

Center for Machine Perception

Improving Cascade of Classifiers by Sliding Window Alignment

*Karel Zimmermann, David Hurych, Tomáš Svoboda
Czech Technical University in Prague
Faculty of Electrical Engineering
Department of Cybernetics*



Overview



Overview



Overview



Overview



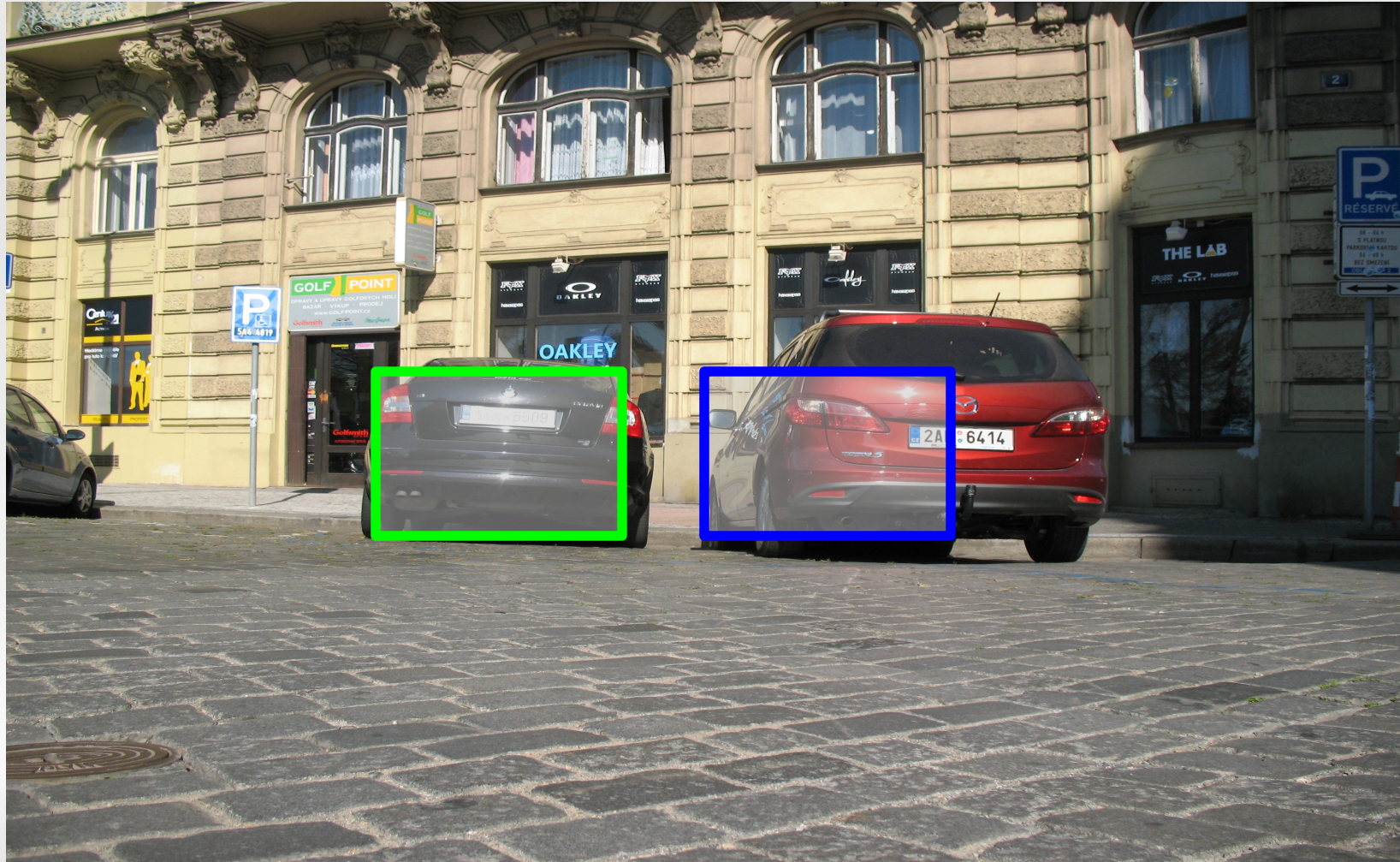
Overview



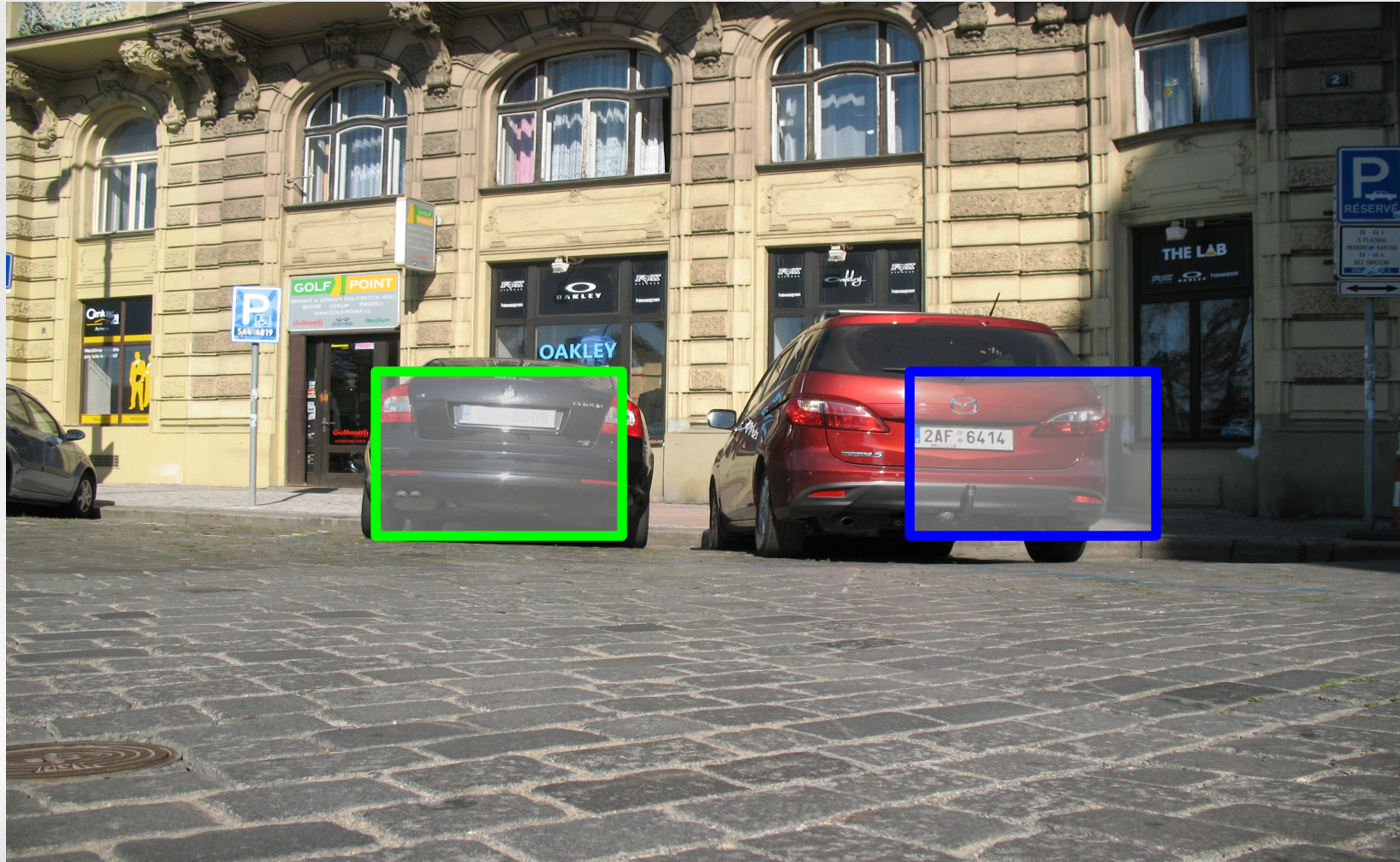
