ETH
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Training Sequential On-line Boosting Classifiers for Visual Tracking

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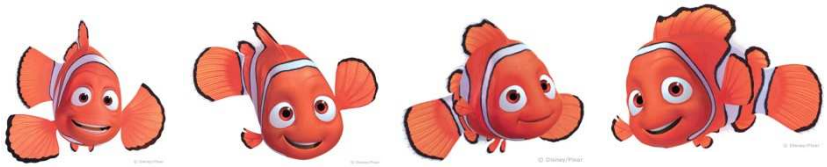
M. Grabner, H. Grabner and H Bischof. **Real-time tracking with on-line feature selection.** CVPR 2006.

Tracking Requirements

- Adaptivity



- Robustness

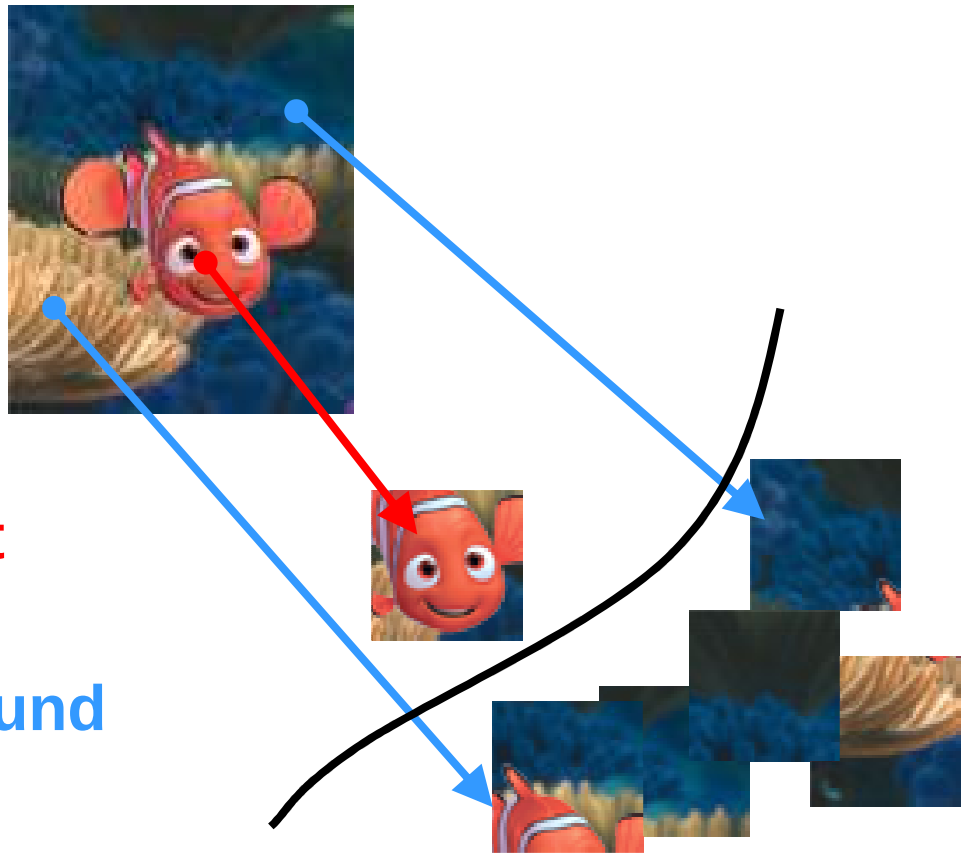
- Generality

Agenda

- Introduction
- Tracking as Binary Classification
- On-line Boosting for Feature Selection
- **Sequential On-line Boosting**
- Experiments
- Conclusion

