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# Beyond bag of latent topics: spatial pyramid matching for scene category recognition

**Key words:** Scene category recognition, Probabilistic latent semantic analysis, Bag-of-words, Adaptive boosting

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# Motivation/Main ideas

- **Motivation**

  Establish a robust method for the representation and subsequent recognition of scene categories, so as to achieve higher recognition accuracies in the case of a large number of scene categories.

- **Main ideas**

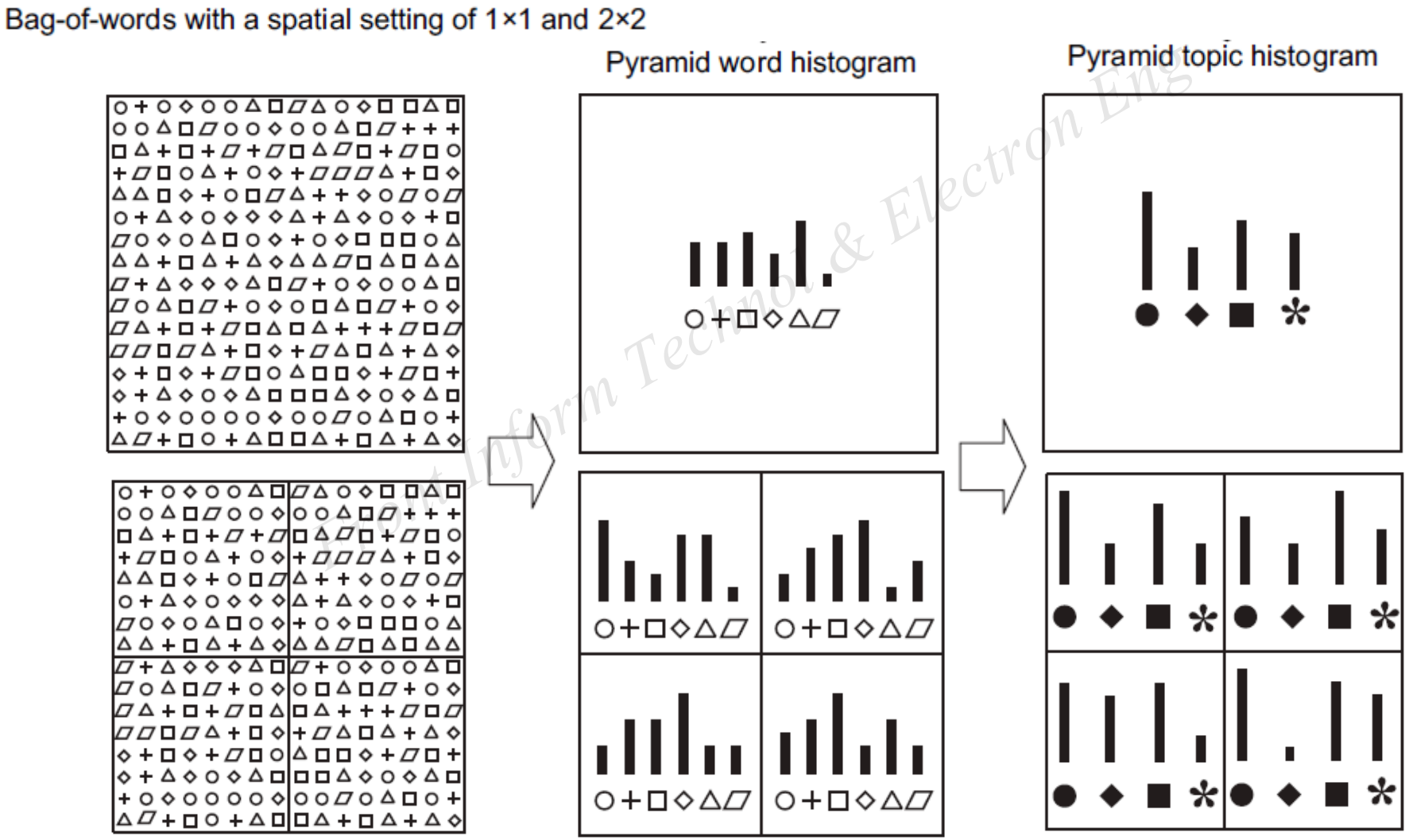
  – Introduce spatial position relationships among latent topics to probabilistic latent semantic analysis (pLSA).

  – Make performance improvement for real-world applications by combining various interest point detectors and region descriptors.

  – Use a two-stage framework to perform multi-class classification.

# Method (I)

1. Main steps of computing the pyramid topic histogram for an image



# Method (II)

2. Two-stage multi-class classification

**Stage 1**: For each of possible detector/descriptor pairs, use adaptive boosting classifiers to select the most discriminative topics and further compute posterior probabilities of a novel image from those selected topics.

**Stage 2**: use the prod-max rule to combine information coming from multiple sources and assigns the novel image to the scene category with the highest 'final' posterior probability. For *M* pyramid topic histograms and *K* classes, let $H_{mk}(\boldsymbol{x}^m)$ be AdaBoost classifiers learned from the training set by using Algorithm 3. Then, the prod-max rule is defined as follows:



$$y = \arg\max_{k\in\{1,2,\cdots,K\}} \prod_{m=1}^{M} H_{mk}\left(\boldsymbol{x}^m\right)$$

# Major results (I)

**Table 2** The average of per-category recognition rates over OT, LP, and LSP obtained using the pyramid topic histogram based on the grid detector and SIFT descriptor

| $D$ | Recognition rate (%) | | |
|---|---|---|---|
| | OT | LP | LSP |
| 1 | $81.4 \pm 0.2$ | $71.8 \pm 0.8$ | $65.8 \pm 0.8$ |
| 2 | $82.3 \pm 0.7$ | $75.0 \pm 1.1$ | $70.2 \pm 0.1$ |
| 3 | $84.6 \pm 0.1$ | $80.1 \pm 0.9$ | $75.4 \pm 0.1$ |

# Major results (II)

**Table 3 The average of per-category recognition accuracies obtained using each of the individual pyramid topic histograms and their combination for OT, LP, and LSP**

| Channal number | Recognition accuracy (%) | | |
|---|---|---|---|
| | OT | LP | LSP |
| 1 | $77.2 \pm 0.6$ | $69.1 \pm 0.5$ | $61.2 \pm 1.5$ |
| 2 | $83.4 \pm 0.8$ | $74.3 \pm 0.6$ | $69.2 \pm 0.6$ |
| 3 | $84.6 \pm 0.1$ | $80.1 \pm 0.9$ | $75.4 \pm 0.6$ |
| 4 | $81.0 \pm 0.3$ | $77.7 \pm 1.0$ | $75.5 \pm 0.7$ |
| 5 | $80.8 \pm 0.6$ | $74.9 \pm 0.3$ | $68.1 \pm 1.3$ |
| 6 | $80.5 \pm 0.5$ | $77.7 \pm 0.9$ | $75.5 \pm 0.4$ |
| prod-max | $\mathbf{88.8} \pm 0.2$ | $\mathbf{86.7} \pm 0.2$ | $\mathbf{83.7} \pm 0.5$ |

# Conclusions

- Pyramid topic histograms were proposed to represent an image.
  - Given an interest point detector and a local region descriptor, the pyramid histogram consistently outperforms standard pLSA.
  - Significant improvement can be made by combining various interest point detectors and local region descriptors involved in the bag-of-words representation.
- A two-stage framework was proposed to perform multi-class classification. The prod-max fusion rule employed in the framework works well in the case of a large number of scene categories.