CATEGORIZATION OF SIMILAR OBJECTS USING BAG OF VISUAL WORDS AND SUPPORT VECTOR MACHINES

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Abstract: This paper studies the problem of visual subcategorization of objects within a larger category. Such categorization seems more challenging than categorization of objects from visually distinctive categories, previously presented in the literature. The proposed methodology is based on "Bag of Visual Words" using Scale-Invariant Feature Transform (SIFT) descriptors and Support Vector Machines (SVM). We present the results of the experimental session, both for categorization of visually similar and visually distinctive objects. In addition, we attempt to empirically identify the most effective visual dictionary size and the feature vector normalization scheme.

1 INTRODUCTION

This paper is devoted to the problem of generic visual categorization within the same class of objects. In particular, the goal is to subcategorize the images depicting objects which belong to the same high level visual category. As an example, let us consider a set of shoe images, such as those presented in Figure 1.

Then, the objective is to subcategorize the shoe images by type (i.e. as sneakers or trekking shoes).

It can be noted that although both types of shoes are generally similar in shape and appearance, human observers can easily identify many fine details, which are decisive for categorization.

In recent years, Bag of Visual Words (BoVW) image representation method has received much attention in solving generic visual categorization problems (Csurka et al., 2004). The approach is derived from bag-of-words approach, successively applied in text categorization (Lewis, 1998; Joachims, 1998), where the idea is to describe the text document using the frequencies of the words occurrences. The image can be described in a similar way using the frequently occurring local image patches, so also known as 'visual words'.

Figure 1: A sample of shoe images, retrieved from Internet, that can be subcategorized as sneakers or trekking shoes.

The first step in representing an image using visual words is to detect and describe image keypoints - small image patches that contain relevant local information about the image. The choice of keypoint detector is important as it has a significant impact on the successive phases of the categorization process.

Among many descriptors proposed in the literature, Scale-Invariant Feature Transform (SIFT) (Lowe, 2004) and Speeded Up Robust Features (SURF) (Bay et al., 2008) are reported to be the most effective, since they provide keypoints invariant to image rotation, scale, perspective and illumination changes. For a comprehensive survey of keypoint detectors see (Tuytelaars and Mikolajczyk, 2008; Mikolajczyk et al., 2005).

In the next step, a dictionary of visual words is constructed by means of unsupervised clustering. Each visual word is a subset of image patches that are similar to each other. Hence, a visual word represents some local pattern which is shared across many images. Typically, *k*-means algorithm or similar is applied to build the visual dictionary from image keypoints.
Given the dictionary, the representation of an image is obtained by assigning its image patches to the cor-

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responding visual words and then by building a histogram of these words. From this point, the image can be categorized in a similar way to a text document. To categorize the images, a multi-class classifier can be employed, using visual word histograms as feature vectors (Winn et al., 2005; Csurka et al., 2004; Cai et al., 2010).

This paper is organized as follows. Section 2 describes the proposed methodology which consists of keypoint identification, visual dictionary construction and categorization using Support Vector Machines (SVM) (Boser et al., 1992; Chang and Lin, 2011).

Section 3 presents the details of the experimental sessions. Section 4 concludes the paper.

2 METHODOLOGY

The following section presents the details of the image categorization process, based on BoVW representation. Our approach consists of three main phases.

Firstly, the SIFT algorithm was applied for keypoint identification in imagery datasets. Secondly, these keypoints was exploited to create instances of visual words by means of unsupervised learning technique.

It was achieved by the *k*-means clustering algorithm. For each image the vector representation was obtained with different normalization schemes and the components of that vector correspond to ”visual words” from dictionary. During the last phase, datasets were classified by means of the SVM method.

2.1 Keypoint Identification

For keypoint identification the SIFT algorithm described in (Lowe, 2004) was chosen. This method is proven to be resistant against the changes in image scale, rotation, illumination and 3D viewpoint (Kleek, ; Mikolajczyk and Schmid, 2005). Regardless of how the image was transformed, any of the descriptors found using the SIFT algorithm retains its original features. This makes it possible to find corresponding points in the images containing similar objects, but in a different scale, perspective or with different light intensity.

The process of key point identification is divided into four phases. Initially, ”Scale-space extrema detection” is performed. In this stage all scales and image locations are searched for potential interest points, with the use of a difference-of-Gaussian technique. In the stage named ”Keypoint localization”, the keypoint candidates with the worst stability measure are discarded. During the third phase called ”Orientation assignment”, each keypoint is enriched with information about its relative orientation based on local image gradients. Finally, keypoint descriptors, which are robust on local distortion and change in illumination, are created from the local image regions around the keypoints. This phase is called ”Keypoint descriptor”.