Tracking as Classification

H. Grabner, M. Grabner and H. Bischof. **Real-time tracking via On-line Boosting,** BMVC 2006.



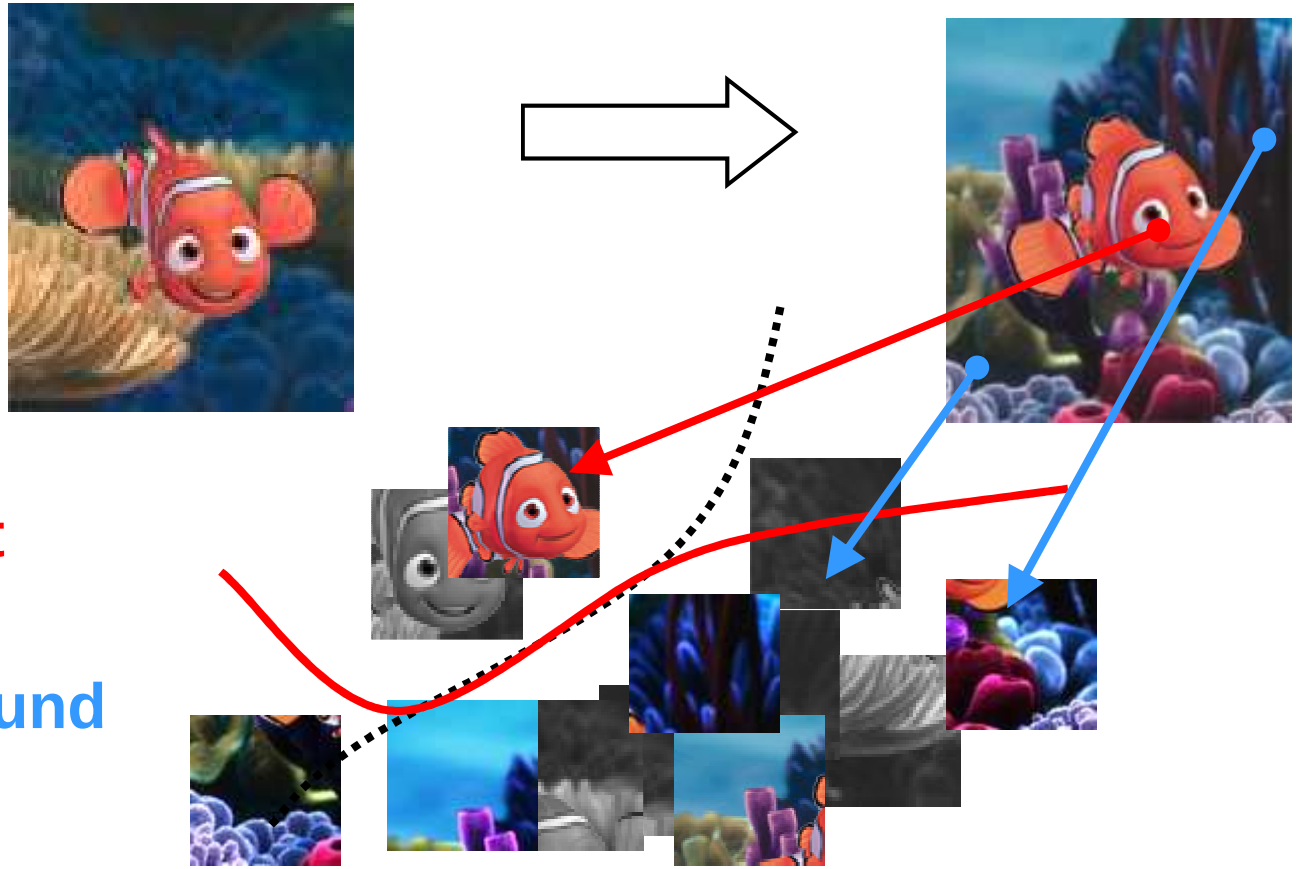
object

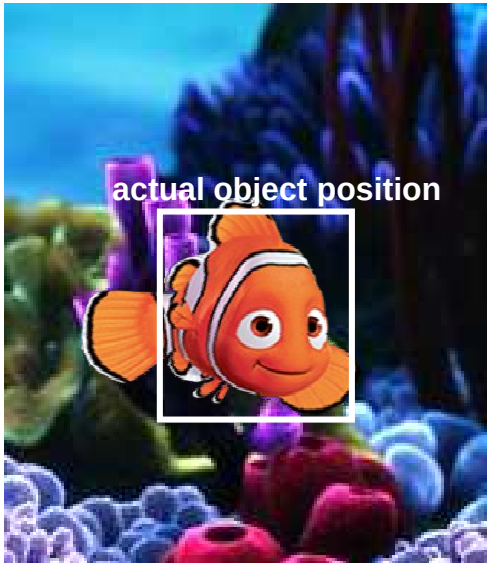
vs.

background

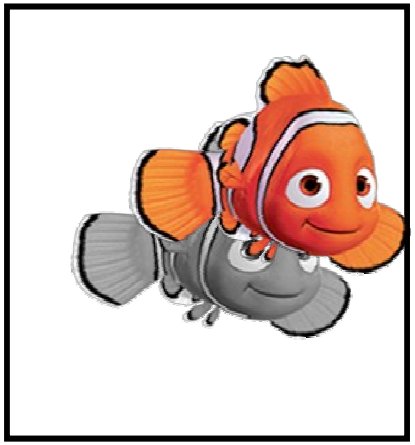
Tracking as Classification

H. Grabner, M. Grabner and H. Bischof. **Real-time tracking via On-line Boosting,** BMVC 2006.

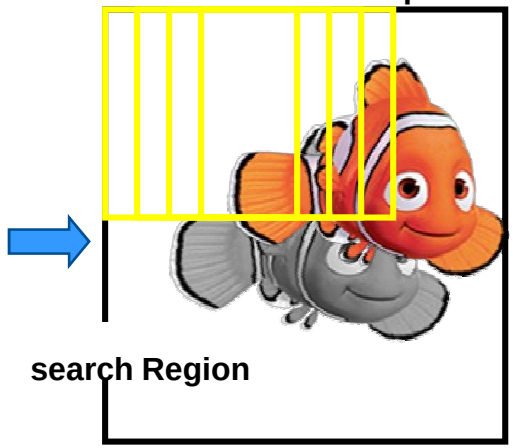




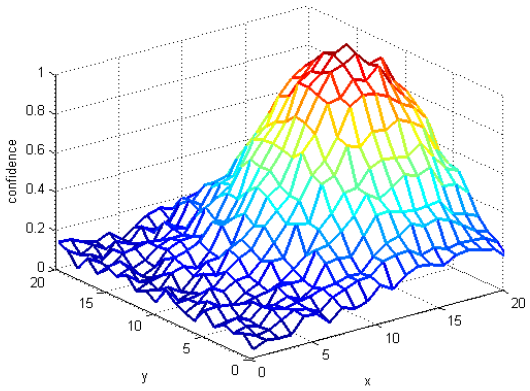
from time t to t+1



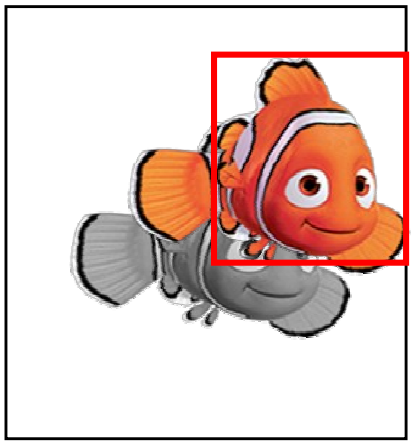
evaluate classifier on sub-patches



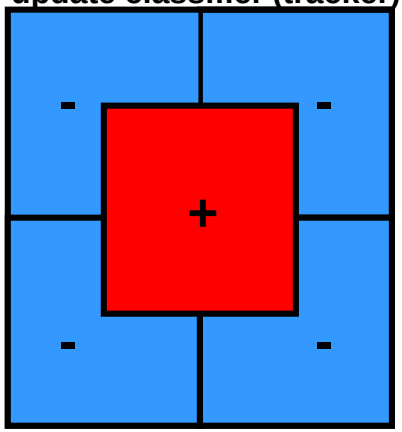
create confidence map



analyze map and set new object position

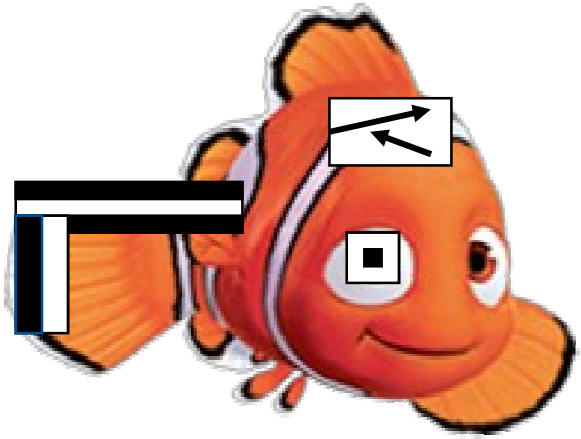


update classifier (tracker)



The Classifier

Combination of simple image features
using Boosting as Feature Selection



$$\text{sign}(\alpha_1 \cdot \boxed{} + \alpha_2 \cdot \boxed{} + \alpha_3 \cdot \boxed{} + \ldots)$$

P. Viola and M. Jones. **Rapid object detection using a boosted cascade of simple features.** CVPR 2001.

Boosting

Strong classifier **Weak classifier**

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

Reweighting the training Examples

Y. Freund and R. Schapire. **A decision-theoretic generalization of on-line learning and an application to boosting.** Journal of Computer and System Sciences, 1997.

