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Learning Representations for Visual Object Class Recognition

Marcin Marszałek  Cordelia Schmid
Hedi Harzallah  Joost van de Weijer

LEAR, INRIA Grenoble, Rhône-Alpes, France

October 15th, 2007
Bag-of-Features (BoF) is an orderless distribution of local image features sampled from an image.

The representations are compared using $\chi^2$ distance.

Channels can be combined to improve the accuracy.

Classification with non-linear Support Vector Machines.
Spatial pyramid
Lazebnik, Schmid and Ponce [CVPR’06]

- Spatial grids allow for locally orderless description
- They can be viewed as an extension to Bag-of-Features

They were shown to work on scene category and object class datasets
Combining kernels
Bosch, Zisserman and Munoz [CIVR’07], Varma and Ray [ICCV’07]

- It was shown that linear kernel combinations can be learned
  - Through extensive search [Bosch’07]
  - By extending the C-SVM objective function [Varma’07]

- We learn linear distance combinations instead
  - Our approach can still be viewed as learning a kernel
  - We exploit the kernel trick (it’s more than linear combination of kernels)
  - No kernel parameters are set by hand, everything is learned
  - Optimization task is more difficult
Our approach: large number of channels

- In our approach images are represented with several BoFs, where each BoF is assigned to a cell of a spatial grid.
- We combine various methods for sampling the image, describing the local content and organizing BoFs spatially.
- With few samplers, descriptors and spatial grids we can generate tens of possible representations that we call “channels”.
- Useful channels can be found on per-class basis by running a multi-goal genetic algorithm.
Overview of the processing chain

Image $\rightarrow$ Sampler $\times$ Local descriptor $\times$ Spatial grid $\Rightarrow$ Fusion $\rightarrow$ Classification

- Image is sampled
- Regions are locally described with feature vectors
- Features are quantized (assigned to a vocabulary word) and spatially ordered (assigned to a grid cell)
- Various channels are combined in the kernel
- Image is classified with an SVM
PASCAL VOC 2007 challenge

Image $\rightarrow$ Sampler $\times$ Local descriptor $\times$ Spatial grid $\Rightarrow$ Fusion $\Rightarrow$ Classification

bottle  car  chair  dog  plant  train
Image sampling

Image → Sampler × Local descriptor × Spatial grid ⇒ Fusion → Classification

- Interest points detectors
  - Harris-Laplace — detects corners [Mikołajczyk’04]
  - Laplacian — detects blobs [Lindeberg’98]

- Dense sampling
  - Multiscale grid with horizontal/vertical step of 6 pixels (half of the SIFT support area width/height) and scaling factor of 1.2 per scale-level
Local description

Image $\rightarrow$ Sampler $\times$ Local descriptor $\times$ Spatial grid $\Rightarrow$ Fusion $\rightarrow$ Classification

- SIFT — gradient orientation histogram [Lowe’04]
- SIFT+hue — SIFT with color [van de Weijer’06]

- PAS — edgel histogram [Ferrari’06]
Spatial organization

Visual vocabulary is created by clustering the features using k-means ($k = 4000$)

Spatial grids allow to separately describe the properties of roughly defined image regions
- 1x1 — standard Bag-of-Features
- 2x2 — defines four image quarters
- horizontal 3x1 — defines upper, middle and lower regions
Support Vector Machines

We use non-linear Support Vector Machines
The decision function has the following form
\[ g(x) = \sum_i \alpha_i y_i K(x_i, x) - b \]

We propose a multichannel extended Gaussian kernel
\[ K(x_j, x_k) = \exp\left(-\sum_{ch} \gamma_{ch} D_{ch}(x_j, x_k)\right) \]
\[ D_{ch}(x_j, x_k) \] is a similarity measure (\(\chi^2\) distance in our setup) for channel \(ch\)
Support Vector Machines

Image $\rightarrow$ Sampler $\times$ Local descriptor $\times$ Spatial grid $\Rightarrow$ Fusion $\rightarrow$ Classification

- We use non-linear Support Vector Machines
- The decision function has the following form
  \[
g(x) = \sum_i \alpha_i y_i K(x_i, x) - b
  \]
- We propose a multichannel extended Gaussian kernel
  \[
  K(x_j, x_k) = \exp\left(-\sum_{\text{ch}} \gamma_{\text{ch}} D_{\text{ch}}(x_j, x_k)\right)
  \]
- $D_{\text{ch}}(x_j, x_k)$ is a similarity measure ($\chi^2$ distance in our setup) for channel $\text{ch}$
- Problem: How to set each $\gamma_{\text{ch}}$?
Weighting the channels

If we set $\gamma_{ch}$ to $\frac{1}{D_{ch}}$ we almost obtain (up to channels normalization) the method of Zhang et al.

