



# Speeding Up Semi-Supervised On-line Boosting for Tracking\*

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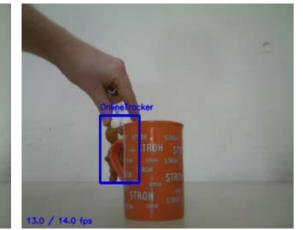
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**Abstract** Recently, object tracking by detection using adaptive on-line classifiers has been investigated. In this case, the tracking problem is reduced to the discrimination of the current object view from the local background. However, on-line learning may introduce errors, which causes drifting and let the tracker fail. This can be avoided by using semi-supervised on-line learning (i.e., the use of labeled and unlabeled training samples), which allows to limit the drifting problem while still staying adaptive to appearance changes. In particular, this paper extends semi-supervised on-line boosting by a particle filter to achieve a higher frame-rate. Furthermore, a more sophisticated search-space sampling, and an improved update sample selection have been added.

#### **Motivation**

On-line supervised learning within Tracking-by-Detection may introduce errors into the object model and cause drifting due to the unsupervised nature of the tracking task.

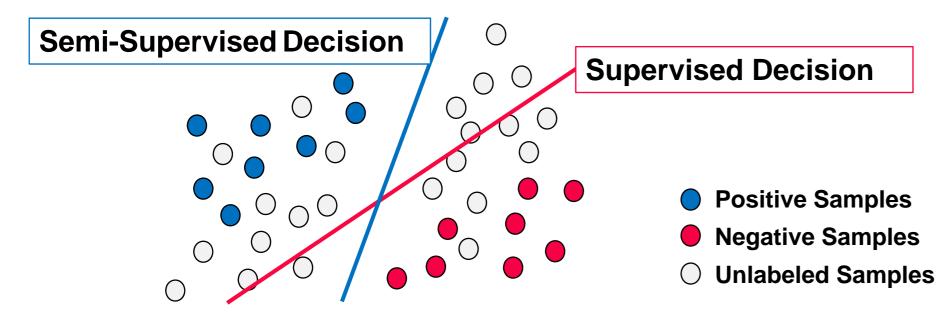






### **Semi-Supervised Learning**

Include unlabeled data into training set to improve performance of resulting classifier (use cluster and manifold assumption).



### 65.0 / 49.0 fps

Motion model helps handling temporary occlusions.

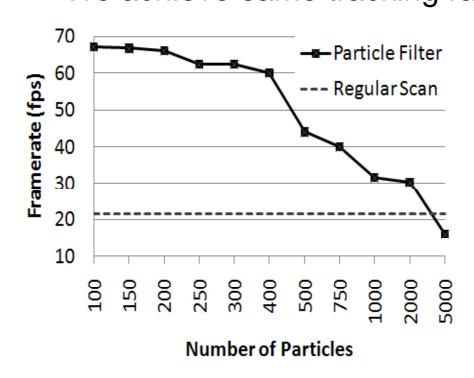
Dense sampling at interesting locations

• We achieve same tracking rate with a sample reduction of 90%.

