Visual Homograph: A Novel Basic Visual Element

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Abstract

The bag-of-visual-words (BoW) model has been broadly applied to represent images in a variety of image retrieval applications. Ideal visual word vocabulary should obtain two important properties, completeness and distinctiveness (i.e., containing all the similar image patches and eliminating different ones accurately). However, the traditional definition of basic visual elements tend to lack in either generality or particularity, which will lead to the incoherence problem and further ruin the image retrieval performance. To address this issue, in this article, we propose a novel basic visual element called Visual Homograph – groups of local patches which have indivisible descriptors but differ in origins. To generate Visual Homograph based vocabulary, we also propose a novel similarity metric named Integrated Perceptual Similarity which systematically combines center-based and boundary-based measures. Experimental results on standard datasets demonstrate the superiority of Visual Homograph based method over state-of-the-art visual vocabulary generation approaches, in terms of alleviating incoherence problem, and enhancing retrieval performance in practical applications.

Keywords: Image retrieval, Integrated Perceptual Similarity, Visual Homographs

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Figure 1: An analogy between image and text retrieval.

1. Introduction

Inspired by text retrieval, bag-of-visual-words(BoW) model has been successfully applied in a variety of image retrieval applications [1, 2, 3, 4]. Visual words are regarded as clusters of similar local patches, and generated based on a simple assumption – the descriptors of similar patches will be close to each other in some appropriate metric. Based on the BoW description, many algorithms in text retrieval such as inverted file and context analysis can be directly applied to large-scale image retrieval applications [5, 6, 7].

However, in contrast to words in text retrieval, such intrinsic entities do not exist in the visual domain. Therefore, the generation of visual words/elements from image patches is an essential component, and has been extensively explored in the prior literature. As illustrated in Figure 1, the existing basic visual ele-

Figure 2: Interpretation and some instances of different basic visual elements.

15 elements can be summarized as: traditional visual words [2], visual synonyms [8]
 and identical visual words [9]. These visual elements respectively corresponds
 to three types of patch similarity metrics, Euclidean similarity [2, 4], semantic
 similarity [10, 11] and origin similarity [9, 8]. Traditional visual words are cre-
 20 ated by clustering image patches in unsupervised ways based on local feature
 Euclidean distance. Traditional visual words are the most common and popular
 visual elements, however, the performance is not satisfied since Euclidean dis-
 tance between descriptors is a good indicator of patch similarity only in certain
 range. Visual synonyms leverage supervised methods to learn semantic similar-
 ities for particular object recognition. However, the patch similarities are often
 defined towards particular object recognition, and thus lack extensibility—only
 suitable for classification tasks within limited number of object categories. Iden-
 25 tical visual words refer to the patches which come from the same object/origin
 under different viewpoints. The performance is unsatisfied because of the large
 variation of local patches and descriptors.

Due to the limitation of existing basic visual elements (the definition of patch

Figure 3: Instances of Visual Homographs which have indivisible descriptors but differ in origins.

similarity tend to be either too general or too specific), the performance of visual patch clustering is not ideal. As illustrated in Figure 2 (a)(b), the results from traditional visual words tend to be over-partitioning (similar patches are assigned into different groups), while results from visual synonyms turn to be under-partitioning (noise/errors are included in clusters). This phenomenon is called "Incoherence Problem" [8].

To address this issue, in this article, we aim to explore the appropriate definition of basic visual elements in order to construct the complete and distinctive visual vocabulary (that is to say, all of the similar patches should be clustered together and different ones should be eliminated accurately). Inspired by text homograph (group of words that have the same spelling but differ in meanings), in this article, we propose a novel definition of basic visual elements called Visual Homographs, which denotes groups of image patches with similar appearance (with indivisible descriptors) but may come from different objects, see Figure 3. These patches with similar appearance should not be separated, although they come from different objects/origins. Separating them coercively will lead to the over-partitioning problem, and also result in a very huge visual vocabulary. Moreover, to establish the relationship between these over-partitioned words using exhaustively search in this huge vocabulary is too expensive. Therefore, Visual Homograph based vocabulary can significantly alleviate the incoherence problem.