- This approach demonstrated remarkable performance in both VOC’05 and VOC’06
- We submit this approach as the “flat” method

As $\gamma_{ch}$ controls the weight of channel $ch$ in the sum, it can be used to select the most useful channels

- We run a genetic algorithm to optimize per-task $\gamma_{ch,t}$ kernel parameters and also $C_t$ SVM parameter
- The learned channel weights are used for the “genetic” submission
Genetic algorithm to optimize SVM parameters

Image $\rightarrow$ Sampler $\times$ Local descriptor $\times$ Spatial grid $\Rightarrow$ Fusion $\rightarrow$ Classification

- The genomes encode the optimized parameters.
- In every iteration (generation):
  1. Random genomes are added to the pool (population).
  2. Cross-validation is used to evaluate the genomes (individuals) simultaneously for each class.
  3. The more useful the genom is the more chance it has to be selected and combined with another good genom.
  4. Information from combined genomes is randomly mixed (crossed) and forms the next generation.
  5. To better avoid local minima, random genes are altered (mutated).

- Useful genes and gene combinations survive and multiply.
Genetic algorithm to optimize SVM parameters

The genomes encode the optimized parameters

In every iteration (generation)

1. Random genomes are added to the pool (population)
2. Cross-validation is used to evaluate the genomes (individuals) simultaneously for each class
3. The more useful the genom is the more chance it has to be selected and combined with another good genom
4. Information from combined genoms is randomly mixed (crossed) and forms the next generation
5. To better avoid local minimas, random genes are altered (mutated)

Useful genes and gene combinations survive and multiply
## Multiplying channels

### Table: Class-averaged AP on VOC’07 validation set

<table>
<thead>
<tr>
<th>Channels ((\gamma_{ch} = 1/D_{ch}))</th>
<th>#</th>
<th>Average AP</th>
</tr>
</thead>
<tbody>
<tr>
<td>HS,LS × SIFT, × 1,2x2</td>
<td>4</td>
<td>47.7</td>
</tr>
<tr>
<td>HS,LS,DS × SIFT × 1,2x2</td>
<td>6</td>
<td>52.6</td>
</tr>
<tr>
<td>HS,LS,DS × SIFT × 1,2x2,h3x1</td>
<td>9</td>
<td>53.3</td>
</tr>
<tr>
<td>HS,LS,DS × SIFT,SIFT+hue × 1,2x2,h3x1</td>
<td>18</td>
<td>54.0</td>
</tr>
<tr>
<td>HS,LS,DS × SIFT,SIFT+hue,PAS × 1,2x2,h3x1</td>
<td>21</td>
<td>54.2</td>
</tr>
<tr>
<td>DS × SIFT,SIFT+hue,PAS × 1,2x2,h3x1</td>
<td>9</td>
<td>51.8</td>
</tr>
</tbody>
</table>

- Combination of interest points and dense sampling boosts the performance, color and 3x1 grid are important.
- The performance monotonically increases with the number of channels.
- Last experiments show, that anything sensible (HoGs, different vocabularies) further helps the performance.
## PASCAL VOC’07 Challenge results

