Computational Imaging VI

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Eric L. Miller
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Editors

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INTRODUCTION

DETECTION (cont.)

HIERARCHY OF CLASSIFIERS

Advantages
- Highly efficient scene parsing;
- Organized focusing on hard examples.

Disadvantages
- Many classifiers to learn;
- Inefficient learning (unless training examples can be synthesized).
INTRODUCTION

Part-based Models
- Constellation (M. Weber, M. Welling, P. Perona),
- Composite (D. J. Crandall, D. P. Huttenlocher),
- Implicit Shape (E. Seemann, M. Fritz, B. Schiele),
- Patchwork of Parts (Y. Amit, A. Trouvé),
- Compositional (S. Geman).

Wholistic
- Convolutional Networks (Y. Lecun),
- Boosted Cascades (P. Viola, M. Jones),
- Bag-of-Features (A.Zisserman, F.F.Li).

POSE SPACE

Let $\mathcal{Y}$ be the space of poses and $\mathcal{Y}_1, \ldots, \mathcal{Y}_K$ a partition.

Let $I$ be an image and $\mathbf{Y} = (Y_1, \ldots, Y_K)$, where, for each $k$, $Y_k$ is a Boolean variable stating if there is an object in $I$ with pose in $\mathcal{Y}_k$.

INTRODUCTION

POSE SPACE (CONT.)

For faces, typically $y = (u_c, v_c, \theta, s)$. Cats are more complex.

A coarse description is $y = (u_h, v_h, s_h, u_b, v_b)$.

TRAINING A DETECTOR

FRAGMENTATION

Given a training set
$$\left\{ (I(i), Y(i)) \right\}_{i'},$$
we are interested in building, for each $k$, a classifier
$$f_k : I \rightarrow \{0, 1\}$$
for predicting $Y_k$.

Without additional knowledge about the relationship between $k$, $Y_k$ and $I$, we would train $f_k$ with
$$\left\{ (I(i), Y_k(i)) \right\}_{i'}.$$

Hence, each $f_k$ is trained with a fragment ($\approx 1/K$) of the positive population.
To avoid fragmentation, samples are often normalized in pose. Let
\[ \xi : I \rightarrow \mathbb{R}^N \]
denote an \( N \)-dimensional vector of features. Let
\[ \psi : \{1, \ldots, K\} \times I \rightarrow I \]
be a transformation such that the conditional distribution of \( \xi(\psi(k, I)) \) given \( Y_k = 1 \) does not depend on \( k \).

Then train a single classifier \( g \) with the training set
\[ \left\{ \left( \psi(k, I(t)), Y_k(t) \right) \right\}_{t, k} \]
and define
\[ f_k(I) = g(\psi(k, I)). \]
Here, samples are aggregated for training: all positive samples are used to build each \( f_k \).

However:
- Evaluating \( \psi \) is \textit{computationally intensive} for any non-trivial transformation.
- The mapping \( \psi \) \textit{does not exist} for a complex pose.

Hence, in practice, fragmentation is still the norm to deal with many deformations. But how does one deal with complex poses?
STATIONARY FEATURES

DEFINITION

Hence, we define a family of pose-indexed features as a mapping
\[ X : \{1, \ldots, K\} \times I \rightarrow \mathbb{R}^N \]
such that they are stationary in the following sense: for every \( k \in \{1, \ldots, K\} \), the probability distribution
\[ P(X(k, I) = x | Y_k = 1), \ x \in \mathbb{R}^N \]
does not depend on \( k \).

INTERPRETATION

Suppose there is exactly one object in \( I (\sum_k Y_k = 1) \) and let \( Z = Z(Y) \in \{1, \ldots, K\} \) be the corresponding pose cell. Then stationarity means that
\[ X(Z) \perp Z \]
In other words, knowing \( X(Z) \), the feature values, tells you nothing about \( Z \), the pose.