To generate Visual Homograph based vocabulary, we also present a novel similarity metric called Integrated Perceptual Similarity which appropriately integrates center-based measure and boundary-based measure to generate local

patch similarities. Experiments on standard datasets demonstrate that the proposed visual element–Visual Homograph can effectively alleviate the incoherence
 55 problem, and achieve better image retrieval performance, compared with conventional visual elements. We summarize the main contribution of this article as follows.

- Propose a novel definition of basic visual elements called Visual Homographs, to effectively alleviate the incoherence problem.
- 60 • Present Integrated Perceptual Similarity which appropriately integrates center-based measure and boundary-based measure to group the relevant visual patches.
- Describe the efficient approach to assign new patch to Visual Homograph based vocabulary.
- 65 • Conduct experiments on standard dataset to demonstrate the effectiveness and efficiency of the proposed method.

The rest of our work is organized as follows. We start by introducing conventional basic visual elements in Section 2. And then in Section 3, we present the proposed Integrated Perceptual Similarity, and the algorithm to generate
 70 and assign Visual Homographs. The proposed method is empirically evaluated in Section 4. Finally, we conclude in Section 5 by highlighting the key points of our work.

2. Related Work

In this section, we briefly introduce the three types of conventional visual
 75 elements (traditional visual words [2], visual synonyms [8] and identical visual words [9]), as well as the corresponding three kinds of patch similarity metrics.

Traditional visual words are created by clustering local descriptors of image patches in unsupervised ways using Euclidean distance, such as k-means and

hierarchical clustering [2, 3]. Each cluster is taken as a visual word like Figure 2(a). A new descriptor is assigned to its nearest word, according to the Euclidean distance between the descriptor and cluster centers. Although visual word has been very popular in recent years, it is often proven not as effective as the textual words due to the incoherence problem [4, 8]. The reason might be that the Euclidean distance between descriptors is a good indicator of patch similarity only in certain range [9], thus the accuracy of patch classification will be seriously affected by clustering number, initial centers and noise data.

Since only relying on Euclidean distance is too general to classify patches accurately, researchers have developed many supervised methods to learn semantic similarities for particular object recognition [10, 11, 12, 13]. By assigning semantic class labels such as “cars” and “bikes” to local descriptors, the semantic similarities between descriptors are learned with Extremely Randomized Clustering Forests [10], and patches sharing the same semantic label are supposed to be clustered into the same visual words. Based on a universal vocabulary, particular class vocabularies such as cat and dog vocabularies are obtained through the adaptation of the universal vocabulary using class-specific data [11]. These methods provide “middle -level” representations which help to bridge the semantic gap between the low-level features and the high-level concepts to be categorized. However, the patch similarities are often defined toward particular object recognition, thus lack extensibility and are only suitable for classification tasks within limited number of object categories. Moreover, due to the semantic gap, the incoherence problem especially “under-partitioning problem” is hard to avoid, that is to say, there are many patches belonging to different semantic categories existing in the same patch groups, as shown in Figure 2(b).

Recently, using a fine partitioned vocabulary to avoid the under-partitioning problem has been popular [9, 8]. Because only patches extracted from identical objects (the same origin) are considered to be similar, a very large vocabulary including several million words is constructed (one or two orders of magnitude larger than commonly used). Furthermore, although the probabilistic relationships between words are learned and stored additionally in [9], the

110 over-partitioning problem is inevitable due to the variation of local patches and descriptors.

More advanced methods have been proposed to optimize the vocabulary, such as soft assignment and Hamming embedding [4, 5, 14]. Some prior work [15, 16, 17, 18] conduct a comprehensive study on the representation choices of BoW, including vocabulary size, weighting scheme, stop word removal, feature
115 selection, spatial information, and visual bi-gram. However, since the basic definitions of patch similarity are not improved in essence, there is no guarantee that the patch classification of those methods can be complete and distinctive at the same time.

120 Therefore, it is a fundamental issue to define the patch similarity and construct a meaningful visual vocabulary. Only with a proper definition of patch similarity, can we find a proper way to generate complete and distinctive basic visual elements based on existing local feature extraction methods. Thus in this paper, we propose the novel definition of visual element – visual homograph, which denotes groups of image patches with similar appearance (with indivisible
125 descriptors) but may come from different objects. In addition, we also propose a novel similarity metric called Integrated Perceptual Similarity to generate VH based vocabulary.

