Online Multiple Instance Learning Applied to Hand Detection in a Humanoid Robot

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Machine Learning Day
June 8th, 2010
Overview

- Why the hand?
- Multiple Instance Learning
- Online Boosting
- Online Multiple Instance Learning
- Experiments
- Conclusions
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Necessary to Exploration

Exploration is the best way for an autonomous agent to obtain information regarding the surrounding environment.

In order to interact with the environment, a robotic system needs to recognize the means through which, such interaction is happening.

For a humanoid robot this is the case of its **hands**.
Unique Object

The hand is a very unique object to learn. The poses in which it appears to the robot are strongly connected to the current **joint** and **motor states**.

**Visual** motion detection and **motor** information can be combined to roughly infer whether the robot’s hand is present in the Field of View.

Even if inaccurate, this expedient can be exploited to apply supervised learning techniques in a less supervised way.
Online Learning

Changes in an unstructured environment are unpredictable.

In order to keep a robust representation of the world, an autonomous agent must be able to integrate previous knowledge with new data as it arrives.

We are after an online framework able to constantly keep track of the robotic hand’s structure even when it is subject to changes in appearance. (e.g. illumination, rotation).
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![Image showing positive and negative instances]
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- The **individual label** of an instance is not known. Only the label of the entire bag is known.

Goal: Correctly classify the bags without knowing exactly which instances were responsible for the positive/negative label of the bag.
MIL & Boosting
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Boosting is a class of techniques employed in data classification.
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Weights are associated to weak learners according to their accuracy over a given training set.

Weak learners are combined to obtain an accurate **strong classifier.**
MIL & Boosting: AdaBoost
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AdaBoost adopts an iterative greedy strategy to select which weak learners combine in the strong classifier.
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MIL & Boosting: MIL balls
A bag is a collection of instances in the feature space.

Auer et al. 2004
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Online Boosting
Initialization.

- Let $\mathcal{H} = \{h_1, \ldots, h_N\}$ be a set of weak classifiers with Learning Principle $L$.
- Set $\lambda_n^w = \lambda_n^c = 0 \quad \forall n \in \{1, \ldots, N\}$.

Training.

At each iteration step $t$ a novel sample $I_t$ is presented to the system:

- Set the importance weight of the sample to $\lambda = 1$.
- For $n \in \{1, \ldots, N\}$ do:
  1. update $h_n \leftarrow L(h_n, I_t, \lambda)$
  2. if $h_n$ correctly classifies $I_t$:
     - $\lambda_n^c \leftarrow \lambda_n^c + \lambda$; $\epsilon_n = \frac{\lambda_n^w}{\lambda_n^c + \lambda_n^w}$; $\lambda \leftarrow \lambda \frac{1}{2(1 - \epsilon_n)}$
     else:
     - $\lambda_n^w \leftarrow \lambda_n^w + \lambda$; $\epsilon_n = \frac{\lambda_n^w}{\lambda_n^c + \lambda_n^w}$; $\lambda \leftarrow \lambda \frac{1}{2\epsilon_n}$
  3. Define the relevance weight of the $n$-th weak learner as $\alpha_n = \log \left( \frac{1 - \epsilon_n}{\epsilon_n} \right)$
- end.

Strong Classifier.

After every learning iteration, the score assigned by the strong classifier to a bag $I \in \mathcal{I}$ is:

$$S(I) = \sum_{n=1}^{N} \alpha_n \cdot h_n(I).$$

Oza et al. 2001
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**Learning principle:** whenever a novel training sample is provided to the system, the radius of the weak learner is updated in order to keep its accuracy optimized.
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On the other hand, the online boosting algorithm requires all the weak learners to be determined a priori. It is not possible to extract new ones from the data.
Weak Learners: Selectors
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A selector is a meta-weak learner associated to a fixed pool of other weak classifiers.

Grabner et al. 2006
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Decision Criteria: The selector classify a bag, according to the weak classifier in its pool that has exhibited the best accuracy so far.
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Weak Learners: Selectors

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The weak learner with lowest error rate is selected.
**Weak Learners: Selectors**

**Learning principle:** When a novel training sample is presented to the selector, each of the weak learners in its pool is trained accordingly. The weak learner with lowest error rate is selected. The weak learner with worst classification performance is substituted with a new one.
Main Framework

• New weak learners extraction.
• Online boosting of selectors.
Main Framework

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positive bag
Main Framework

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Hand Detection

Different experimental conditions:
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• **Background**: Uniform Vs Cluttered.
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• **Background**: Uniform Vs Cluttered.

• **Labeling**: Manual Vs Automatic.
Hand Detection

Different experimental conditions:

- **Background**: Uniform Vs Cluttered.

- **Labeling**: Manual Vs Automatic.

- **Order**: Natural Vs Shuffled.
Hand Detection: learning over time
Hand Detection: statistics

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Labelling</th>
<th>Order</th>
<th>EER Online</th>
<th>EER Offline</th>
</tr>
</thead>
<tbody>
<tr>
<td>uniform</td>
<td>Manual</td>
<td>Natural</td>
<td>(9.0 ±0.7)%</td>
<td>7.3%</td>
</tr>
<tr>
<td>uniform</td>
<td>Manual</td>
<td>Shuffled</td>
<td>(7.4±2.5)%</td>
<td>7.3%</td>
</tr>
<tr>
<td>cluttered</td>
<td>Manual</td>
<td>Natural</td>
<td>(13.0±1.9)%</td>
<td>7.5%</td>
</tr>
<tr>
<td>cluttered</td>
<td>Manual</td>
<td>Shuffled</td>
<td>(12±1)%</td>
<td>7.5%</td>
</tr>
<tr>
<td>cluttered</td>
<td>Auto</td>
<td>Natural</td>
<td>(18±2)%</td>
<td>9.9%</td>
</tr>
<tr>
<td>cluttered</td>
<td>Auto</td>
<td>Shuffled</td>
<td>(19±5)%</td>
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</tbody>
</table>
Hand Detection: ROC curves

![ROC curves diagram]
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- Multiple Instance Learning needs only weak supervision over data in order to be trained (e.g. positive or negative label over entire samples).

- The MIL paradigm allows to deal with **inaccurate** and possibly **noisy** training data (e.g. coarse labeling of images).

- In our framework learning is performed online in order to adapt to potential changes in the scene (e.g. illumination or orientation).

- Experiments were conducted on a real problem and under quite hard conditions (e.g. cluttered background). Nevertheless online performances remained comparable to those of batch algorithms.
Future work: localization

Selectors have originally been conceived to perform feature selection.
Future work: localization

Selectors have originally been conceived to perform **feature selection**. Feature selection could be exploited to perform hand localization:
Future work: localization

Selectors have originally been conceived to perform feature selection. Feature selection could be exploited to perform hand localization: The positive classifying weak learners within the selector pools can be plotted on the current image.
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Selectors have originally been conceived to perform feature selection. Feature selection could be exploited to perform hand localization:

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In theory they should all be on the object.
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Selectors have originally been conceived to perform feature selection. Feature selection could be exploited to perform hand localization: The positive classifying weak learners within the selector pools can be plotted on the current image. In theory they should all be on the object.
Future work: localization

Thanks:

• Fabrizio Smeraldi
• Lorenzo Natale
• Giorgio Metta
Thank you!