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On-line Boosting and Vision*

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Abstract Boosting has become very popular in computer vision, showing impressive performance in detection and recognition tasks. Mainly off-line training methods have been used, which implies that all training data has to be a priori given; training and usage of the classifier are separate steps. Training the classifier on-line and incrementally as new data becomes available has several advantages and opens new areas of application for boosting in computer vision. In this paper we propose a novel on-line AdaBoost feature selection method. In conjunction with efficient feature extraction methods the method is real time capable. We demonstrate the multifariousness of the method on such diverse tasks as learning complex background models, visual tracking and object detection. All approaches benefit significantly by the on-line training.

On-line boosting for feature selection

Motivation

- Boosting successfully used in a wide variety of tasks
- Many applications where on-line learning is essential

Related work

- Off-line boosting: Freund, Schapire [1]
- Off-line boosting for feature selection: Tieu and Viola [2]
- On-line boosting: Oza and Russell [3]

Principle

- Weak classifier

$$h^{weak}(\mathbf{x})$$

- Selector

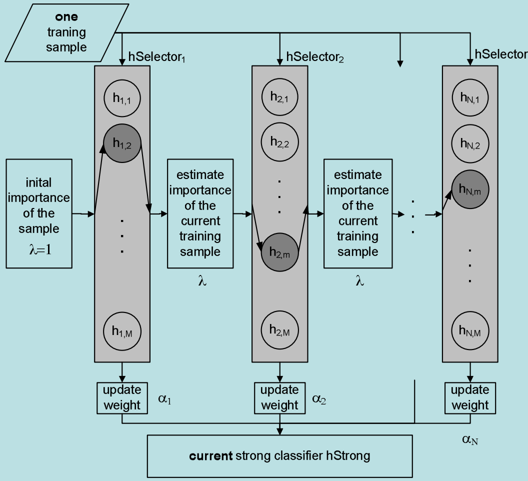
$$\mathcal{H}^{weak} = \{h_1^{weak}, ..., h_M^{weak}\}$$
$$\mathcal{F}_{sub} = \{f_1, ..., f_M | f_i \in \mathcal{F}\}$$

$$h^{sel}(\mathbf{x}) = h_m^{weak}(\mathbf{x})$$
$$m = \arg\min_i e_i$$

The main idea is to apply on-line boosting not directly on the weak classifiers but on the selectors.

- Strong classifier

$$h^{strong}(\mathbf{x}) = \text{sign}\left(\sum_{n=1}^{N} \alpha_n \cdot h_n^{sel}(\mathbf{x})\right)$$



Training

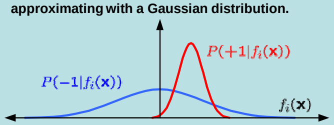
- for each selector
  - update selector
    - update each weak classifier
    - estimate error in respect to λ
    - choose weak classifier with lowest error
  - calculate voting weight α
  - update importance weight λ
  - replace worst classifier in local feature pool

Features ⇨ Weak classifier

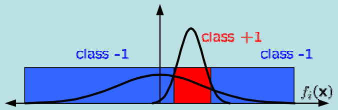
- Haar-like features
- Orientation histograms
- Local binary patterns

Integral data structures are used for efficiency (integral images, integral histograms)

estimate distribution of pos. and neg. samples by approximating with a Gaussian distribution.



⇨ **generate hypothesis**



References

[1] Y. Freund and R. Schapire. A decision-theoretic generalization of on-line learning and an application to boosting, Journal of Computer and System Science, 55(1):119-139, 1997.
[2] K. Tieu and P. Viola. Boosting image retrieval. In Proc. CVPR, pages 228-235, 2000.
[3] N. Oza and S. Russell. Online bagging and boosting. In Proc. Artificial Intelligence and Statistics, pages 105-112, 2001.

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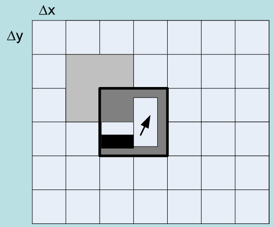
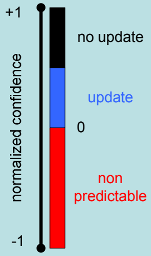
Background Model

overlapping classifiers

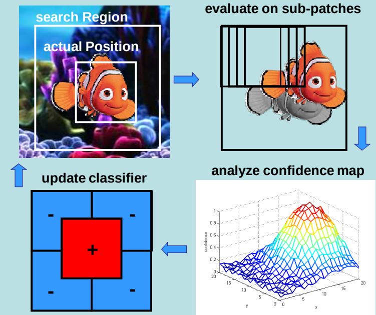


update policy

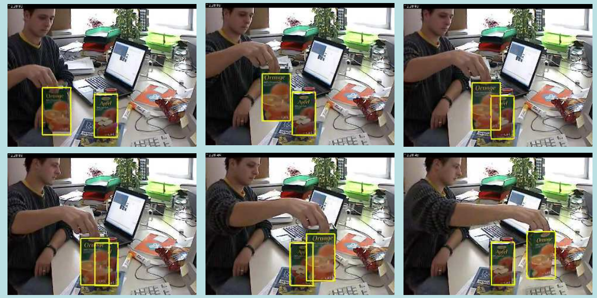


Experiments

Tracking

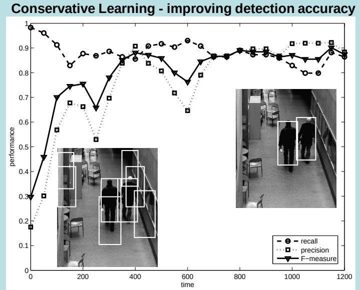


Experiments
(see also: Video proceedings, Video Real-Time Tracking with On-line Feature Selection)



Object Detection

Conservative Learning - improving detection accuracy

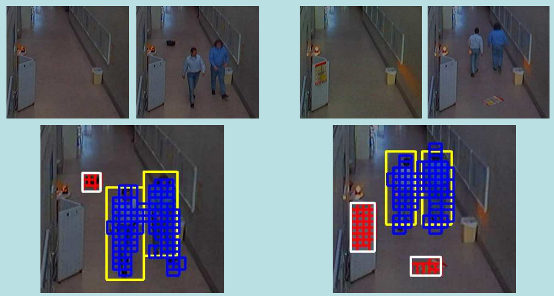


P. Roth, H. Grabner, D. Skočaj, H. Bischof, A. Leonardis.
On-line conservative Learning for person detection. In Proc. Workshop on VS-PETS, 2005

Experiments
(see also: Video proceedings, On-line learning a person model from video data)

Combination

Video Surveillance Task
(left luggage, vandalism, theft)



Experiments
(see also: PETS 2006 WS, Autonomous Learning of a Robust Background Model for Change Detection)