Boosting for Feature Selection

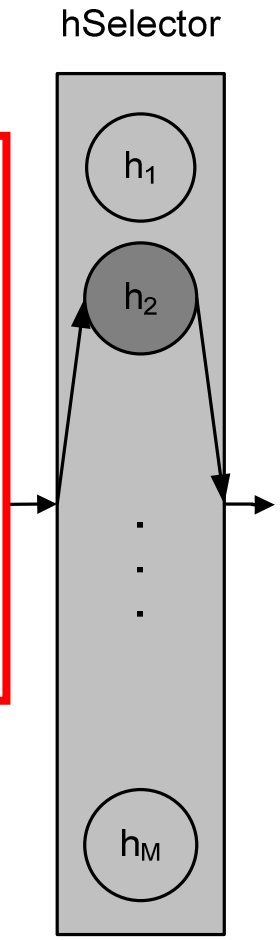
- **Each feature corresponds to a weak classifier**

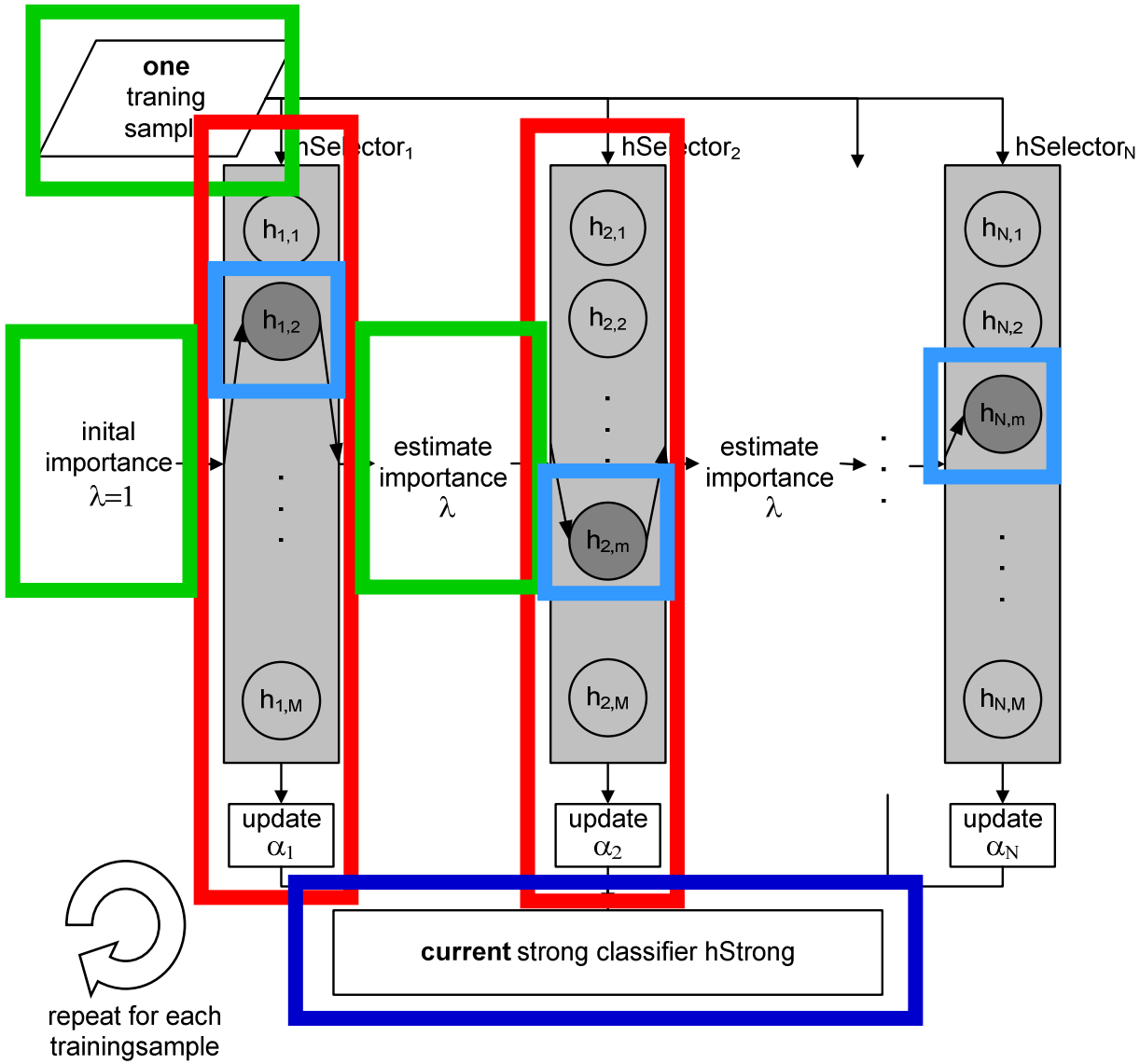
K. T

- **On-line**
  - Introducing "
  - selects one f

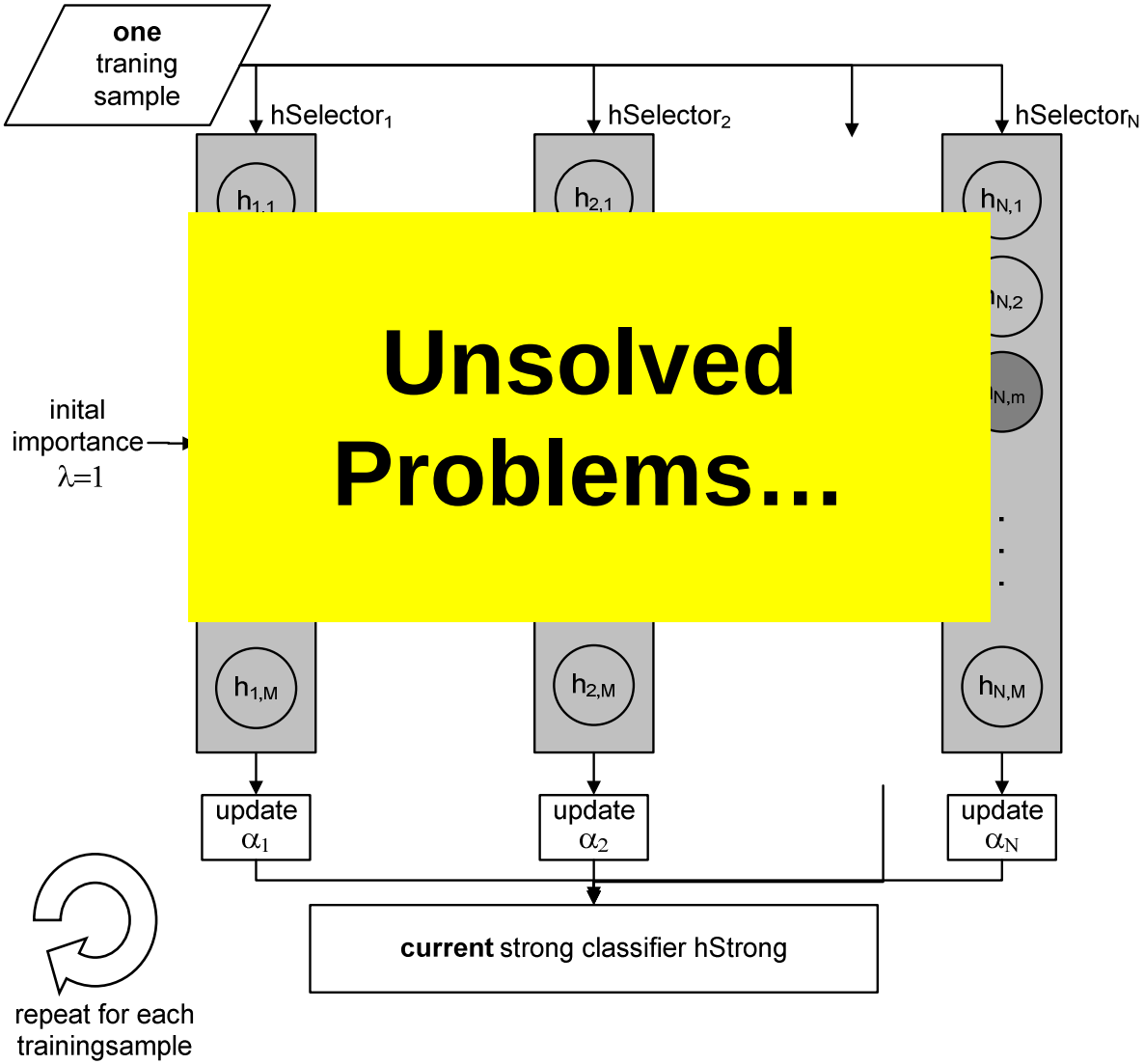
Boosting is performed on the Selectors and not on the weak classifiers directly.