TOY EXAMPLE, 1D SIGNAL

\[ Y = \{(\theta_1, \theta_2) \in \{1, \ldots, N\}^2, 1 < \theta_1 < \theta_2 < N\} \]
\[ P(l | Y = (\theta_1, \theta_2)) = \prod_{n < \theta_1} \phi_0(l_n) \prod_{\theta_1 \leq n \leq \theta_2} \phi_1(l_n) \prod_{\theta_2 < n} \phi_0(l_n) \]
\[ X((\theta_1, \theta_2), l) = (l(\theta_1 - 1), l(\theta_1), l(\theta_2), l(\theta_2 + 1)) \]
\[ P(X = (x_1, x_2, x_3, x_4) | Y = (\theta_1, \theta_2)) = \phi_0(x_1) \phi_1(x_2) \phi_1(x_3) \phi_0(x_4) \]
We then define
\[ f_k(I) = g(X(k, I)), \quad k \in \{1, \ldots, K\}, \]
where one single classifier \( g: \mathbb{R}^N \rightarrow \{0, 1\} \) is trained with
\[ \{ (X(k, I(t)), Y(t)_k) \}_{t, k}. \]

Notice that stationarity is the main condition required to ensure that the training samples are identically distributed.

Let \( e_{\phi, \sigma}(l, u, v) \) be the presence on an edge in image \( l \) at location \((u, v)\) with orientation \( \phi \in \{0, \ldots, 7\} \) at scale \( \sigma \in \{1, 2, 4\} \).
**CAT DETECTION**

**EDGE DETECTORS (CONT.)**

We use three types of stationary features:

- Proportion of an edge \((\phi, \sigma)\) in a window \(W\).
- \(L^1\)-distance between the histograms of orientations at scale \(\sigma\) in two windows \(W\) and \(W'\).
- \(L^1\)-distance between the histograms of gray-levels in two windows \(W\) and \(W'\).

The windows \(W\) and \(W'\) are indexed either with respect to the head or with respect to the head-belly.

**STATIONARY FEATURES**

The windows \(W\) and \(W'\) are indexed either with respect to the head or with respect to the head-belly.

**CLASSIFIER**

We build classifiers with Adaboost and an asymmetric weighting by sampling. If the weighted error rate is

\[
L(h) = \sum_{t,k} \omega_{t,k} \mathbb{1}\{n(k, t) \neq Z_k(t)\},
\]

we use all the positive samples, and sub-sample negative ones with

\[
\mu(k, t) \propto \omega_{t,k} \mathbb{1}\{y_k(t) = 0\}.
\]

Total of 2327 scenes containing 1683 cats, 85% for training.
**FOLDED HIERARCHIES**

**SUMMARY**

Experiments (not shown) demonstrate:
- Fragmentation applied to complex poses is disastrous in practice;
- Naive, brute-force exploration of the pose space is computationally intractable.

Alternatively:
- Stationary features largely avoid fragmentation;
- Hierarchical search concentrates computation on ambiguous regions.

We call this alternative a *folded hierarchy of classifiers*.

---

**SCENE PARSING**

**STRATEGY**

![Scene Parsing Strategy Diagram]

```
g_{1} \downarrow \quad g_{2} \downarrow
```

---

**SCENE PARSING**

**ERROR CRITERION**

![Scene Parsing Error Criterion Diagram]
### Scene Parsing

**Error Rates**

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<th>H</th>
<th>B</th>
<th>HB</th>
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<td>85%</td>
<td>-</td>
<td>11.29 (3.61)</td>
<td></td>
</tr>
<tr>
<td>80%</td>
<td>17.23 (3.87)</td>
<td>5.07 (1.08)</td>
<td></td>
</tr>
<tr>
<td>70%</td>
<td>11.40 (2.89)</td>
<td>1.88 (0.32)</td>
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<tr>
<td>60%</td>
<td>7.80 (1.98)</td>
<td>0.95 (0.22)</td>
<td></td>
</tr>
<tr>
<td>50%</td>
<td>5.41 (1.62)</td>
<td>0.53 (0.13)</td>
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Average number of FAs per 640 x 480

### Scene Parsing

**Results (picked at random)**

![Scene Parsing Results (picked at random)](image)

### Scene Parsing

**Results (picked at random, cont.)**

![Scene Parsing Results (picked at random, cont.)](image)
CONCLUSION

A folded hierarchy of classifiers is highly efficient:
- For (offline) learning;
- For (online) scene processing.
It combines the strengths of:
- Template matching;
- Powerful, wholistic machine learning;
- Hierarchical search.
However, this is achieved at the expense of
- Rich annotation of the training samples.
- Designing stationary features.