3. Visual Homograph

130 In this section, we mainly discuss the proposed basic visual element – Visual Homograph, which refers to groups of image patches with similar appearance (with indivisible descriptors) but may come from different objects. To generate Visual Homograph based vocabulary, we first introduce the novel similarity metric called Integrated Perceptual Similarity, and then discuss the generation
135 and assignment for visual homograph based vocabulary.

3.1. Integrated Perceptual Similarity

The key issue in exploring a meaningful visual vocabulary is the definition of patch similarities/relevance. Based on the obtained relevance score, a given

Figure 4: Two types of similarity calculation methods.

patch can be regarded as relevant or non-relevant to a particular visual group.

140 In our case, according to the definition of visual homograph, we define the “relevant patches” as the patches with similar appearance but may come from different objects.

Generally, the existing relevance calculation methods can be broadly categorized into two categories: center-based measure and boundary-based measure, 145 as illustrated in Figure 4. The traditional visual words and the identical visual words are often generated with center-based measure, while visual synonyms with similar semantic are obtained using boundary-based measure. The former is easy to calculate thus support fast search in huge database using indexes such as k-d tree or LSH [19], but it is a good indicator of patch similarity only in 150 certain range [9]. The latter has better generalization by exploring the potential association between descriptions, but heavily rely on the choice of training data.

To generate and assign Visual Homographs, we propose “Integrated Perceptual Similarity” which systematically integrate the aforementioned two measures. As illustrated in Figure 5, a coarse-partitioning vocabulary is first calculated using center-based measure, such as k-means. Within each cluster, 155 begin with patches sharing the same origins, every set of relative patches are found out using boundary-based measure based on similarity propagation. Such groups of patches are regarded Visual Homographs in this paper. Given a new patch, it will be assigned to the most similar Visual Homograph based on both

Figure 5: Visual Homographs generation based on similarity propagation.

center-based distance and boundary-based distance. In this way, the incoherence
 problem existing in current methods can be mitigated effectively and efficiently.

3.2. Visual Homographs Generation

In order to generate complete and distinctive Visual Homographs, the key
 issue is to find out which patches are relative and hard to be separated by
 descriptors.

First, inspired by [9, 8], images containing the same objects are found out
 with high visual similarity and strict geometric verification. Only patches ex-
 tracted from the same objects with similar locations are regarded as relative.

However, due to variations of patches and descriptors, relative patches de-
 fined in this way are usually very limited. Therefore, we learn from [20, 21] and
 expand the above methods. A large set of synthetic images are generated for
 each original image by simulating different transitions of camera optical axis.
 Random noise and Gaussian blur are also added. Using this method, many more
 images can be matched correctly, and the basic groups of many more relative
 patches are generated.

The second issue is how to establish the relationship between different basic
 groups. We solve this problem using similarity propagation with one-class SVM
 [22]. The reason for choosing one-class SVM is that: the number of positive in-
 stances is still very small compared with all possible variations, and the negative
 instances are hard to determine in this task. Thus one-class SVM is suitable for
 describing the boundary of relative patches in each group.

Let $x_1, x_2, \dots, x_l$ be relative patches belonging to a basic group X. Using
 a kernel map which transforms the training descriptors to another space, one-

class SVM separates the positive data from the origin, by solving the following
185 quadratic programming problem:

$$\min \frac{1}{2} \|w\|^2 + \frac{1}{vl} \sum_{i=1}^l \xi_i - \rho \quad (1)$$

Subject to

$$(w \cdot \Phi(x_i)) \geq \rho - \xi_i, \quad i = 1, 2, \dots, l, \quad \xi_i \geq 0 \quad (2)$$

Where l denotes the number of relative patches, and $\Phi(x_i)$ is the kernel map
function. More details can be found in [22]. The algorithm for Visual Homo-
graphs generation is summarized in algorithm 1, and the process of similarity
190 propagation is illustrated in Figure 4.