H. Grabner and H., Bischof. **On-line Boosting and Vision,** CVPR 2006

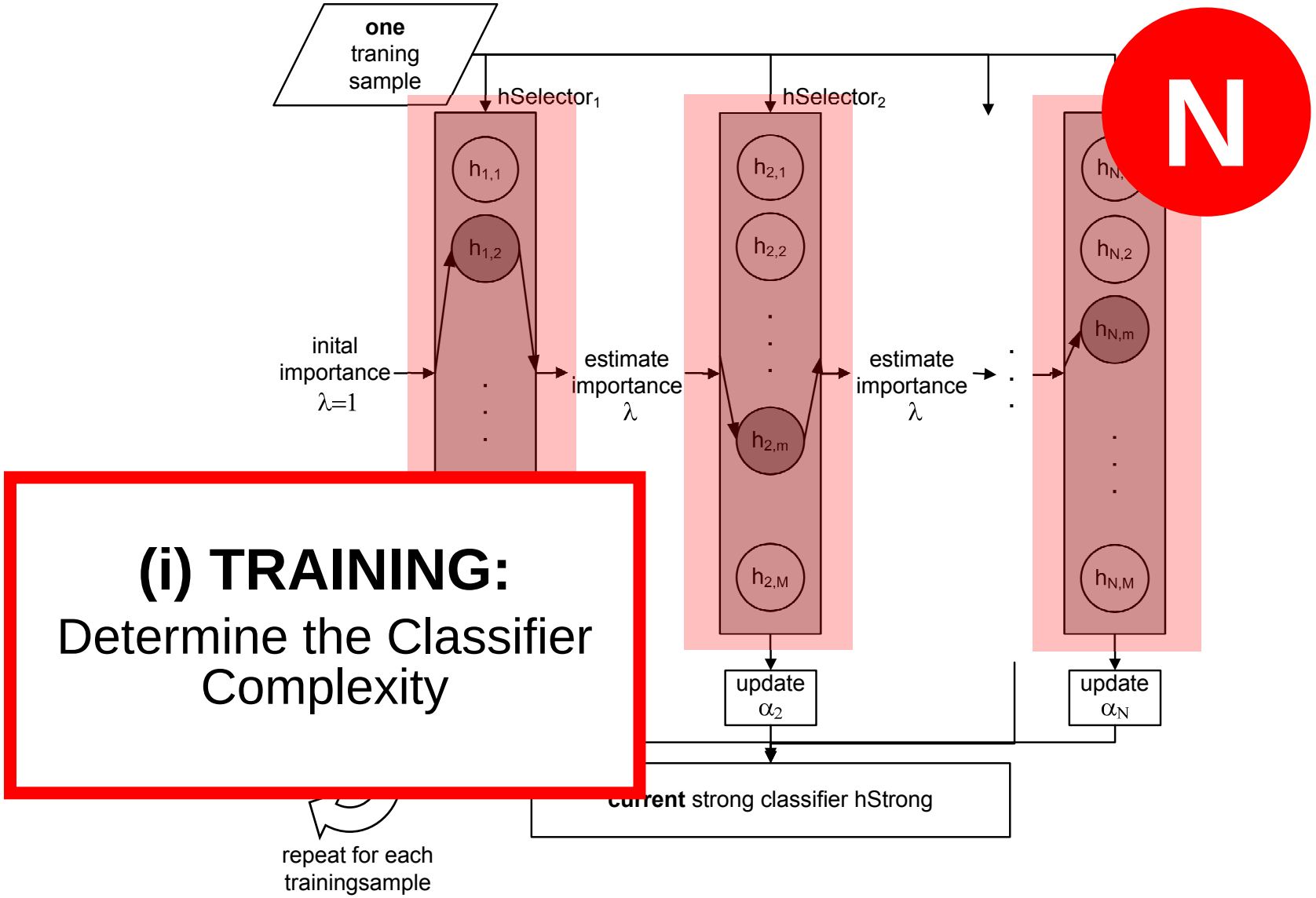




H. Grabner and H., Bischof. **On-line Boosting and Vision,** CVPR 2006

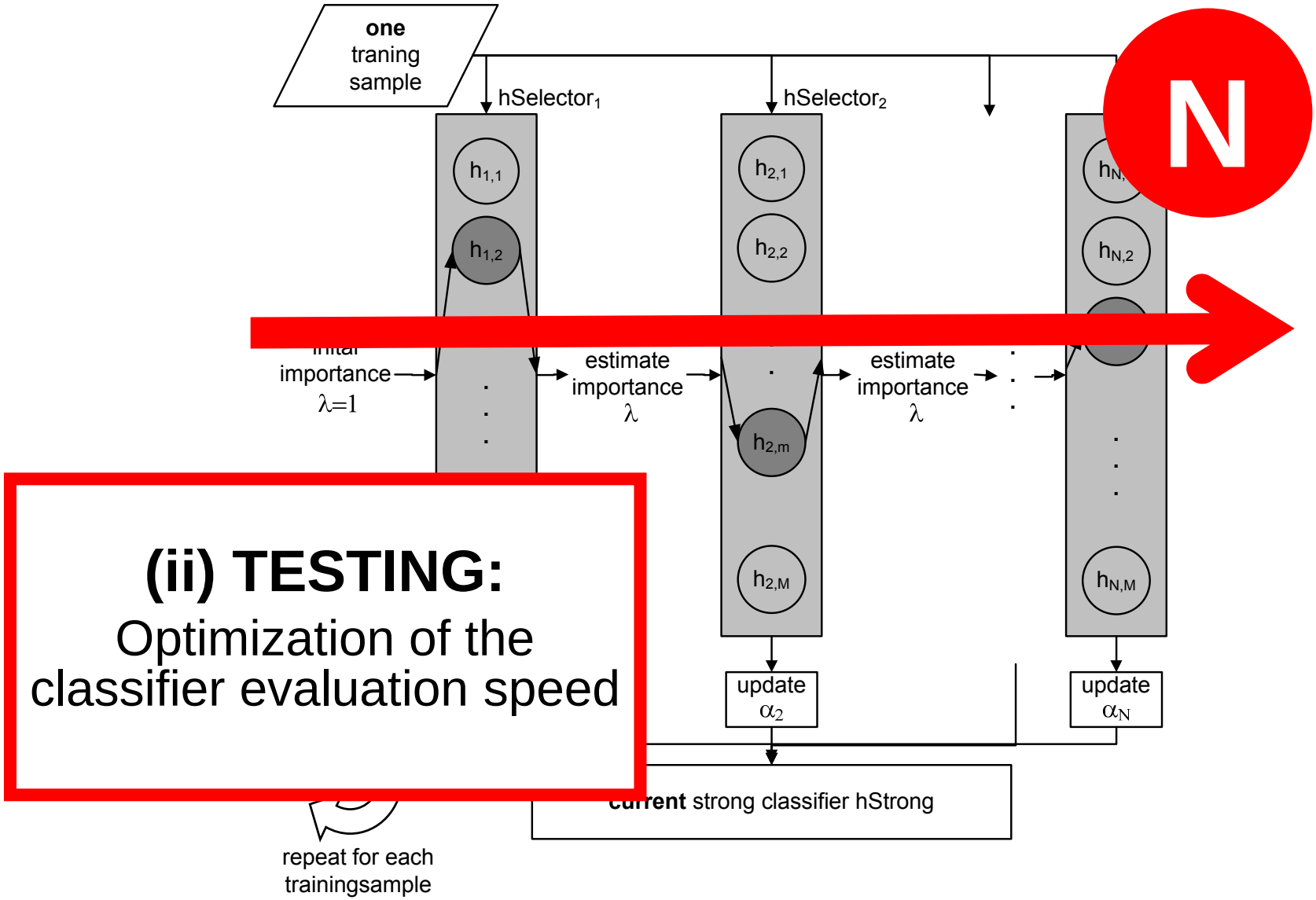


Unsolved Problems…



(i) TRAINING:

Determine the Classifier Complexity



(ii) TESTING:

Optimization of the classifier evaluation speed

Wald's Sequential Probability Rate Test (SPRT)

Abraham Wald (1902-1950)

Sequential Decision Making

- Sequential Decision Strategy S

decision

$$S : \{x_1, \ldots, x_n\} \rightarrow \{-1, +1, \text{continue}\}$$

Ordered sequence of measurements

- Goal: Train (look for)

$$S^\star = \arg\min_S \bar{T}_S \qquad s.t. \qquad \beta_S \leq \beta, \alpha_S \leq \alpha$$

Average time-to-decision (-1/+1)

Allowed false positive and false negative rate

Sequential Probability Ratio Test