The result of the SIFT algorithm execution is a set of keypoints which captures important details of the image. Each keypoint contains information about scale, orientation and location and its descriptor is represented as a numerical vector. The size of the vector is fixed in advance and depends on the choice of the local region size. The vector usually has 128 dimensions, which is determined by the choice of a 4x4 descriptor region. Depending on the image size and complexity the number of obtained keypoints varies from a hundred to a few thousand.

2.2 Visual Dictionary Construction

Due to the fact that many keypoints retrieved by the SIFT algorithm are similar, it’s necessary to generalize and group the points into clusters which represent ”visual words”. For this purpose, *k*-means, an unsupervised learning algorithm, was used due to its simplicity and satisfactory performance. The idea of *k*-means lies in a division of the observation into predefined number of sub-sets, so that the sum of the distances from each keypoint to the center of particular cluster is minimized. This can be formalized using the following formula:

$$\arg\min_{\mathbf{S}} \sum_{i=1}^{k} \sum_{\mathbf{x}_j \in S_i} \left\| \mathbf{x}_j - \mu_i \right\|^2, \tag{1}$$

where $(x_1, x_2, \ldots, x_n)$ are observation vectors, μ_i is mean of i-th centroid and k is the number of clusters.

As a result of clusterization process, k ”visual words” are obtained, which allows the assignment of the particular ”visual word” for each descriptor. An important issue is the choice of parameter k, which affects the performance and accuracy. If the number of clusters is too small, the algorithm will assign distinctive keypoints to the same ”visual word”.

Thus, classification accuracy would be significantly reduced. On the other hand, too big k leads to over-representation, so that similar keypoints are represented by different ”visual words”, which results in a decrease of performance and accuracy. Tests for different values of parameter k were performed, all details are described in the experimental section.

2.3 Categorization

On the basis of image keypoint assignment to visual words (clusters), the histogram of incidence is created for each image from imaginary dataset. As a result, a *k*-dimensional feature vector is obtained.

This allows us to unify the representation of the images, reducing the problem of a visual categorization process to a simpler task of feature vector classification.

However, the results of classification based solely on the histograms are rarely satisfactory. Therefore, the different forms of vector normalization and word weighting can be applied to increase the classification accuracy. In this paper, for the feature vector $x = (x_1, \ldots, x_k)$, three schemes of normalization are considered, in particular:

1. Max norm

$$\|x\|_\infty = \max\left(|x_1|, \ldots, |x_k|\right), \tag{2}$$

2. Euclidean norm

$$\|x\|_2 = \left(\sum_{i=1}^{k} |x_i|^2\right)^{\frac{1}{2}}, \tag{3}$$

3. Manhattan norm

$$\|x\|_1 = \sum_{i=1}^{k} |x_i|. \tag{4}$$

The normalized feature vector $\hat{x}$ is given by:

$$\hat{x} = \frac{x}{\|x\|}, \tag{5}$$

where $\|x\|$ can be $\|x\|_1, \|x\|_2, \|x\|_\infty$.

The SVM (Boser et al., 1992; Chang and Lin, 2011) was used as a classification method. The SVM is a binary classifier that searches for the optimal hyperplane which separates observations from both classes of training set by solving the quadratic optimization task.

Given a set of instance-label pairs (x_i, y_i); $i = 1, \ldots, l$; $x_i \in R^n; y_i \in \{-1, +1\}$, SVM solves the following dual problem (6) derived from the primal problem described in (Chang and Lin, 2011):

$$\min_{\alpha} \frac{1}{2}\alpha^T Q\alpha - e^T\alpha, \tag{6}$$

subject to

$$y^T\alpha = 0; \quad 0 \le \alpha_i \le C; i = 1, \ldots, l; \tag{7}$$

where $C > 0$ is a penalty parameter that determines the tradeoff between the margin size and the amount of error in training, α is a vector of Lagrange multipliers introduced during conversion form the primal to dual problem, e is the unit vector, Q is an l by l positive semidefinite matrix such that $Q_{ij} = y_i y_j K(x_i, x_j)$ and $K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$ is the kernel function, which maps training vectors into a higher dimensional space via function ϕ.

The problems which are non-linearly separable can be solved by the SVM using the ”Kernel Trick”.

Apart form the linear, the most frequently used kernels of the SVM are RBF and polynomial. During the experimental session the RBF kernel (8) was chosen.

$$K(x_i, x_j) = \exp(-\gamma\|x_i - x_j\|^2), \tag{8}$$

where x_i, x_j are observations and $\gamma > 0$.