Algorithm 1: Algorithm for Visual Homographs Generation

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1 foreach unsettled patch  $x_k$  in coarse-partitioned cluster  $a$  do
2   Suppose  $x_k$  is included in basic group  $X_i$  with the same
   origin, train a one-class SVM “ $SV M_i$ ” with all patches from group
    $X_i$  within cluster  $a$ 
3   Classify other patches within cluster  $a$  using the classifier  $SV M_i$ 
   foreach positive patch from group  $X_j$  do
4     Suppose group  $X_j$  has  $M$  patches within cluster  $a$  and  $N$ 
     patches are positive
5     if  $\frac{N}{M} > T_{ratio}$  then
6       Combine group  $X_i$  and  $X_j$ 
7       Train new classifier  $SV M_{i+j}$ 
8       Repeat from step 3 until no more group added;
9     else
10      Repeat from step 4 for other groups;
11 return the sets of relative groups

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In this way, growing from a small and over-partitioned group of patches, an indivisible and complete set of relative patches can be obtained. And these sets of patches are called Visual Homographs in this paper.

3.3. Visual Homographs Assignment

195 With a large vocabulary consisting of many Visual Homographs, how to assign a new patch to the most similar Visual Homographs effectively and efficiently is also very important for practical applications.

Aforementioned, Visual Homographs has been generated by combining two similarity metrics. Among them k-means is used to obtain a coarse-partitioning
200 result, thus delimits the search range of relative patches during the Visual Homographs generation process. The same method could also support fast assignment of Visual Homographs.

Given a new patch, top K nearest Visual Homographs are first found out as candidates ($K = 10$ in this paper), based on Euclidean distance between the
205 patch and Visual Homograph centers. Using index such as k-d tree or LSH methods, this step can be accomplished very quickly.

And then, the new patch is further classified using one - class SVM models trained during generation step. The new patch will be finally assigned to the Visual Homographs with positive classification result. The patch with all negative
210 classification values is directly assigned to the nearest Visual Homograph for simplicity.

4. Experiments

The goal of this work is to explore the novel basic elements to construct a visual vocabulary which are more complete and distinctive, in order to support
215 a wide range of visual based applications. To evaluate the performance of the proposed “Visual Homograph” element, we conduct a series of experiments on several standard datasets, including the Ukbench dataset [3], INRIA holidays dataset [5] and internet partial-duplicate image database (IPD) [23]. The Ukbench dataset contains 10200 images totally, involving 2550 image categories;

220 each category has 4 instances of one object with different viewpoints and distances. The INRIA holidays dataset contains 500 image groups, each of which represents a distinct scene or object. The IPD dataset consists of 10 image collections which has 200 partial-duplicates in each, and 8,000 non-duplicate web images. Thus it contains totally 10,000 images, including 2000 images with 10
 225 collections and 8000 non-duplicate images.

To extract local patches and descriptions, MSER detector and SIFT descriptor [24] are leveraged, since they can achieved the best repeatability and accuracy [24]. Although many modified versions are reported to obtain better performance in some particular tests, they are not suitable for a wide range of
 230 applications.

In the experiments, we mainly focus on three aspects: (a) The effectiveness of Visual Homographs in alleviating the incoherence problem. (b) Retrieval accuracy in practical applications. (c) The memory and time cost of Visual Homographs generation and assignment.

235 4.1. Alleviation of Incoherence Problem

In this subsection, experiments are conducted to demonstrate the effectiveness of the proposed Visual Homographs in alleviating the incoherence problem. To optimize the local similarity measures of patch similarity, a large training set is required. Enough instances for each object should be provided for training. Here, we use the Ukbench dataset [3] as the training set, which consists of
 240 10200 images in 2550 image categories. To obtain more instances with different viewpoints and distances for each category, we leverage the expansion methods to generate more relative images. For each category, we generate 41 synthetic images. These synthetic images can be utilized for patch similarity learning. Finally, using this training dataset, about 120,000 visual homographs are gen-
 245 erated, which will be leveraged throughout the later experiments. Figure 3 demonstrated the examples of visual homographs generated in our experiments.

We compare the performance of Visual Homographs (VH) with several the-state-of-art vocabulary generation methods, including traditional visual words

Figure 6: Integrity comparisons between three methods.

250 (TVW) [4] and the identical visual words (IVW) [9]. In the experiments, 3 nearest TVWs are taken into account as suggested in paper [4] (TVW Top3), and 5 alternative words of IVW are utilized based on paper [9] (IVW Top5, the performance improves slowly when the number is larger than 5).