$$S_n^\star = \begin{cases} +1, & R_n \leq B \\ -1, & R_n \geq A \\ \text{continue}, & \text{otherwise} \end{cases}$$

Likelihood ratio

$$R_n = \frac{p(x_1,\ldots,x_n|y=-1)}{p(x_1,\ldots,x_n|y=+1)}$$

(near) optimal setting

$$A = \frac{1-\beta}{\alpha}, \quad B = \frac{\beta}{1-\alpha}$$

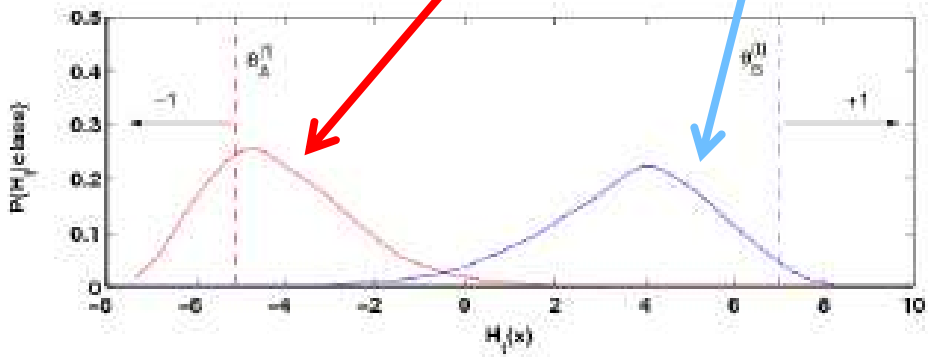
J. Sochman, J. Matas, **WaldBoost – Learning for Time Constrained Sequential Detection,** CVPR, 2005.

WaldBoost (1)

- Likelihood ratio $$R_n = \frac{p(x_1,\ldots,x_n|y=-1)}{p(x_1,\ldots,x_n|y=+1)}$$
- Replace with weak classifier $$R_n = \frac{p(h_1(x),\ldots,h_n(x)|y=-1)}{p(h_1(x),\ldots,h_n(x)|y=+1)}$$
- 1D projection $$R_n = \frac{p(H(x)|y=-1)}{p(H(x)|y=+1)}$$

$$H(x) = \sum_{n=1}^{N} \alpha_n h_n(x)$$

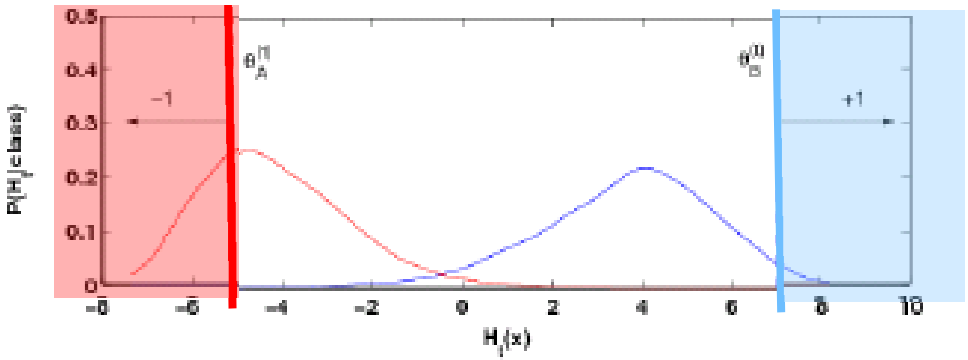
Boosting



J. Sochman, J. Matas, **WaldBoost – Learning for Time Constrained Sequential Detection,** CVPR, 2005.

WaldBoost (2)