The label $F(x)$ of the feature vector x can be predicted using the following equation:

$$F(x_{new}) = sign\left(\sum_{i=1}^{l} y_i \alpha_i K(x_i, x_{new}) + b\right). \tag{9}$$

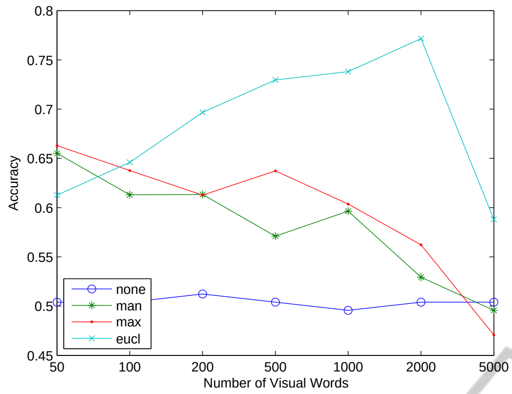
The results of the SVM image classification with the RBF kernel are described in the experimental section.

3 RESULTS OF EXPERIMENTS

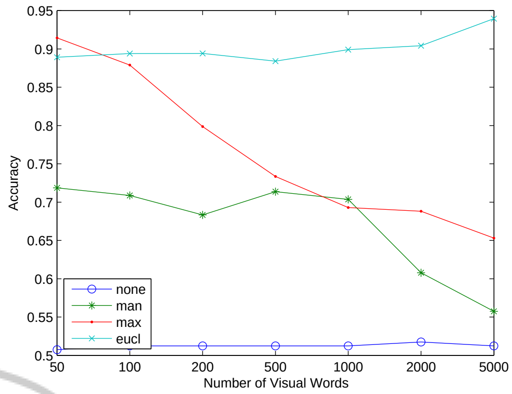
The goal of the experimental session was to assess the performance of the classification of visually similar objects compared with the classification of visually distinctive objects. For this purpose, six datasets were created by combining images depicting objects from different visual categories. Each main category consisted of 60 images downloaded from the Internet. The datasets contained the following categories of images:

1. tulips vs. roses - 120 images (26368 image keypoints),
2. sneakers vs. trekking boots - 120 images (19499 image keypoints),
3. men’s watches vs. women’s watches - 120 images (75846 image keypoints),
4. flowers (dataset 1) vs. shoes (dataset 2) - 240 images (45867 image keypoints),
5. shoes (dataset 2) vs. watches and flowers (datasets 3 and 4) - 360 images (121713 157881 image keypoints),
6. flowers (dataset 1) vs. watches (dataset 3) - 240 images (10214 image keypoints).

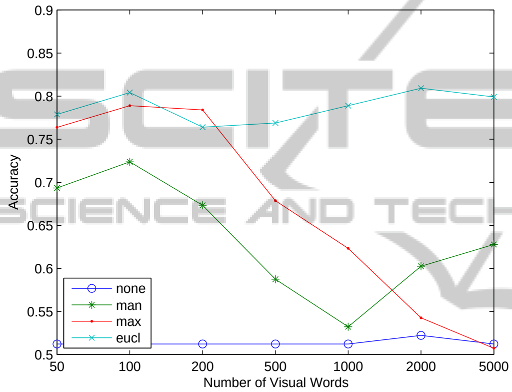
The number of images for dataset 1–3 in each class was even (i.e. dataset 1 contained 60 tulip and 60 rose images) only dataset 5 contains unbalance number of the objects in each class (120 vs 240). In addition, an



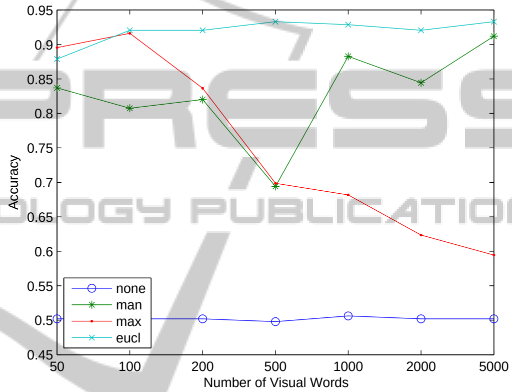
(a) Classification of tulips vs. roses



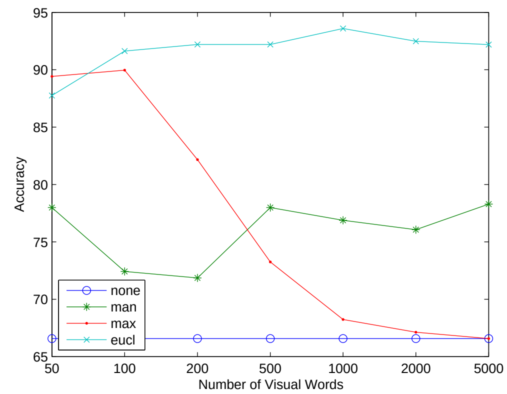
(b) Classification of sneakers vs. trekking boots



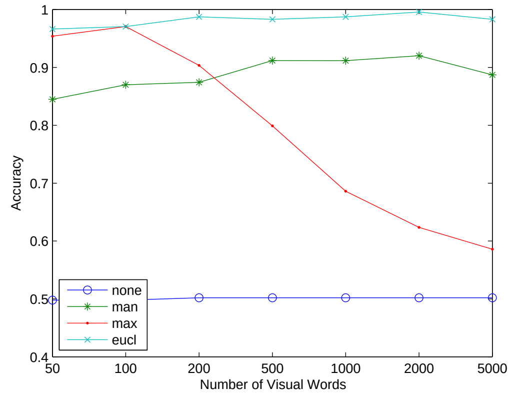
(c) Classification of men's vs. women's watches



(d) Classification of flowers vs. shoes.



