Learning for Tracking and Lessons Learned from it

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Outline

ON-LINE Machine learning

Computer Vision: Tracking

Lessons Learned

D'OH!
Tracking by fast (re-) detection

Time t  from time t to t+1  „find“ again
Tracking Cues

- Object Appearance
- Background

Objective/Background discrimination

- Object Boundary
- Motion
[Grabner et al. VideoProc.CVPR 2006]
Tracking Requirements (model free tracking)

- Adaptive

- Robustness

- Generality

And of course, REAL TIME!
PART I

On-line Boosting based Tracking

CVPR’06, BMVC’06
Boosting and Vision

- Boosting
  [Freund and Schapire, JCSC, 1997]

- Boosting for Feature Selection
  [Tieu and Viola, CVPR 2000], [Viola and Jones, CVPR 2001]

- On-line boosting
  [Oza and Russel, AIS, 2001]

- On-line Boosting for Feature Selection
  [Grabner and Bischof, CVPR 2006]
Off-line learning
On-line learning

Learning Algorithm

Labeled Information

Teacher
Sir, could you please tell me what boosting is?

Boosting needs just some guy who is a little bit better than guessing.
Off-line boosting

**Strong classifier**

\[ H(x) = \text{sign} \left( \sum_{n=1}^{N} \alpha_n \cdot h_n(x) \right) \]

**Weak classifier**

Reweighting the training examples
Boosting for Feature Selection

- **Combination of Simple Image Features** for distinguishing two classes
  - Features = weak classifier
  - Boosting to select a subset (strong classifier)

\[ \text{sign}(\alpha_1 \cdot \square + \alpha_2 \cdot \Box + \alpha_3 \cdot \blacksquare + \ldots) \]
On-line Boosting

\[ H_{t}^{on} \leftarrow \text{update} \left( H_{t-1}^{on}, (x_{t}, y_{t}) \right) \]
On-line Boosting

\[ H_t = \left( \sum_{i=1}^{t} \alpha_i H_i \right) \]

Converges to the off-line result!

2009/08/18, Southampton

H. Grabner, Tracking for Learning and Lessons Learned from it - ETH-Zurich, Computer Vision Lab
On-Boosting for Feature Selection

- Combination of Simple Image Features for distinguishing two classes
- Features = weak classifier
- Boosting to select a subset (strong classifier)

\[ \text{sign}(\alpha_1 \cdot \text{feature} + \alpha_2 \cdot \text{feature} + \alpha_3 \cdot \text{feature} + \ldots) \]
On-Boosting for Feature Selection

- Coarse
- Image Features
- Features
- Boosting to select a subset (strong classifier)

General approach for on-line feature selection.

$$\text{sign}(\alpha_1 \cdot \mathbf{v} + \alpha_2 \cdot \mathbf{w} + \alpha_3 \cdot \mathbf{u} + ...)$$
Tracking as Classification

object

vs.

background
Tracking as Classification

object vs. background
from time t to t+1

evaluate classifier on sub-patches

search Region

create confidence map

update classifier (tracker)

analyze map and set new object position
Object Detector

Fixed Training set
General object detector

Object Tracker

On-line update
Object vs. Background

Off-line Boosting for Feature Selection

On-Line Boosting for Feature Selection
Lesson learned 1

Tracking is a simple task!
(When formulating it properly)
“Simple tracking”
“Tracking the Invisible”
Tracking Solved 😊

Does it fail?
If yes, when?
When does it fail...
When does it fail...

Often, all too often!
When does it fail...

WHY?
Self-learning

From time $t$ to $t+1$, evaluate classifier on sub-patches.

Create confidence map, analyze map and set new object position.

Update classifier (tracker).
Drifting due to self-learning policy

Tracked Patches

Confidence
Self-learning → drifting!
PART II

Semi-Supervised On-line Boosting for Tracking

ECCV’08
Review: Supervised Tracking
Problems of...

- Label Jitter
- Label Noise
Semi-Supervised Tracking

Un-labeled data

Labeled data
Supervised learning
Can Unlabeled Data Help?

decision boundary in low density region
Semi-Supervised On-line Boosting

Prior

\[ H_{off}(x) \]

\[ H_{on}(x) \]
Semi-Supervised On-line Boosting

Prior

fix

“stable”

dynamic

Nobody is perfect!
But, be a honest Teacher!

$H^{off}$ (Prior) can be wrong with low confidence.
Tracking Loop

Prior

- actual object position
- search Region
- evaluate classifier on sub-patches
- update classifier (tracker)
- create confidence map
Object Detector  Our approach  Object Tracker

Fixed Training set  Fixed Prior for updating an  On-line update
General object detector  Adaptive on-line classifier  Object vs. Background

Prior
Labeled data  Un-labeled data
LESSON LEARNED 3

On-line Semi-supervised learning → limited drifting.
Occlusions
Object disappearance
Long term tracking (1h)

Click here to start
Tracking Solved 😊

Does it fail?
If yes, when?
Prior is too generic (e.g., drift to similar objects)
Prior restricts too much (e.g., partial occlusions)
Prior is essential in semi-supervised learning.
(c.f., Stability Plasticy Dilemma)
PART III

Beyond Semi-Supervised Tracking

ICCV’09 WS on On-line Learning for Computer Vision
Review: Detection

Non adaptive at all!
Review: Supervised Tracking

Tracking

Too adaptive
Review: Semi-Supervised Tracking

Limit drifting but too restrictive / general
NEW PRINCIPLE: Active Sampling via Tracking