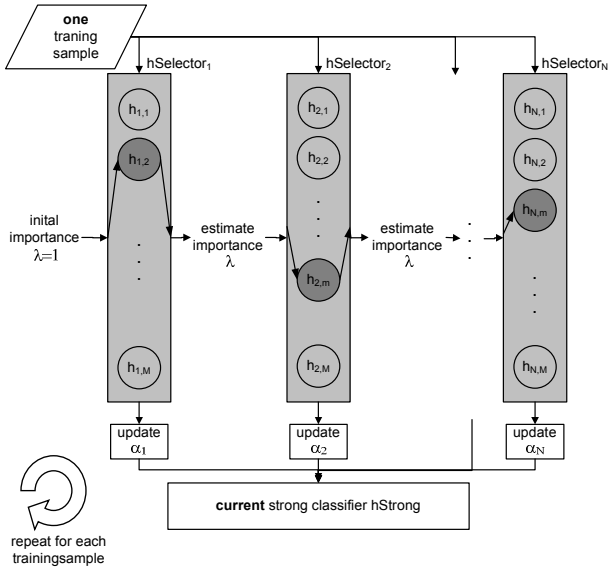
- Threshed on the boosted classifier response



$$H_n(x) = \begin{cases} +1, & H_n(x) \geq \theta_B^{(n)} \\ -1, & H_n(x) \leq \theta_A^{(n)} \\ \text{continue}, & \text{otherwise} \end{cases}$$

- Used in…
  - … training for bootstrapping important samples
  - … testing for early stopping (fast decision making)

On-line Boosting

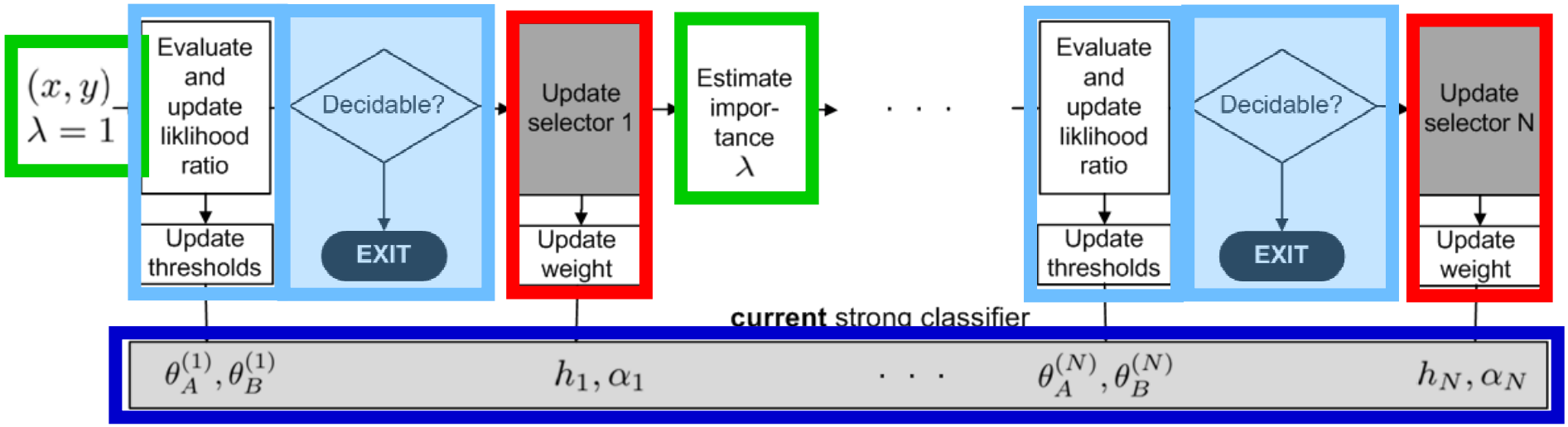


WaldBoost

$$H_n(x) = \begin{cases} +1, & H_n(x) \geq \theta_B^{(n)} \\ -1, & H_n(x) \leq \theta_A^{(n)} \\ \text{continue}, & \text{otherwise} \end{cases}$$

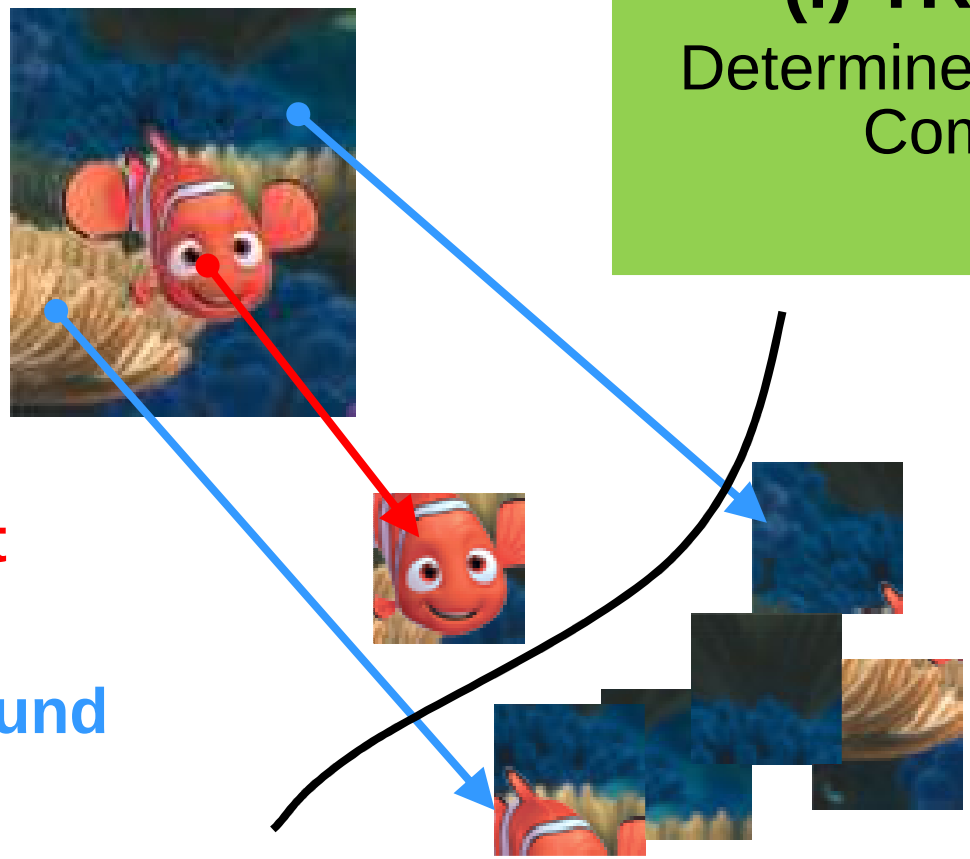
On-line Wald Boost

On-line WaldBoost



Back to Visual Tracking...