To measure the completeness and distinctiveness of the visual vocabulary, 255 we choose integrity as the evaluation metric. It refers to the ratio of corrected patches to all the clustered patches, as to each type of visual patches, denoted as,

$$\text{integrity} = \frac{\# \text{ corrected patches}}{\# \text{ total patches}} \quad (3)$$

In our experiments, to compute integrity, we select 10 types of patches randomly from different objects in the Ukbench dataset, and manually record the 260 relative patches as ground truth. Note that total count of relative patches in this dataset is larger than 4, since the original images are expanded to a large set of synthetic images.

Figure 6 illustrates the comparison between our Visual Homograph (VH) method with traditional visual words (TVW) and the identical visual words 265 (IVW). As illustrated in Figure 6, the integrity of our VH method is comparable with IVW and much better than TVW. Besides, TVW is generated leveraging unsupervised clustering, which will lead to more noise and error patches. This comparison demonstrates the effectiveness of our VH method in alleviating

Figure 7: Some instances for NDD results using Visual Homographs (The leftmost is the query image).

incoherence problem.

270 Compared with IVW, the advantage of our approach is that we leverage the Integrated Perceptual Similarity to group image patches with similar appearance which might come from different objects. IVW only groups patches extracted from identical objects (the same origin), which will lead to a very large vocabulary and over-partitioning problem. Our approach can significantly
 275 alleviate the incoherence problem.

4.2. Performance in Near-Duplicate image Detection

To test the performance of our approach in practical application, we apply the VH based visual vocabulary to the task of Near-Duplicate image Detection (NDD). The notion of near-duplicate images simply refers to the images which
 280 share the identical copies of an original object. The duplicate areas are only parts of the whole images and located in different locations with various of transformations. Thus NDD is a very challenging task, but also a useful practical application.

In this experiment, we combine the INRIA holiday dataset and IPD dataset
 285 to construct a large image dataset to conduct the NDD task. To evaluate the performance of different methods in NDD task, we use the images in IPD database as query image. There are 10 image collections which has 200 dupli-

Figure 8: Performance comparison of NDD retrieval with MAP.

cates for each category. Figure 7 illustrates some instances of detection results utilizing our VH method (the lefemost is the query image).

290 We choose Mean Average Precision (MAP) as the evaluation metric. MAP is calculated for each category with randomly selected query images. Figure 8 demonstrates the comparison between our VH approach with IVW Top5 and TVW Top3. The comparison illustrates the superiority of our VH method to TVW and IVW. However, since we use coarse-partitioning clustering result
295 first to accelerate the training and mapping steps, the MAP performance is unavoidable influenced by the coarse-clustering result. It is a tradeoff between accuracy and speed. With a larger training dataset and a proper expansion method (e.g. considering n nearest clusters during the training and mapping process), the performance of our VH can be significantly improved.

300 It is also obvious that even using a totally different training set, our VH method can still perform well. This demonstrates that the patch similarity definition of VH is feasible for practical application, and learning local similarity metrics with multiple measures can provide good generalization.

4.3. Memory and Time Cost

305 Besides retrieval accuracy, the memory and time cost are also very important for practical applications. Learning distribution models is often prohibitively computationally expensive. However, using integrated metrics as section 3, the generation and assignment of our VH is very efficient.

The similarity propagation process for discovering VHs in the training dataset
310 costs less than 2 hours. And the assignment for a new patch costs less than 0.1 second.

Although our method needs extra memory to record SVM model for each Visual Homograph, the parameters need to be stored in memory is very limited (only several KB for one model). Therefore the memory cost can be neglected
315 in comparison with traditional visual words.

5. Conclusion

In this article, we have explored the appropriate definition of basic visual element to construct more complete and distinctive visual vocabulary, in order to support a wide range of image based applications. Inspired by text retrieval,
320 we have proposed a novel basic visual element called Visual Homograph which denotes groups of patches with indivisible descriptors but extracted from different objects. To generate the Visual Homograph based vocabulary, we have also presented a novel patch similarity metric called Integrated Perceptual Similarity to group relevant patches together. Experimental results on standard
325 datasets demonstrate the superiority of Visual Homograph based method over state-of-the-art visual vocabulary generation approaches, in terms of alleviating incoherence problem, and retrieval performance in practical applications.

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