

Orientational Pyramid Matching for Recognizing Indoor Scenes

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ABSTRACT

Scene recognition is a basic task towards image understanding. Spatial Pyramid Matching (SPM) has been shown to be an efficient solution for spatial context modeling. Although SPM is very efficient in scene recognition tasks, it still fails to discriminate categories with similar layouts.

In this paper, we introduce an alternative approach, Orientational Pyramid Matching (OPM), for orientational context modeling. Our approach is motivated by the observation that the 3D orientations of objects are a crucial factor to discriminate indoor scenes. The major novelty lies in that OPM uses the estimated 3D orientations to form the pyramid and produce the pooling regions, which is unlike SPM that uses the spatial positions to form the pyramid. Experimental results on challenging scene classification tasks show that OPM achieves the performance comparable with SPM and that OPM and SPM make complementary contributions so that their combination gives the state-of-the-art performance.

NOVELTY

In this paper, we propose a novel framework named Orientational Pyramid Matching (OPM) to incorporate the 3D orientation information into scene classification models.

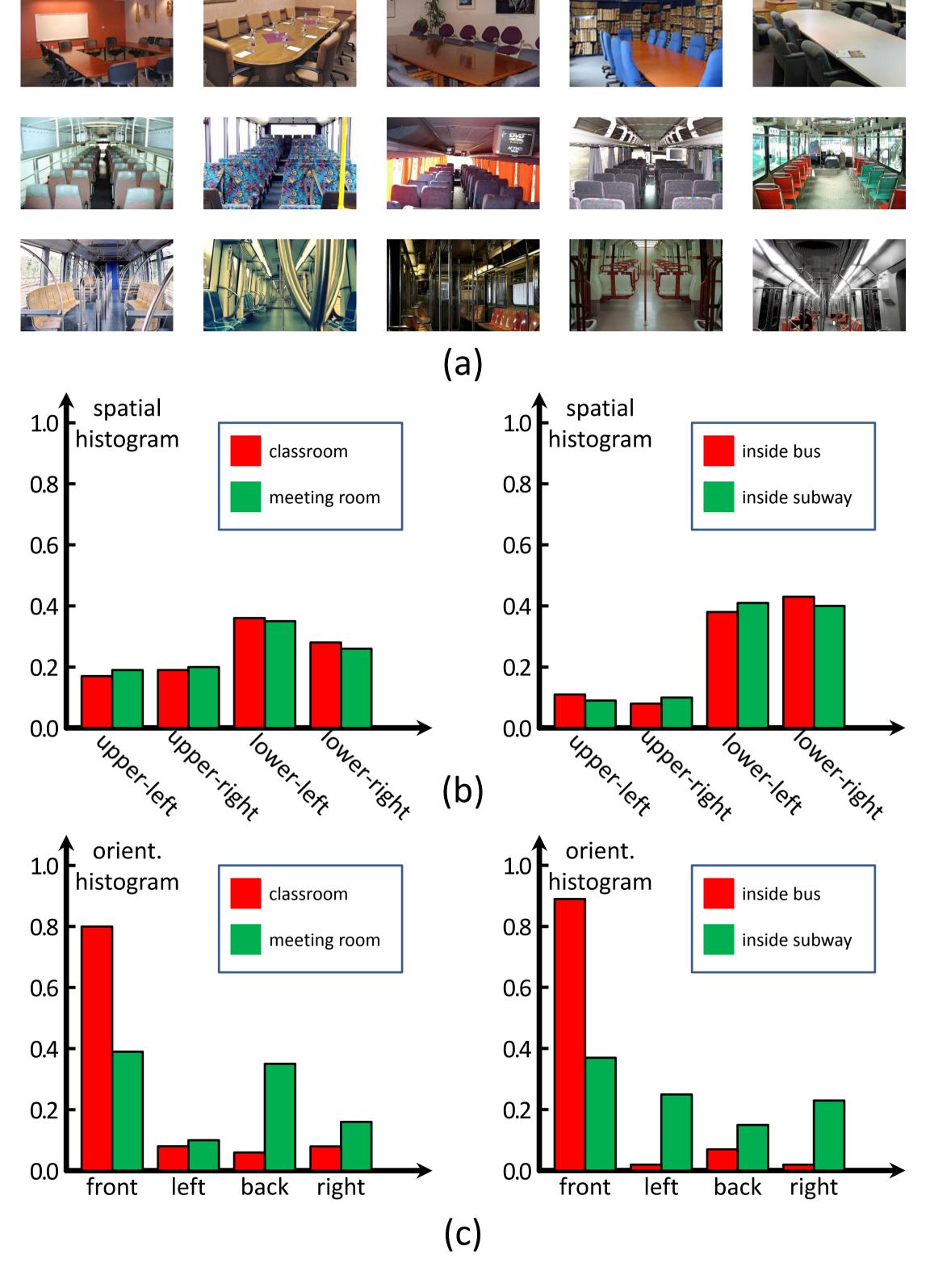
- Our motivation comes from the observation that orientation of objects, e.g., chairs, is the main difference between some very similar scene categories, e.g., classroom vs. meeting room.
- We propose to extract 3D orientational features using a similar manner of that in the SPM model. Each local descriptor is assigned with a 3D orientation and the image is partitioned into several regions based on the 3D orientation. Individual pooling process is performed on each
- To extract 3D orientational information, we use a naïve yet efficient method [15]. It is a data-driven approach that assigns orientation to each local patch based on the nearest-neighbor regressor. The orientation in training images is labeled manually.