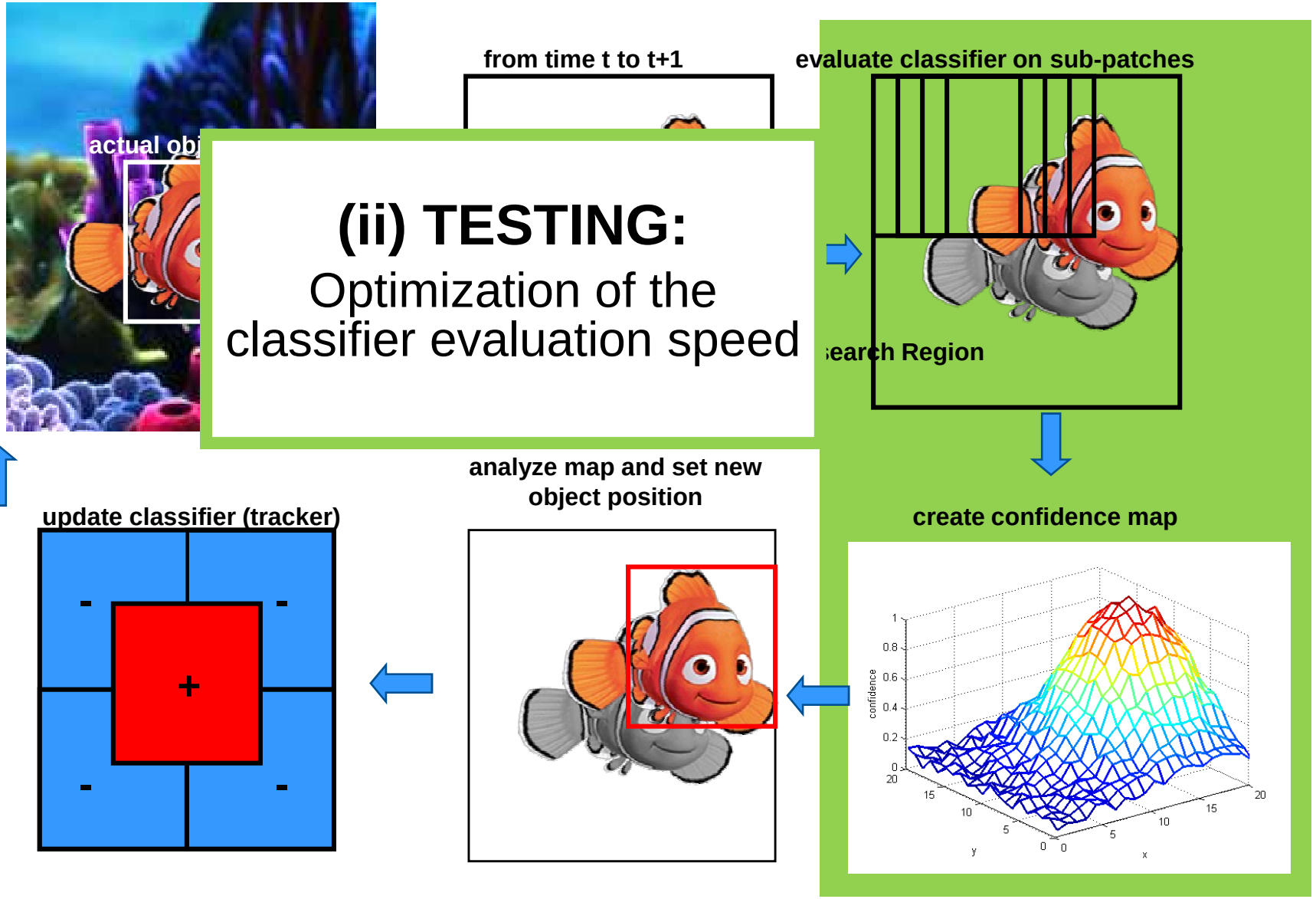
(i) TRAINING:
Determine the Classifier Complexity



object

vs.

background



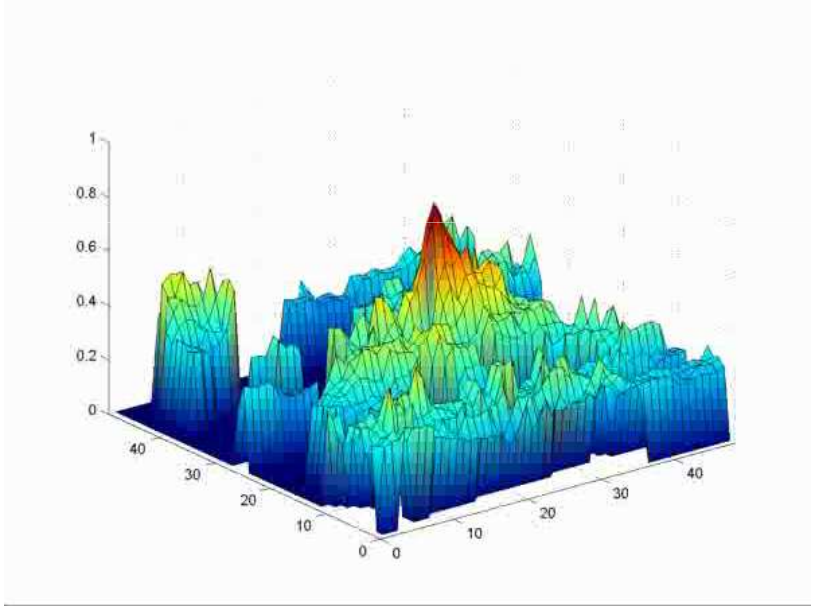
(ii) TESTING:

