



# Creating Compact and Discriminative Visual Vocabularies Using Visual Bits

T. Kirishanthi and A. Ramanan

Department of Computer Science, University of Jaffna, Sri Lanka.



## Introduction

The generic framework of a bag-of-features (BoF) approach is depicted in Figure 1 (1,8-15). The problem with this approach lies in that constructing a vocabulary for each single dataset is not efficient. Usually the construction of a vocabulary is achieved by cluster analysis.

- A larger size of vocabulary increases the computational needs.
- On the other hand, a smaller size vocabulary degrades the classification rate.

Therefore, the choice of the size of a vocabulary should be balanced between the recognition rate and computational needs.

## Objectives

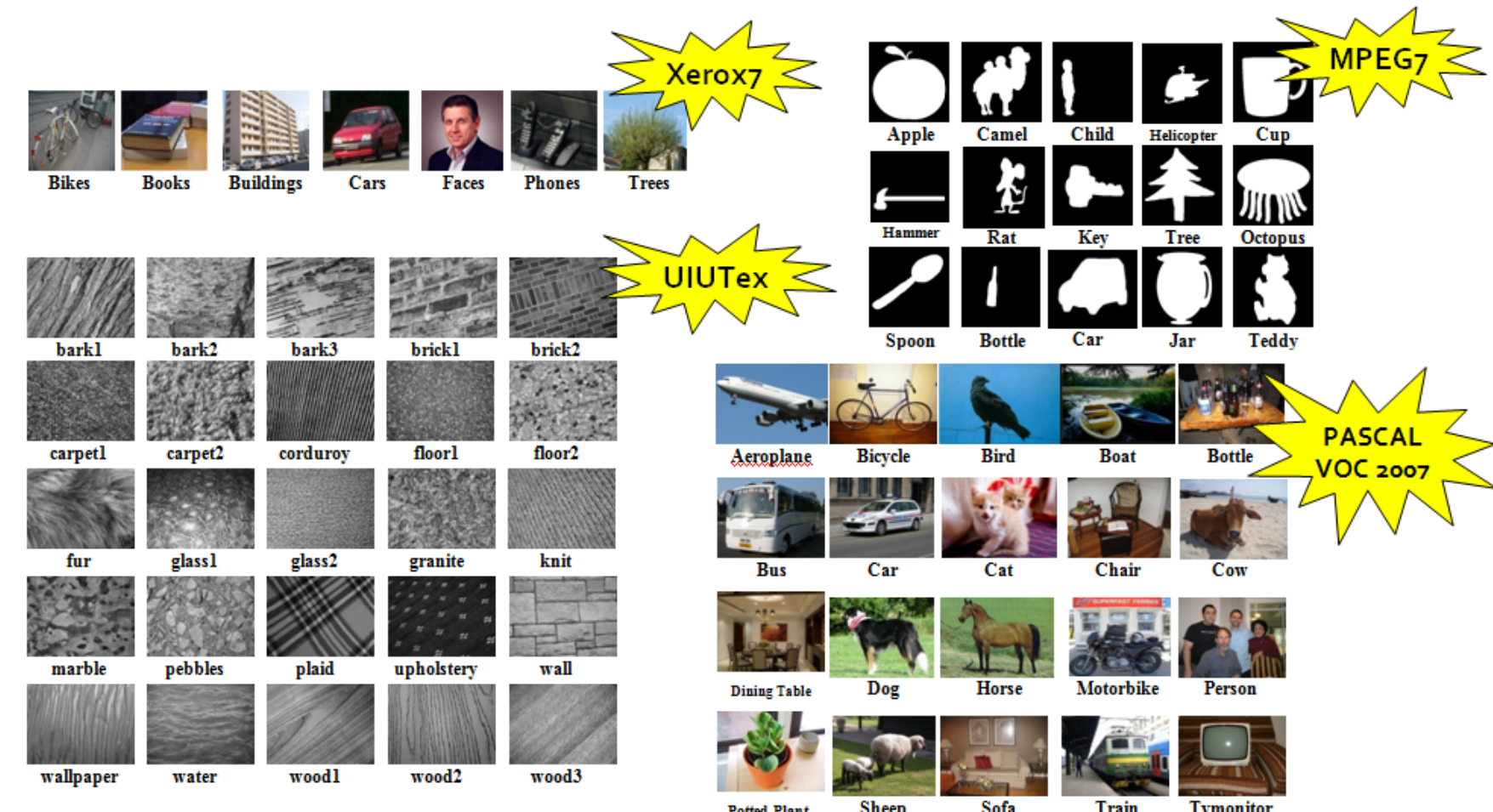
To map an initial high-dimensional vocabulary into a compact vocabulary while maintaining its discriminative power.

