

Spatial Pooling of Heterogeneous Features for Image Applications Lingxi Xie¹, Qi Tian², and Bo Zhang¹ ¹Department of Computer Science and Technology, Tsinghua University, Beijing, China ²Department of Computer Science, University of Texas at San Antonio, Texas, USA THE PROPOSED FRAMEWORK RESULTS Edge-based Spatial Weighting Overall Framework Geometric Phrase Pooling (GPP) Spatial Weighting Original Image Dense Descriptors One Visual Phrase pyramic Feature (8.5%)000000000 SuperVectors 00.000.000 Origina 1 😐 🔴 🔵 00600000 \sim SPM[12] Images `**• • •** • / Weighted Vectors Heatmap Performance on Caltech256 00000000 00000000 Spatial 00000000 Weighting Pooled Vectors Pooled Vector Geometric Phrase Pooling (GPP) GPP Conclusions Gaussian Feature Codes Geometric Word Pair 8 Blur We propose a novel framework for image representation, Visual Phrase LLC[22] and apply it for various image applications. By considering the key shortcomings of the BoF framework, we develop Multi-Descriptors Feature Vectors LLC Coding modules coherently, we obtain a very powerful model that Shape outperforms state-of-the-art algorithms on image Descriptors classifications, retrieval and understanding applications. Texture Descriptors Side Central Word Word SIFT SIFT Summation REFERENCES Raw Image Data Edgemap MAX Spatial Weighting Heatmap Image Supervector Pooled Vector for one Phrase **Fusing Different Descriptors** Model Comparison References are numbered as they appear in the paper. Intuition of GPP [2] A. Bosch, A. Zisserman, and X. Muoz. Image Classification Original Image SIFT Descriptors Our Framework Framework of [2] Pair 1 Computer Vision, pages 1 - 8, 2007. $\bullet \bullet \bullet \bullet \bullet$ Feature SuperVectors SuperVectors No Difference [4] J. Canny. A Computational Approach to Edge Detection. ration SPM Between

ABSTRACT

The Bag-of-Features (BoF) model has played an important role for image representation in many multimedia applications. Despite the advantages of this model, there are also notable drawbacks, including poor power of semantic expression of local descriptors, and lack of robust structures upon single visual words. To overcome these problems, various techniques have been proposed, such as multiple descriptors, spatial context modeling and interest region detection. Though they have been proven to improve the BoF model to some extent, there still lacks a coherent scheme to integrate each individual module. To address the problems above, we propose a novel framework. Our model differs from the traditional ones on three aspects. First, we propose a new scheme for combining texture and edge based local features together at an early stage. Next, we build geometric visual phrases for mid-level representation of images. Finally, we perform a simple and effective spatial weighting scheme. We test our integrated framework on several benchmark datasets for image classification and retrieval applications. The extensive results show the superior performance of our algorithm over state-of-the-art methods.

NOVELTY

Three key observations for improving the BoF framework:

- Enhancing descriptions of local patches.
- Mid-level representation connecting lowlevel and high-level concepts.
- Spatial weighting of images.

Based on the observations, we propose several novel algorithms from new aspects. We claim a THREEFOLD contribution:

- We simultaneously extract SIFT and Edge-**SIFT** descriptors and combine them in the generation of the BoF model. Earlier fusion of descriptors makes it easier to mine complementary information from both descriptors.
- We propose Geometric Visual Phrases (GVP) upon traditional visual words, and take them as mid-level image representation as well as apply a novel pooling algorithm, Geometric Phrase Pooling (GPP), to them.
- We use naive Gaussian blur to obtain a weighting heatmap for spatial weighting on the image plane.

Integrating all the techniques produces a much more powerful framework, which outperforms state-of-the-art systems by a margin on various applications.





Better Discriminativity 1.5 with SIFT Confused Distinct Distinct Confused with SIFT with SIFT with Edge with Edge with SIFT pizza



Performance on Caltech101								
#training	5	10	15	20	30			
Lazebnik[12]			56.4		64.6			
Wang[22]	51.15	59.77	65.43	67.74	73.44			
Bosch[2]					81.3			
Ours	61.95	71.75	76.03	78.53	82.45			

#training	5	15	30	45	60
Wang[22]		34.36	41.19	45.31	47.68
Bosch[2]			44.0		
Ours	26.12	36.35	45.07	48.02	50.33

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