Optimization of the classifier evaluation speed

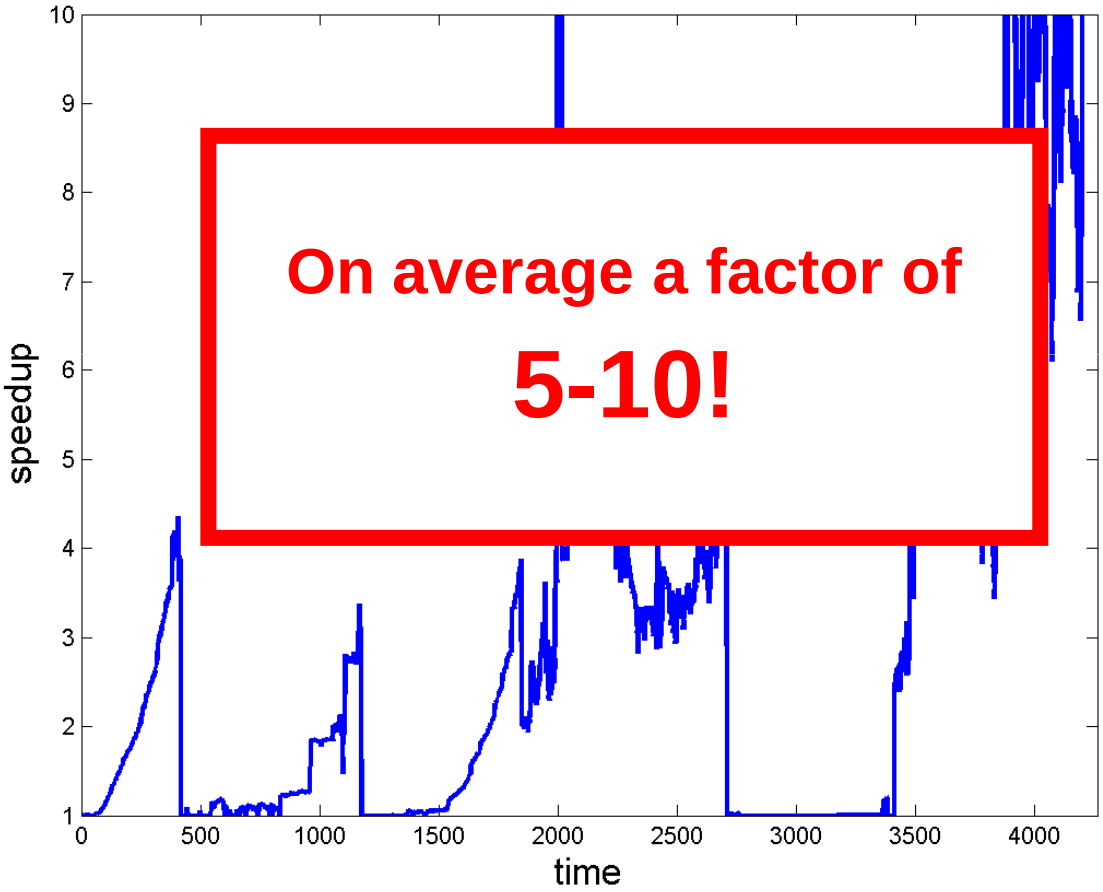
Experiments - Tracking

Tracking Result

Confidence Map



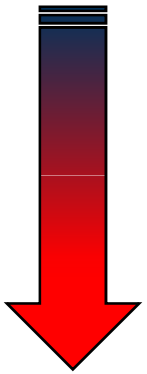
Experiment: Speedup



Conclusion and Outlook

- Wald-decision theory combined with on-line boosting for feature selection
  - (i) optimized classifier evaluation speed
  - (ii) automatic determination of the classifier complexity

On-line Boosting

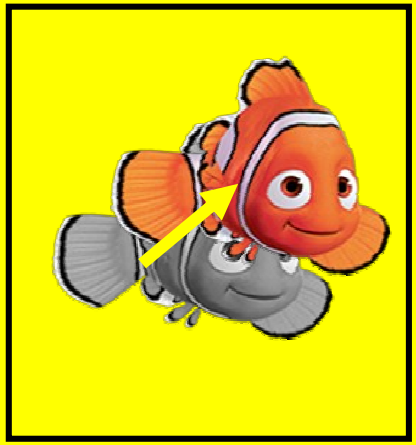


On-line WALD-Boosting

Conclusion and Outlook

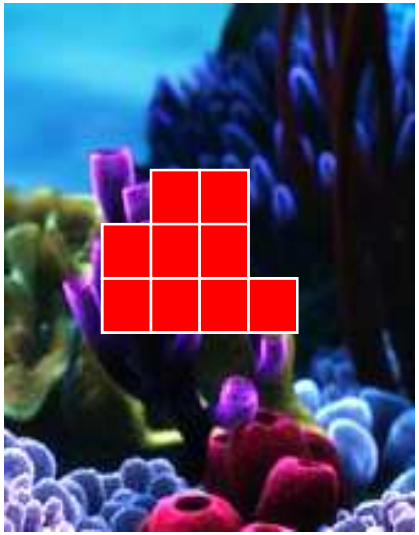
On-line WALD-Boosting

Tracking

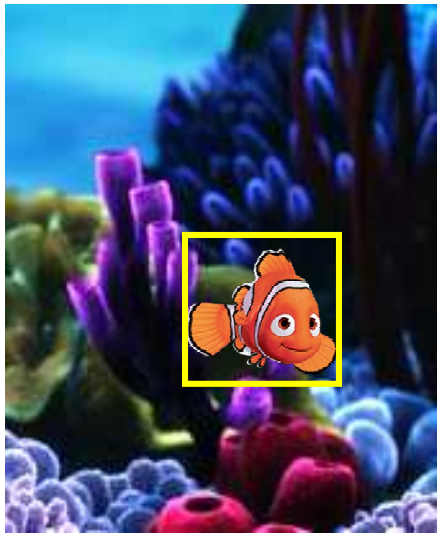


This presentation

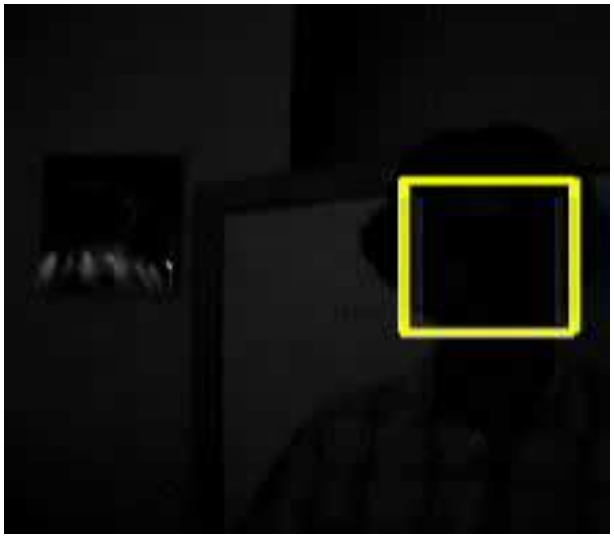
Background Modeling



Detection







Thank you for your attention!