(e) Classification of shoes vs. watches and flowers.



(f) Classification of flowers vs. watches

Figure 2: Final classification results for datasets 1 (a) – 6 (f), none = results for none normalization case, man = results for Manhattan norm, max = results for max norm, eucl = results for Euclidean norm.

overall number of keypoints found by SIFT in each dataset is reported in parentheses.

For each dataset, the visual dictionary was constructed by extracting keypoints from all images in the dataset using SIFT and by clustering with the use of *k*-means, as described in section 2.2. To identify the most suitable dictionary size, the process of dictionary construction was repeated for the following values of *k*: 50, 100, 200, 500, 1000, 2000, 5000.

Additionally, for each of the dictionaries, datasets were classified using various normalization techniques (described in section 2.3) in order to identify the most effective one for the categorization task.

SVM with RBF kernel (with defaults parameters) was employed to classify the datasets. The accuracy of the classification was estimated using 5-fold cross validation. The results of the classification for all datasets and all metrics, as well as none metric case, are presented in Figure 2, which shows the dependence between number of visual words and classification accuracy.

It can be noted that the Euclidean normalization outperforms all other normalization techniques in terms of classification accuracy, especially for a bigger dictionary sizes from the interval [200, 5000]. The exception to that rule is a fully comparable result for 200 visual words of max norm in case of classifying men's vs womens's watches - see (c) in Figure 2. For a smaller size of dictionary in range of 50,100 visual words, max and Euclidean normalization works fully comparable.

Detailed classification results for our best Euclidean normalization are presented in Tables 1 and 2. Interestingly, when feature vectors are not normalized, the classification is completely ineffective since an average accuracy is close to 50%.

Table 1: Final classification results for datasets 1–3 using Euclidean normalization.

No. of visual words	Dataset		
	1	2	3
50	61.27%	88.92%	77.88%
100	64.60%	89.40%	80.41%
200	69.67%	89.42%	76.40%
500	72.97%	88.41%	76.88%
1000	73.80%	89.91%	78.90%
2000	77.17%	90.42%	80.92%
5000	58.80%	93.95%	79.91%

Table 2: Final classification results for datasets 4–6 using Euclidean normalization.

No. of visual words	Dataset		
	4	5	6
50	87.89%	87.75%	96.65%
100	92.05%	91.63%	97.70%
200	92.06%	92.2%	98.74%
500	93.30%	92.2%	98.32%
1000	92.87%	93.59%	98.74%
2000	92.05%	92.48%	99.58%
5000	93.30%	92.19%	98.32%

Regarding the most suitable dictionary size, for most cases where $k = 2000$, the accuracy of classification is the highest for datasets 1, 3 and 6. It can be noted that, for visually distinctive objects (datasets 4–6), the choice of k is not that important - any dictionary larger than 500 visual words seems reasonable. In contrast, for visually similar objects (datasets 1–3), the most optimal dictionary size is 2000 words.

To compare classification results between visually similar and distinctive datasets, $k = 2000$ and Euclidean normalization were chosen. For this case, an average classification accuracy for datasets 1–3 was 82.84% and an average classification accuracy for datasets 4–6 was 96.37%. As expected, the classification of visually similar objects turned out be more challenging compared to visually distinctive ones, and in our case the difference in classification accuracy was 13.53%.

4 CONCLUSIONS AND FUTURE WORK

The main aim of the article was to compare classification images belonging to the same domain and image classification from various categories by means of "Bag of Visual Word" technique. The obtained results show that the former problem is harder to solve and in the majority of cases classification accuracy is lower than in the latter. In addition, studies on the impact of the number of "visual words" in dictionary on the accuracy of classification were undertaken. Taking into account the tradeoff between the performance and effectiveness, the optimal results for 2000 "visual words" were obtained for all datasets. However, for these datasets with visual distinctive objects, the satisfactory results were achieved using at least 500 "visual words". Additionally, the best method of normalization among those studied in terms of classification accuracy proved to be Euclidean normalization.

Bag of visual words opens up opportunities for taking some techniques from classic Information Retrieval discipline, especially the various mechanism of dictionary building and the term weighting methods, which we plan to investigate. Moreover, in the future we are going to pay more attention to the spatial image feature correlation and its impact on classification accuracy.

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