach.

Table 1. Comparison with the state-of-the-art methods on different datasets.*

Dataset	BOV [2]	Soft BOV [7]	Bundled feature [6]	Bundled+ [1]	VLAD [3]	SCSM [15]	k-r NN [16]	CW [15]	Ours
PDID	0.326	0.383	0.599	0.536	0.476	N/A	N/A	0.653	0.688
PDID1M	0.261	0.359	N/A	N/A	0.455	N/A	N/A	0.517	**0.523**
UKbench	3.06	3.19	3.15	N/A	3.54	3.52	**3.67**	3.56	3.58
Mobile	0.683	0.713	0.802	0.783	0.751	**0.816**	0.759	**0.828**	0.815
Caltech256(50)	0.506	0.588	0.682	N/A	N/A	N/A	0.677	0.651	**0.688**

* Bold figures indicate the best results.

BOV approach was base line for our approach. K means clustering was used in our approach with the 0.5 million words was used. To use sparse coding od VSRRs the dictionary with 10236 words in our approach. Table 1 compares with state of art methods on five dataset. Among them many approaches use the technique like soft assignment. Our approach generates better output as compare to other approaches. Our approach make best used of PDID, PDID1M and caltech256(50). k-r NN method gives high performance as compare our approach because our method works better on caltech256(50). The figure 2 compares popular images retrieval methods using PDID1M datasets.

VII. Conclusion

We present a method for using visual matching retrieve duplicate images, Our ordering constraint maps the better observations.

We detect partial duplicate images sets using visual matching we define new algorithm base on image region called as VSRRs these images region contains high visual content. Using a BOV model we are representing the VSRR from the images. By using the visual content analysis algorithm we refilters visual contents

VIII. Future Work

In the future we try to develop mobile application like android for the duplicate image retrieval system. We also try to develop the application which capture the images from mobile and upload that image, after uploading we getting detail information about particular image product or exact location or any relevant information. In this system we try to construct more flexible techniques for image abstraction, including colors or format distance measures will be beneficial.

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