## Methodology

The proposed vocabulary compression technique is depicted in Figure 1 (1-7,9-15). The proposed method maps an initial high dimensional visual vocabulary into a more compact form while maintaining its discriminative power. The reduction of BoF vocabularies to improve coding efficiency is achieved by two-step process:

1. Encode each image as "bits", i.e., the significant presence or absence of each visual word.
2. Remove visual words with bits that are not activated enough in images.

## Experimental Setup



**Xerox7:** 7 classes, 1776 images [1]; **UIUTex:** 25 classes, 40 images/class [4]; **MPEG7:** 15 classes, 20 images/class [3]; **PASCAL VOC 2007:** 20 classes, 9963 images [2].

- Xerox7 & UIUTex: 70% training, 30% testing.
- MPEG7: 50%-50% training-testing.
- PASCAL VOC2007: Provided training & testing sets.
- Features: SIFT descriptors [5].
- Vocabulary Construction: K-means algorithm.
- Classification: Linear OVA-SVMs.

## Methodology ...

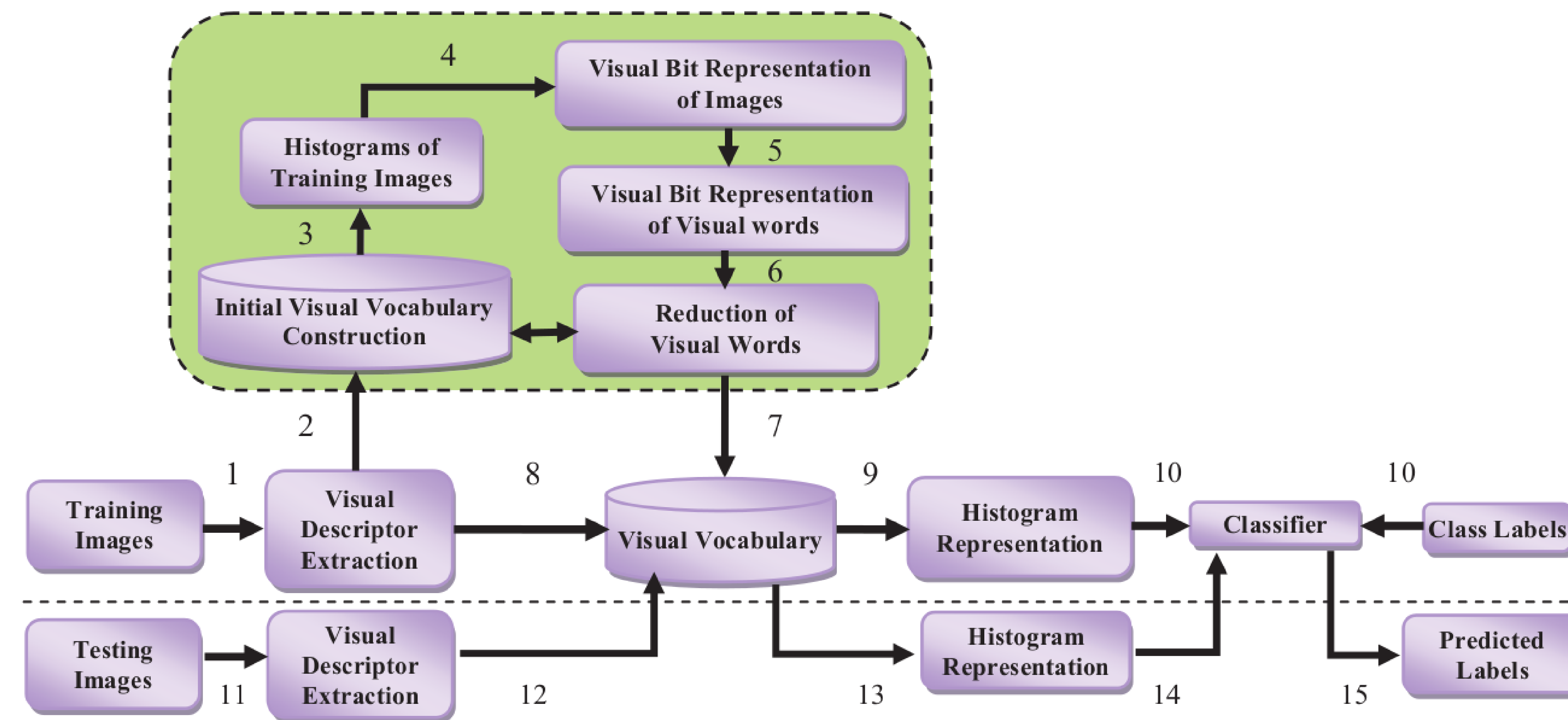


Fig. 1. Framework of creating a compact and discriminative visual vocabulary using visual bit representation. Below the shaded block, diagram in dotted outline shows the traditional bag-of-features (BoF) approach. The proposed method is shown in shaded block diagram (2-7) which adds an additional layer of compression to the traditional way of constructing a vocabulary in the BoF framework (1, 8-15).