Detection

Tracking

H_{OFF}

H_{SEMI}
NEW PRINCIPLE: Active Sampling via Tracking
NEW APPROACH: Adaptive Prior

Additional information for prior update
Specializing (Simplifying)

**Updates**
- No
- Few trustful
- Many semi-supervised

**Learning task**
- Object class vs. everything else
- Particular objects vs. other objects and background
- Current Object appearance vs. local surrounding

**Applicable**
- Any time, everywhere
- Current scene
- Local neighborhood
Multiple classifier system

- `#include "vision.h"` use addition information, e.g., *multiple objects, background image*
- Information aggregation
Performance evaluation

<table>
<thead>
<tr>
<th></th>
<th>On-line</th>
<th>Semi</th>
<th>Beyond Semi</th>
</tr>
</thead>
<tbody>
<tr>
<td>recall</td>
<td>0.15</td>
<td>0.76</td>
<td>0.76</td>
</tr>
<tr>
<td>precision</td>
<td>0.89</td>
<td>0.32</td>
<td>0.99</td>
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<tr>
<td>f-measure</td>
<td>0.26</td>
<td>0.45</td>
<td>0.86</td>
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</tbody>
</table>
Implicit Occlusion handling
Really Long Term Tracking (24h)

Click here to start
Object Detector

Semi-Supervised

No updates

Fixed Prior
On-line updates

Our Approach

Multiple Adaptive Priors
On-line updates

Object Tracker

On-line update
Vision is more then pure Machine Learning!
(keep problems simple)
Extension 1: re-Identification

Detection ➔ Recognition ➔ Tracking

Identifier 1

Identifier 2
Extension 2: Information Aggregation

Detected
Recognition
Tracking
Whole Image
Scene / Current object / local surrounding
Specialization
Object instance / current scene
Specific image location

$H^{OFF}$

$H^{ON}$ (Object 1)

$H^{ON}$ (Object n)

$H^{SEMI}$ (Object 1)

$H^{SEMI}$ (Object n)

$H^{ON}$ (Local)
Pedestrian Detection (PETS)

Generic Detector & Context

Proposed Approach
Vision ≠ Detection + Tracking + Recognition
(benefitting from a lot of – unlabeled – data)
Conclusion

Tracking is simple

Self-learning → drifting

Semi-Supervised learning

Prior ☠

Vision > Machine Learning

Acknowledgments

EU-project SCOVIS under grant agreement no 216465.

Institute for Computer Graphics and Vision
Graz, University of Technology, Austria

Centere of Machine Preception
Czech Technical University

Horst Bischof  Michael Grabner  Christian Leistner  Jiri Matas  Jan Sochamn

Luc van Gool  Severin Stalder
Code/Demos & Tracker Evaluation

on-line boosting trackers  for model-free, single object tracking

download

Here you can download the three on-line boosting based trackers (licensed under LGPL, use at own risk) as

- precompiled win32 binaries
- zipped source code

In this version only linear-like warm starts are used as back: feature and weak classifiers are single decision stumps. Further, no scale/tracking adaptation is used.

download pre-compilled win32 binaries

\texttt{win32\ binaries}

Usage: Start the tracker using one of the following commands:

- BoostingTracker [ymlconfig.txt]
- SeqBoostingTracker [ymlconfig.txt]
- BeyondSeqBoostingTracker [ymlconfig.txt]

Mark the target object in the first frame using the mouse. Then change to the DOS window and press \texttt{<ENTER>}. Tracking starts...

http://vision.ee.ethz.ch/boostingTrackers

ethz tracker evaluation  for model-free, single object tracking algorithms

evaluation metric

Recall and Precision

In object detection, there is the well known trade-off between learning how many of the objects the detector detects, and how often the detection it makes are false. These variations are captured in the precision-recall curve, which the confidence of the tracker is thresholded. Summarizing, true positives are where the bounding box of the tracked object highly overlaps (fix default threshold) with the ground truth. False positives are those detections where no object is selected.

stability vs drifting

Additionally to object tracking, there is trade-off between adaptation to appearance changes of the object to be tracked and drifting into other objects. We would like to illustrate that trade-off with our evaluation metric. Therefore, we introduce the 2D plot... (more details are available here).

http://www.vision.ee.ethz.ch/trackerEvaluation
Additional Slides…
Detector

Valid samples

Confidence map

Detection

Recognition

Tracking

$H_{ON}^{1}$ (Object 1)

$H_{OFF}$

$H_{ON}^{n}$ (Object n)

$H_{SEMI}^{1}$ (Object 1)

$H_{SEMI}^{n}$ (Object n)

Detection flow

Tracking flow

No Updates

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Detector

Detection

Recognition

Tracking

Detection flow

Tracking flow

H\textsuperscript{ON} (Object 1)

H\textsuperscript{OFF}

H\textsuperscript{ON} (Object n)

H\textsuperscript{SEMI} (Object 1)

H\textsuperscript{SEMI} (Object n)

Valid samples

Confidence map

pos. updates

Neg. updates
Detector

Valid samples

Confidence map

Unlabeled updates
(foreground & local background)

Detection

Recognition

Tracking

\(H^{ON}\) (Object 1)

\(H^{OFF}\)

\(H^{ON}\) (Object n)

\(H^{SEMI}\) (Object 1)

\(H^{SEMI}\) (Object n)

Detection flow

Tracking flow