Overview



Overview



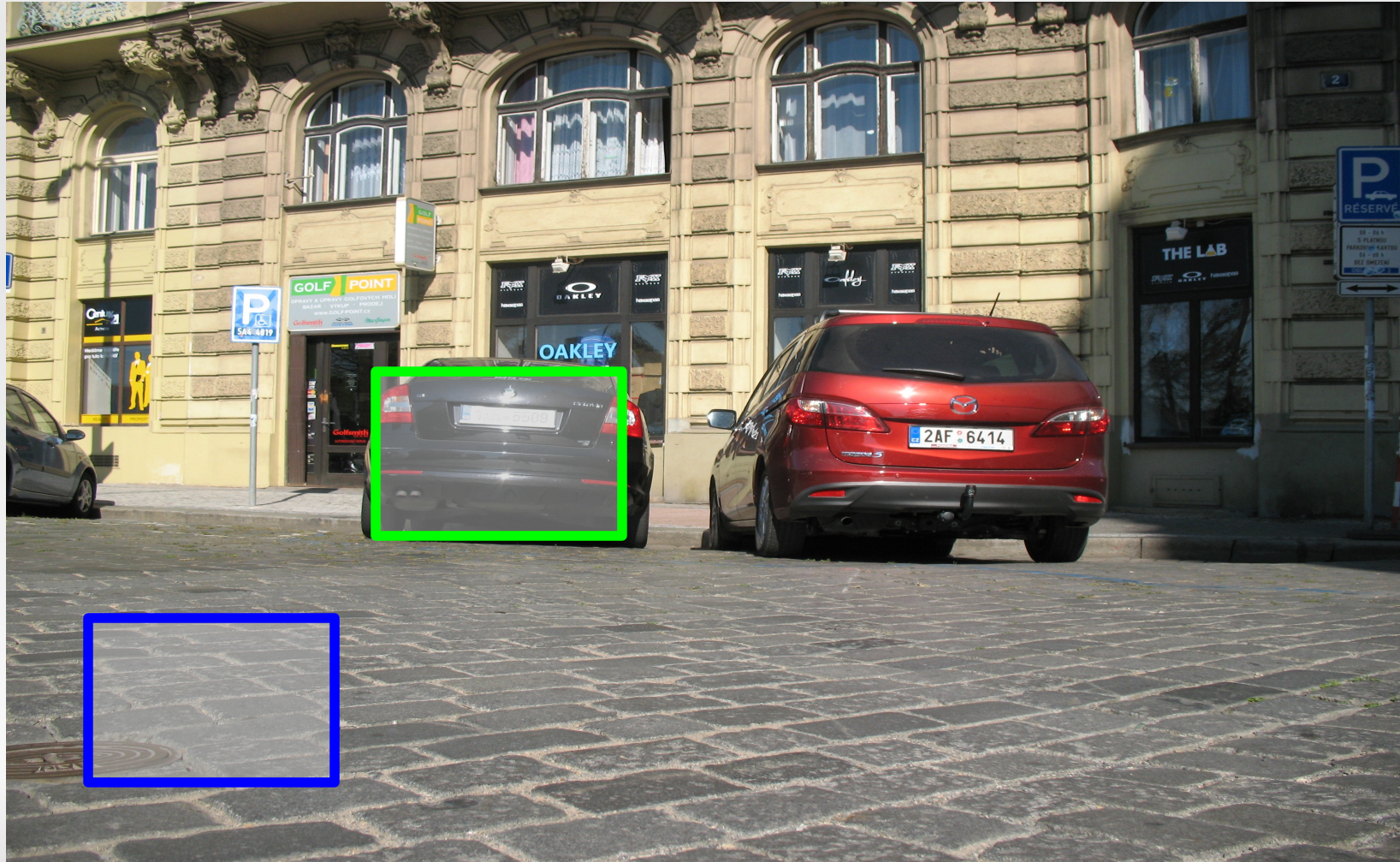
Overview