### Visual Bit Representation of Images

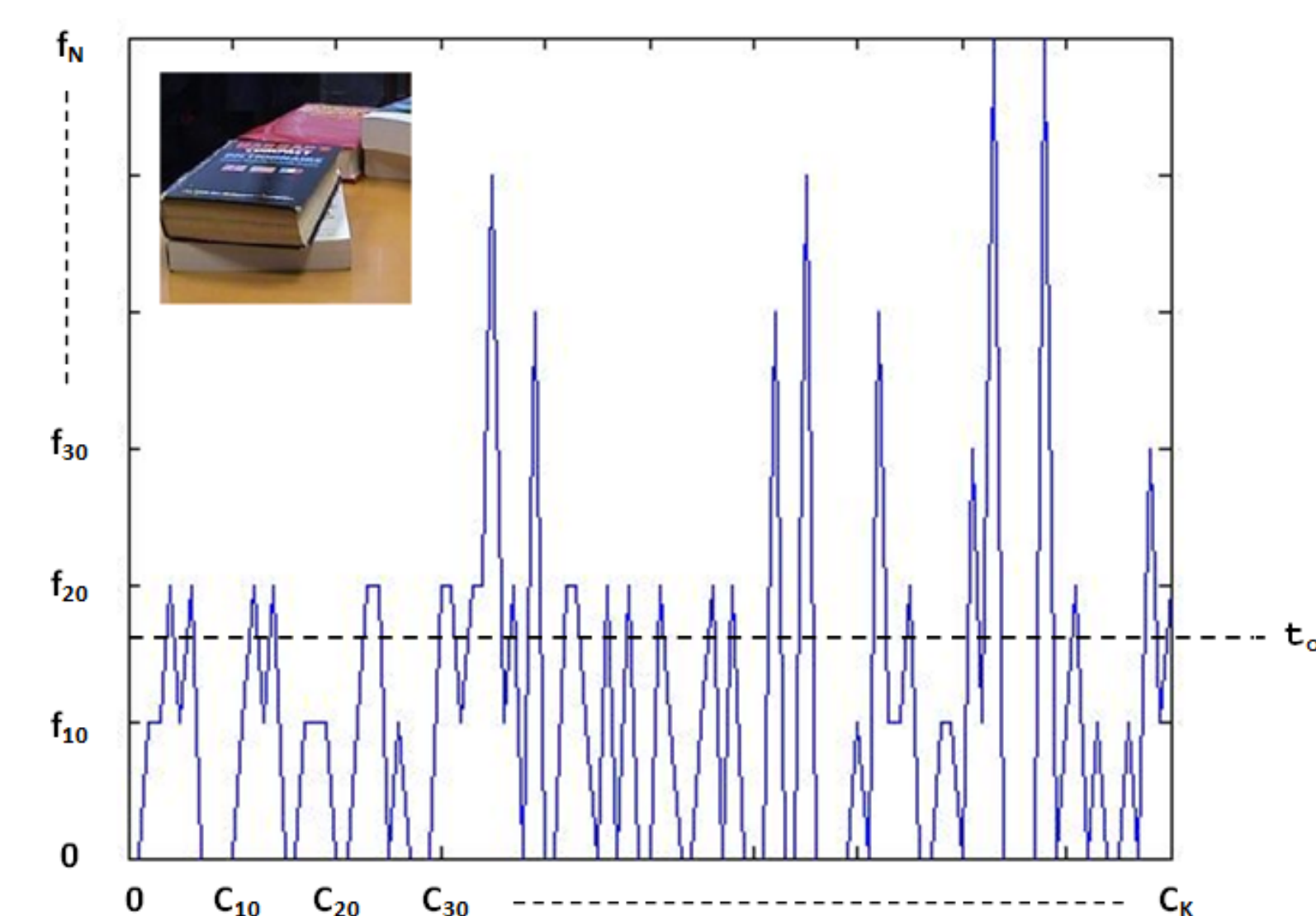


Fig. 2. Visual bit representation of images.

The patch-based descriptors of image,  $I$ , are mapped into a feature vector by computing the frequency histogram,  $h$ , with the initial vocabulary  $V$ . The average number of descriptors that fall into each visual word  $C_i$  of  $V$  is computed as  $t_0$  for each image  $I$  of the training set. The visual bit representation of an image is then coded using equation (1).

$$h_i = \begin{cases} 1 & \text{if } (|C_i| \geq t_0) \\ 0 & \text{otherwise} \end{cases} \quad \forall i = 1, \dots, K \quad (1)$$

where  $K$  is the size of initial vocabulary

This process is repeated to all training images of a specific-category by computing  $t_0$  corresponding to an image.