Experimental results on two challenging scene recognition datasets, i.e., Indoor-67 and SUN-397, verify that our algorithm achieves the state-of-the-art performance.

The success of our algorithm suggests that orientational features are indeed useful for scene recognition tasks, since it provides complementary information to spatial features. It also encourages the computer vision society to develop more accurate and efficient orientational assignment algorithms.

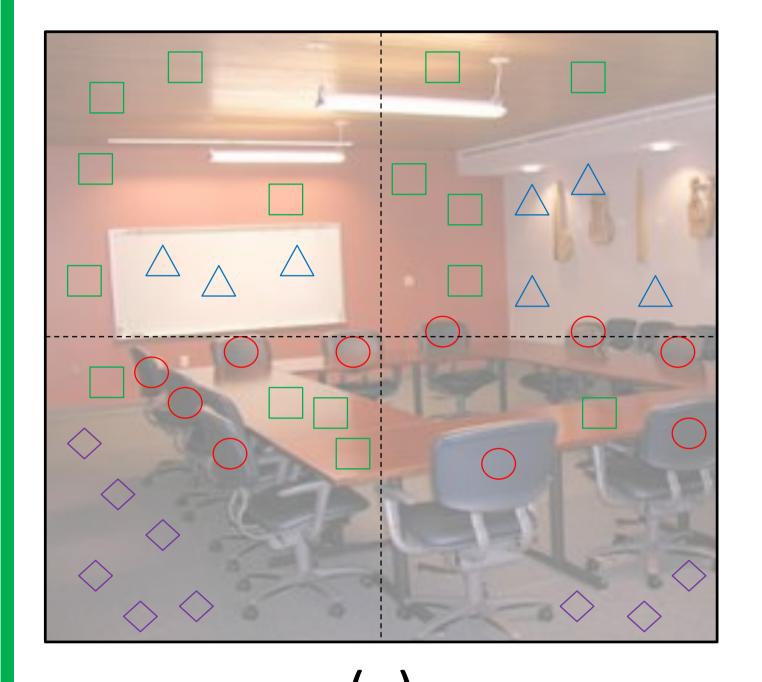
THE PROPOSED FRAMEWORK

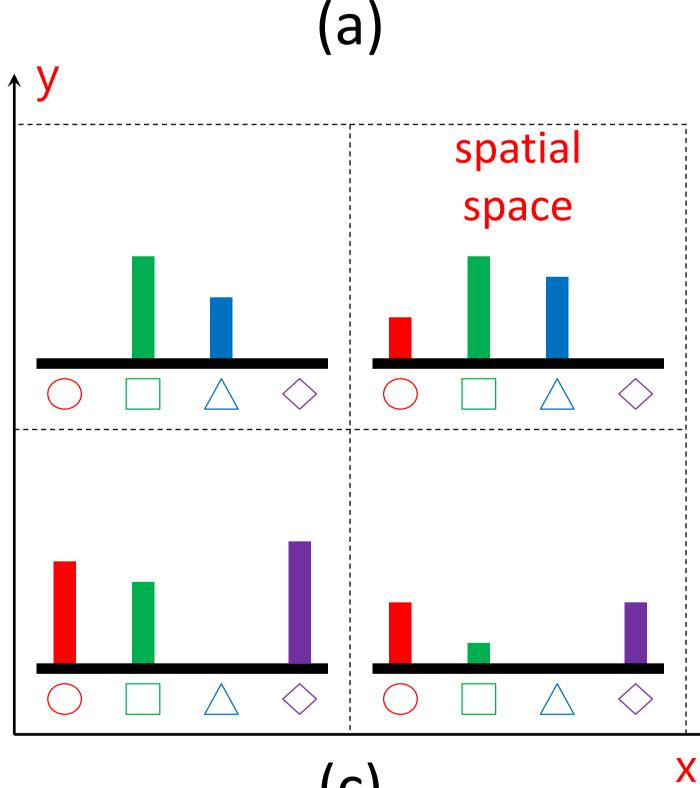
Motivation

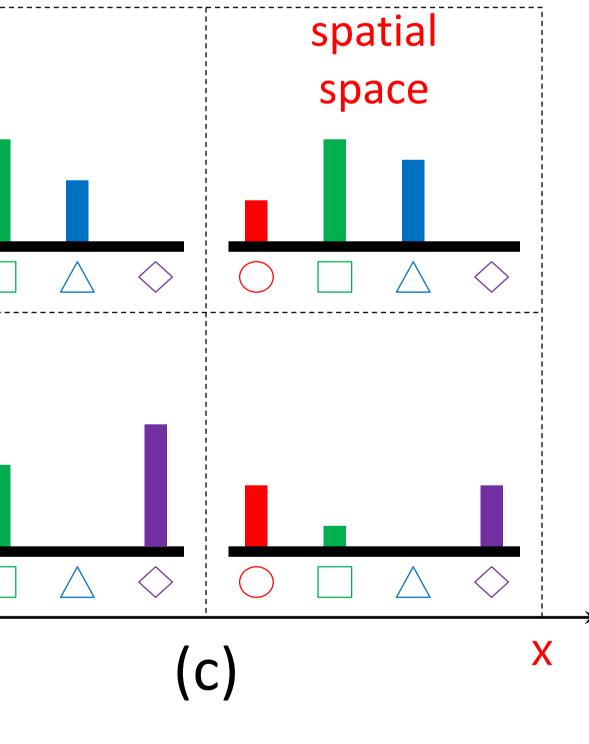


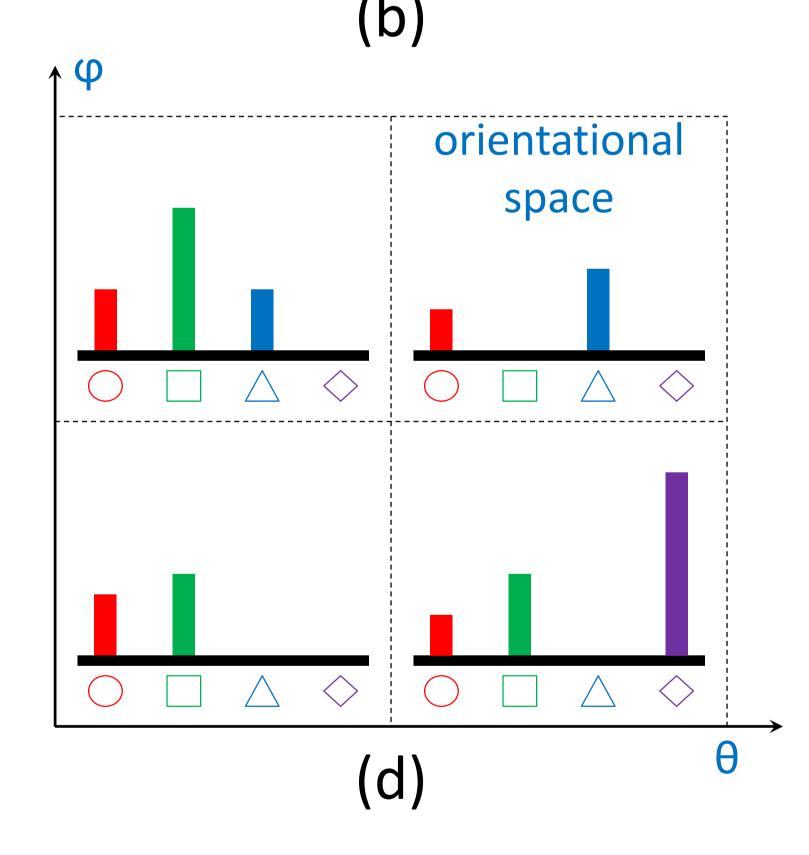
The orientation of *chairs* is the major difference between: classroom vs. meeting room bus carriage vs. subway carriage

Orientational Pyramid Matching













RESULTS

Indoor-67 Accuracy

Quat. [32]	June. [23]	SPM(Sc)	OPM(Sc)	COMB(Sc)
26.0	56.66	57.83	48.83	59.57

	Koba. [24]	June. [23]	SPM(FV)	OPM(FV)	COMB(FV)
	58.91	63.10	61.22	51.45	63.48

SUN-397 Accuracy

Xiao [42]	Sanc. [34]	SPM(FV)	OPM(FV)	COMB(FV)
38.0	43.2	43.58	34.61	45.91

Conclusions

We propose a novel Orientational Pyramid Matching (OPM) algorithm to capture the orientational contexts in the images, and combine the OPM features with SPM features to capture the complementary information for scene recognition. State-of-the-art classification performance is achieved on both MIT Indoor-67 and SUN-397 datasets. In the future, we will investigate the combination of OPM with many other approaches, and look forward to some more accurate orientation assignment algorithms to improve the OPM performance.

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