<table>
<thead>
<tr>
<th>Object</th>
<th>INRIA (genetic)</th>
<th>INRIA (flat)</th>
<th>XRCE</th>
<th>TKK</th>
<th>QMUL (lspch)</th>
<th>QMUL (hsls)</th>
</tr>
</thead>
<tbody>
<tr>
<td>aeroplane</td>
<td>0.775</td>
<td>0.748</td>
<td>0.723</td>
<td>0.714</td>
<td>0.716</td>
<td>0.706</td>
</tr>
<tr>
<td>bicycle</td>
<td>0.636</td>
<td>0.625</td>
<td>0.575</td>
<td>0.517</td>
<td>0.550</td>
<td>0.548</td>
</tr>
<tr>
<td>bird</td>
<td>0.561</td>
<td>0.512</td>
<td>0.532</td>
<td>0.485</td>
<td>0.411</td>
<td>0.357</td>
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<tr>
<td>boat</td>
<td>0.719</td>
<td>0.694</td>
<td>0.689</td>
<td>0.634</td>
<td>0.655</td>
<td>0.645</td>
</tr>
<tr>
<td>bottle</td>
<td>0.331</td>
<td>0.292</td>
<td>0.285</td>
<td>0.273</td>
<td>0.272</td>
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<tr>
<td>bus</td>
<td>0.606</td>
<td>0.604</td>
<td>0.575</td>
<td>0.499</td>
<td>0.511</td>
<td>0.511</td>
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<tr>
<td>car</td>
<td>0.780</td>
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<td>0.754</td>
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<tr>
<td>cat</td>
<td>0.588</td>
<td>0.576</td>
<td>0.503</td>
<td>0.512</td>
<td>0.551</td>
<td>0.540</td>
</tr>
<tr>
<td>chair</td>
<td>0.535</td>
<td>0.531</td>
<td>0.522</td>
<td>0.517</td>
<td>0.474</td>
<td>0.466</td>
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<tr>
<td>cow</td>
<td>0.426</td>
<td>0.411</td>
<td>0.390</td>
<td>0.323</td>
<td>0.359</td>
<td>0.366</td>
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<tr>
<td>dining table</td>
<td>0.549</td>
<td>0.540</td>
<td>0.468</td>
<td>0.463</td>
<td>0.374</td>
<td>0.344</td>
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<tr>
<td>dog</td>
<td>0.458</td>
<td>0.428</td>
<td>0.453</td>
<td>0.415</td>
<td>0.415</td>
<td>0.399</td>
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<tr>
<td>horse</td>
<td>0.775</td>
<td>0.765</td>
<td>0.757</td>
<td>0.726</td>
<td>0.715</td>
<td>0.715</td>
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<tr>
<td>motorbike</td>
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<td>0.623</td>
<td>0.585</td>
<td>0.602</td>
<td>0.579</td>
<td>0.554</td>
</tr>
<tr>
<td>person</td>
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<td>0.845</td>
<td>0.840</td>
<td>0.822</td>
<td>0.808</td>
<td>0.806</td>
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<tr>
<td>potted plant</td>
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<td>0.353</td>
<td>0.326</td>
<td>0.317</td>
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<td>0.158</td>
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<td>0.415</td>
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<tr>
<td>train</td>
<td>0.792</td>
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<td>0.751</td>
<td>0.711</td>
<td>0.765</td>
<td>0.731</td>
</tr>
<tr>
<td>tv/monitor</td>
<td>0.532</td>
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<td>0.495</td>
<td>0.410</td>
<td>0.459</td>
<td>0.455</td>
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<td>0.594</td>
<td>0.575</td>
<td>0.556</td>
<td>0.517</td>
<td>0.512</td>
<td>0.503</td>
</tr>
</tbody>
</table>
## Learning channel weights (VOC’07 results)

<table>
<thead>
<tr>
<th>Object</th>
<th>HS</th>
<th>LS</th>
<th>DS</th>
<th>SIFT</th>
<th>+hue</th>
<th>PAS</th>
<th>1</th>
<th>2x2</th>
<th>h3x1</th>
<th>C</th>
<th>flat</th>
<th>genetic</th>
</tr>
</thead>
<tbody>
<tr>
<td>aeroplane</td>
<td>0.7</td>
<td>1.5</td>
<td>2.8</td>
<td>0.04</td>
<td>0.09</td>
<td>0.29</td>
<td>5.7</td>
<td>3.1</td>
<td>4.3</td>
<td>897</td>
<td>0.748</td>
<td>0.775</td>
</tr>
<tr>
<td>bicycle</td>
<td>0.7</td>
<td>1.5</td>
<td>2.8</td>
<td>0.04</td>
<td>0.09</td>
<td>0.12</td>
<td>5.7</td>
<td>1.0</td>
<td>4.3</td>
<td>521</td>
<td>0.625</td>
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<tr>
<td>bird</td>
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<td>1.5</td>
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<td>0.12</td>
<td>5.7</td>
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<td>5.7</td>
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</tbody>
</table>

Learning Representations for Visual Object Class Recognition

M. Marszałek, C. Schmid
We have shown that using a large number of channels helps recognition due to complementary information.

We have demonstrated how it is possible to generate tens of useful channels.

We have proposed to use a genetic algorithm to discover the most useful channels on per-class basis.

The experimental results show excellent performance.
Thank you for your attention

I will be glad to answer your questions