### Visual Bit Representation of Visual Words

	$C_1$	$C_2$	$C_3$	...	$C_K$
$l_1$	1	0	0	...	1
$l_2$	0	1	0	...	0
$l_3$	1	1	1	...	0
$\vdots$	$\vdots$	$\vdots$	$\vdots$		$\vdots$
$l_M$	0	1	1	...	1
<b>Total</b>	$SB_1$	$SB_2$	$SB_3$	...	$SB_K$

Fig. 3. Visual bit representation of visual words.

Following the visual bit representation of images the initial vocabulary  $V$  is coded as a sparse representation by using equation (2) where  $SB_i$  indicates the sum of visual bits associated with the  $i$ th visual word.

$$t_1 = \frac{\lambda p_0 + p_1}{\lambda + 1} \quad (2)$$

where  $p_0 = \min_{1 \leq i \leq K} (SB_i)$  and  $p_1 = \max_{1 \leq i \leq K} (SB_i)$ .

We can now compress the initial visual vocabulary using the subsequent step indicated by equation (3).

## Reduction of Visual Words

We learn the importance of each visual word of the initial visual vocabulary  $V$  through the visual bit representation of visual words.

$$\text{Compact}_{CB} = \begin{cases} \text{eliminate } C_i & : \text{if } (SB_i < t_1) \\ \text{retain } C_i & : \text{otherwise} \end{cases} \quad (3)$$

where  $t_1$  indicates the level of significant activation of a visual word in a category-specific vocabulary.

The same process described in reducing a category-specific vocabulary could also be applied to constructing a global vocabulary.

## Testing Results

Table 1: Mean Classification rate with standard BoF approach having Category-specific vocabularies.

Dataset	Initial vocabulary (Traditional BoF)			Compact vocabulary (Ours)			
	K	NN	SVM	$\lambda$	size	NN	SVM
Xerox7	700	73.55	94.93	1	251	78.05	94.24
				2	459	76.55	95.18
				3	553	75.05	94.80
PASCAL 2007	1000	14.53	94.99	1	437	15.17	94.99
				2	668	15.88	95.00
				3	769	15.44	94.99
UIUTex	1000	96.67	99.79	1	477	97.00	99.72
				2	634	96.00	99.77
				3	730	96.33	99.83
MPEG7PartB	600	44.67	97.56	1	198	58.67	97.42
				2	297	52.67	97.38
				3	373	51.33	97.29

Table 2: Mean Classification rate with standard BoF approach having Globally constructed vocabulary.

Dataset	Initial vocabulary (Traditional BoF)			Compact vocabulary (Ours)			
	K	NN	SVM	$\lambda$	size	NN	SVM
Xerox7	1000	71.67	94.56	1	248	75.61	94.48
				2	844	72.42	94.43
				3	957	72.23	94.75
PASCAL 2007	1000	13.49	94.98	1	142	13.90	95.00
				2	677	14.73	94.99
				3	909	13.76	94.99
UIUTex	1000	95.33	99.69	1	785	96.00	99.65
				2	932	96.00	99.71
				3	958	95.00	99.68
MPEG7PartB	600	32.00	97.33	1	15	66.00	93.42
				2	101	58.00	96.31
				3	199	49.33	96.89

## Discussion and Conclusion

- The proposed method yields compact vocabulary while maintaining its discriminative power.
- It provides a way to choose optimal vocabularies for recognition.
- The classification performance is comparable to or even better than the standard BoF approach.
- Needs less computational overhead.
- Guides the future works in BoF approach to deal with very low-dimensional representation.

## References

- [1] C. Ssurua, R. Dance, L. Fan, J. Willamowski, and C. Bray, "Visual Categorization with Bags of Keypoints", In Workshop on Statistical Learning in Computer Vision, (ECCV), pp. 1-22, 2004.
- [2] M. Everingham, L. Van-Gool, C. K. I. Williams, J. Winn, and A. Zisserman., "The PASCAL Visual Object Classes Challenge 2007 Results", <http://www.pascalnetwork.org/challenges/VOC/voc2007/workshop/index.html>, 2007.
- [3] L. Jan Latecki, R. Lakamper and U. Eckhardt, "Shape Descriptors for Non-rigid Shapes with a Single Closed Contour", In proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 424-429, 2000.
- [4] S. Lazebnik, C. Schmid, and J. Ponce, "A sparse texture representation using local affine regions", In IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI), pp. 1265-1278, 2005.
- [5] D. Lowe., "Distinctive Image Features from Scale-invariant Keypoints", In International Journal of Computer Vision (IJCV), vol. 60, pp. 91-110, 2004.