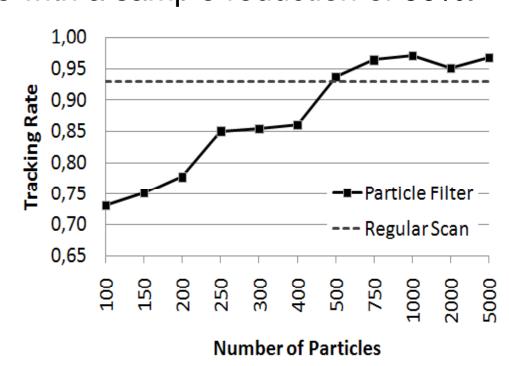
**Particle Filtering** 

We are using the particle filter to estimate the objects location. The

particle weights are set according to the confidence of the learned

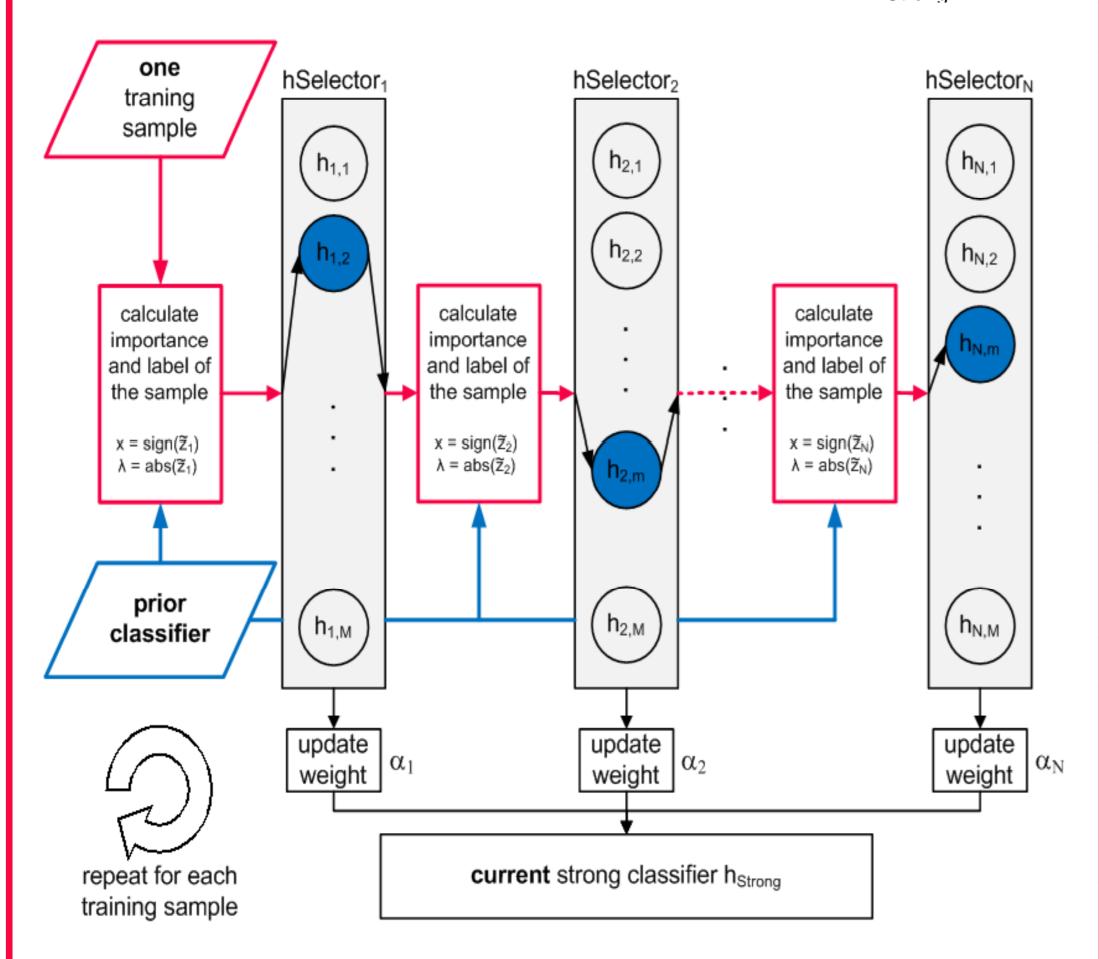


classifier at the particle locations.



### **Semi-supervised On-line Boosting (SSOB)**

On-line Boosting incrementally selects suitable classifiers out of N classifier pools and combines them to a strong ensemble H<sub>Strong</sub>.

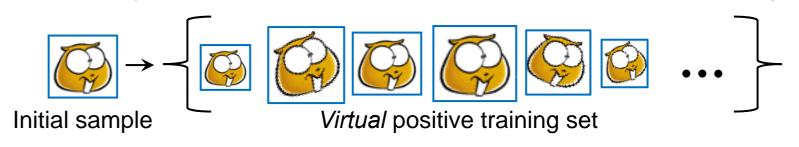


The label and the weight of processed training samples depend on the combined decision of a prior classifier  $H^P$  and the on-line learned classifier  $H_n$ :

 $\widetilde{z}_n(x) = \tanh\left(H^P(x)\right) - \tanh\left(H_{n-1}(x)\right)$ 

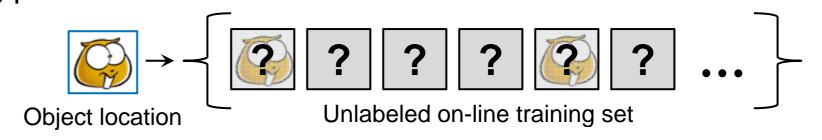
## One-Shot Training of Prior Classifier

Create virtual samples that simulate natural behaviour of the object.



### **Update Patch Selection**

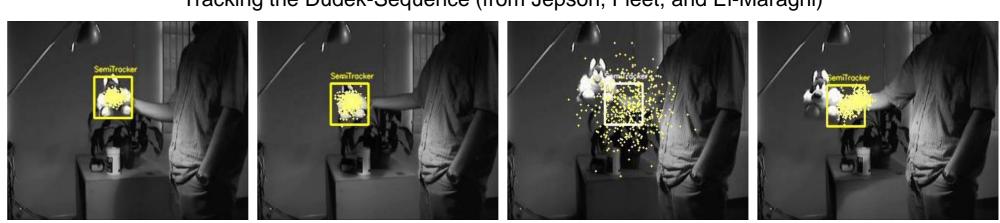
Evaluated different methods for patch selection and their influence on tracking performance.



#### Results



Tracking the Dudek-Sequence (from Jepson, Fleet, and El-Maraghi)



Tracking Sylvester (from David Ross)

#### Conclusion

- Label noise and jitter cause drifting
- SSOB limits drifting but also adaptivity
  - Stability Plasticity Dilemma