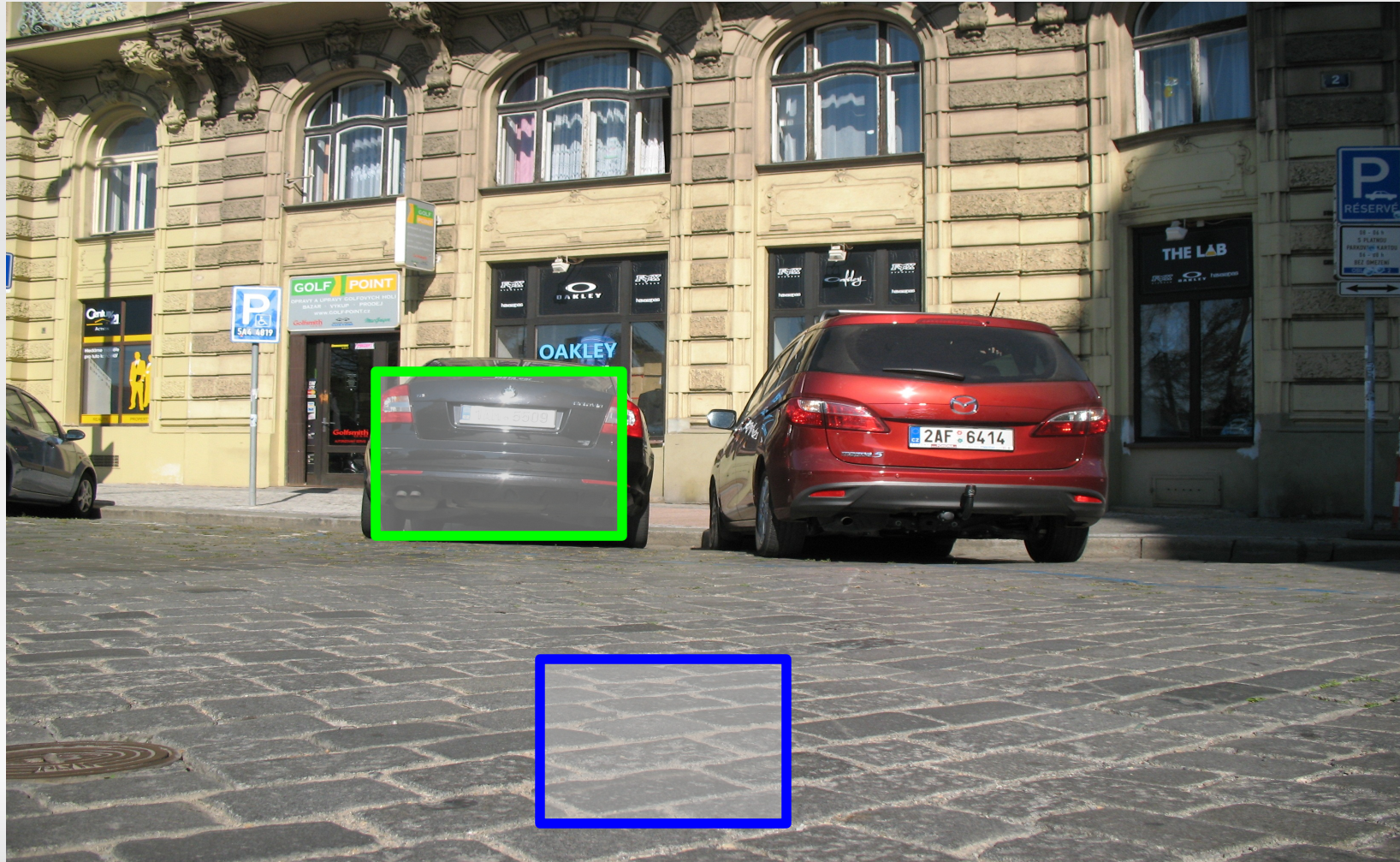
Overview



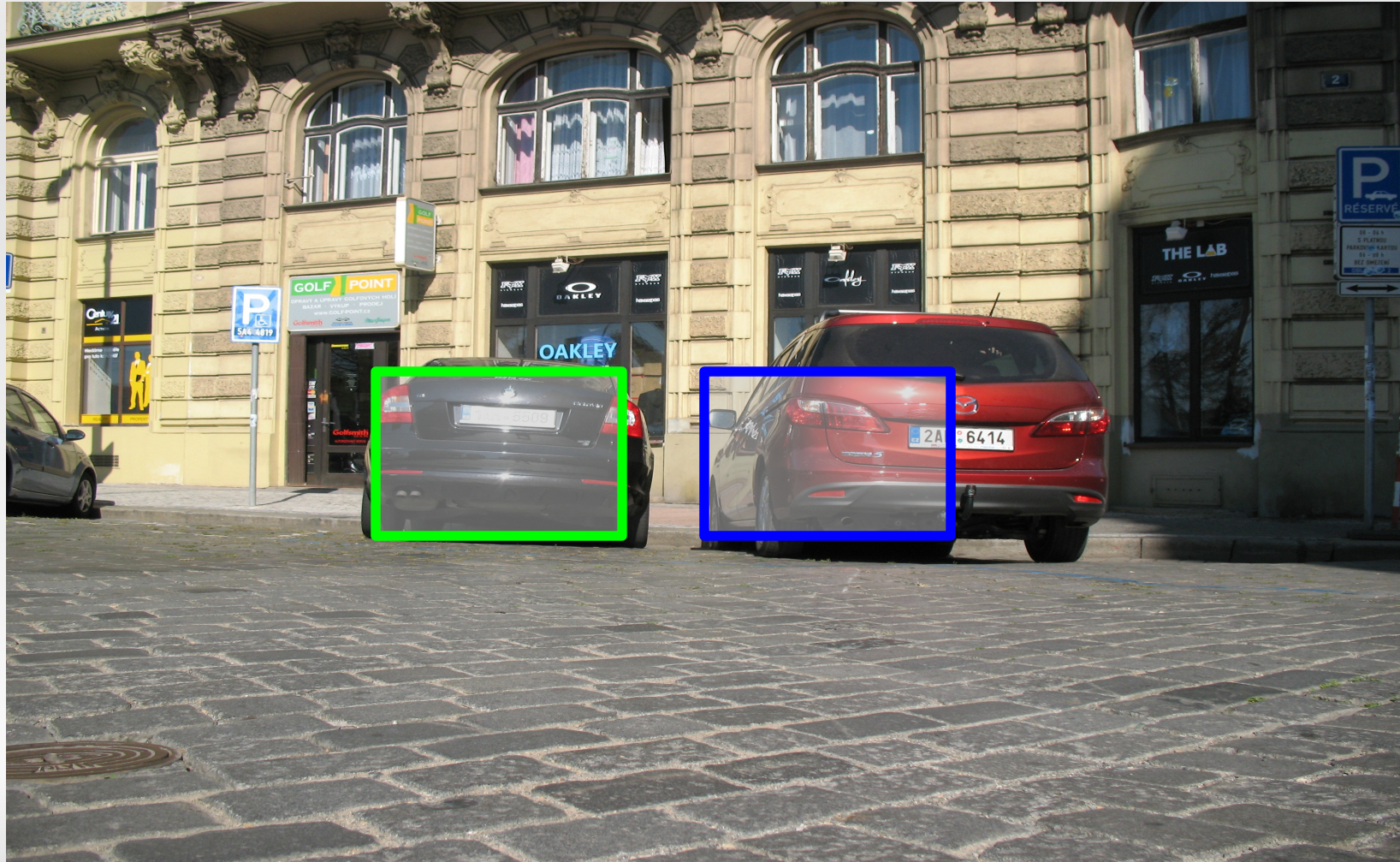
Overview



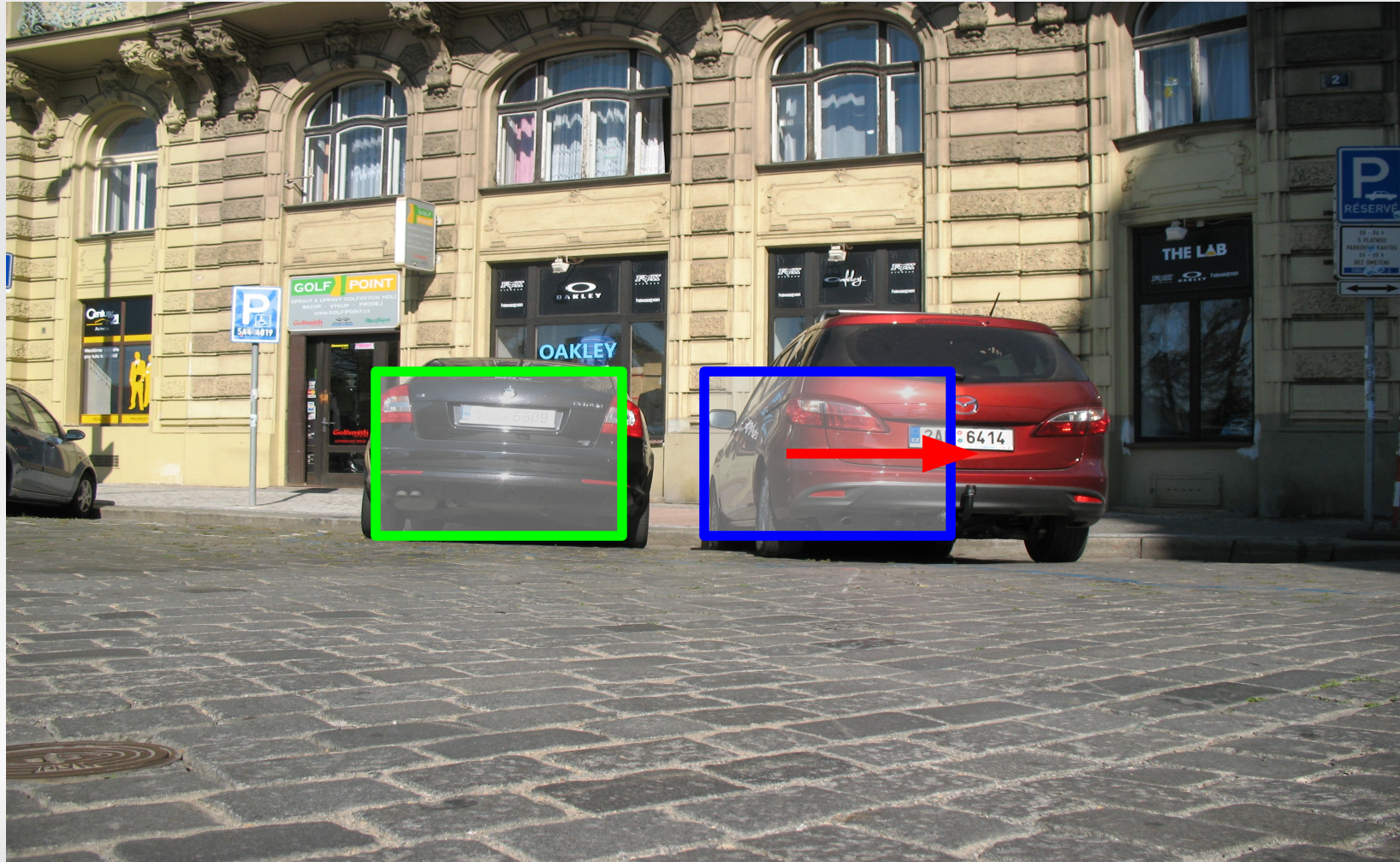
Overview



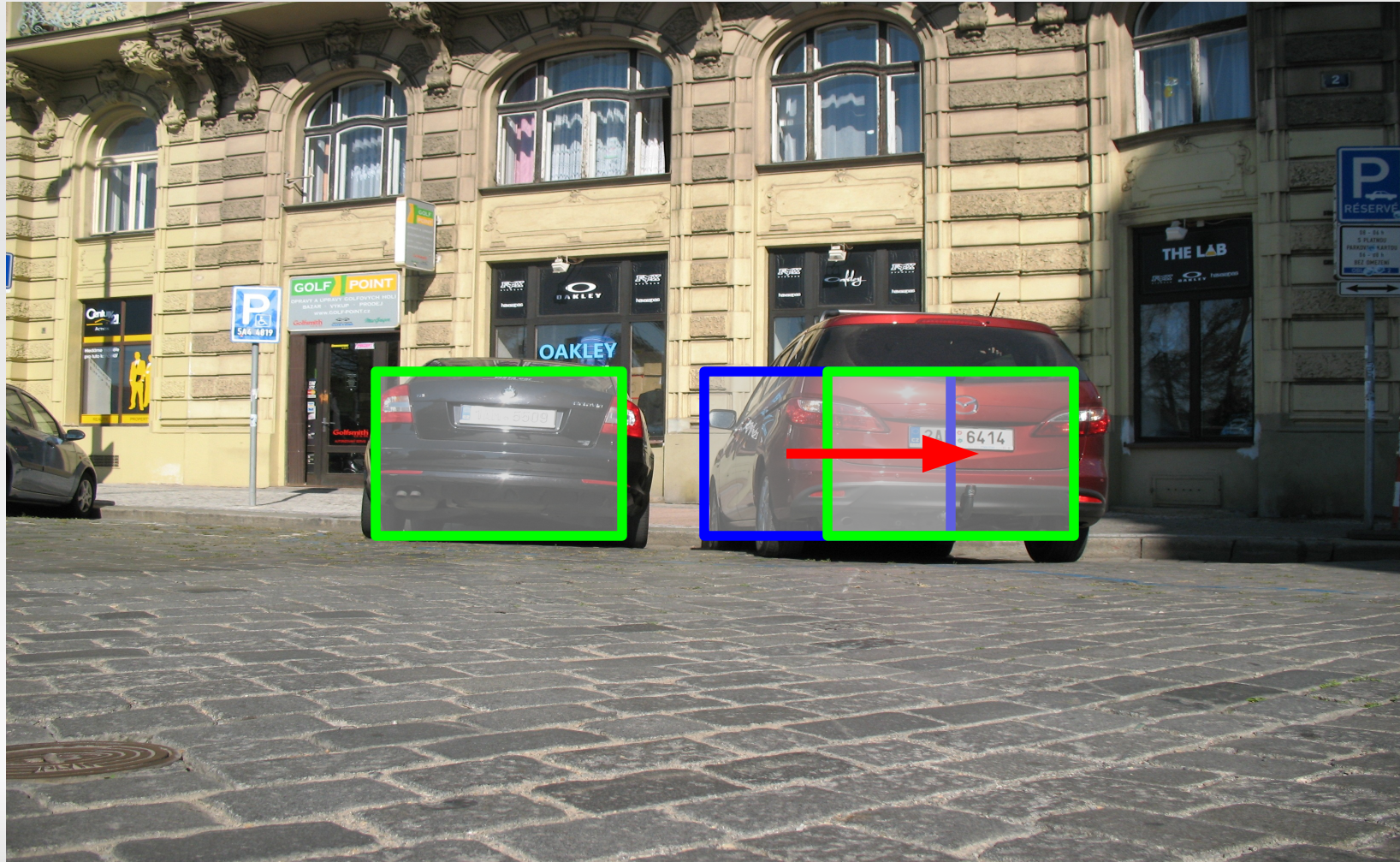
Overview



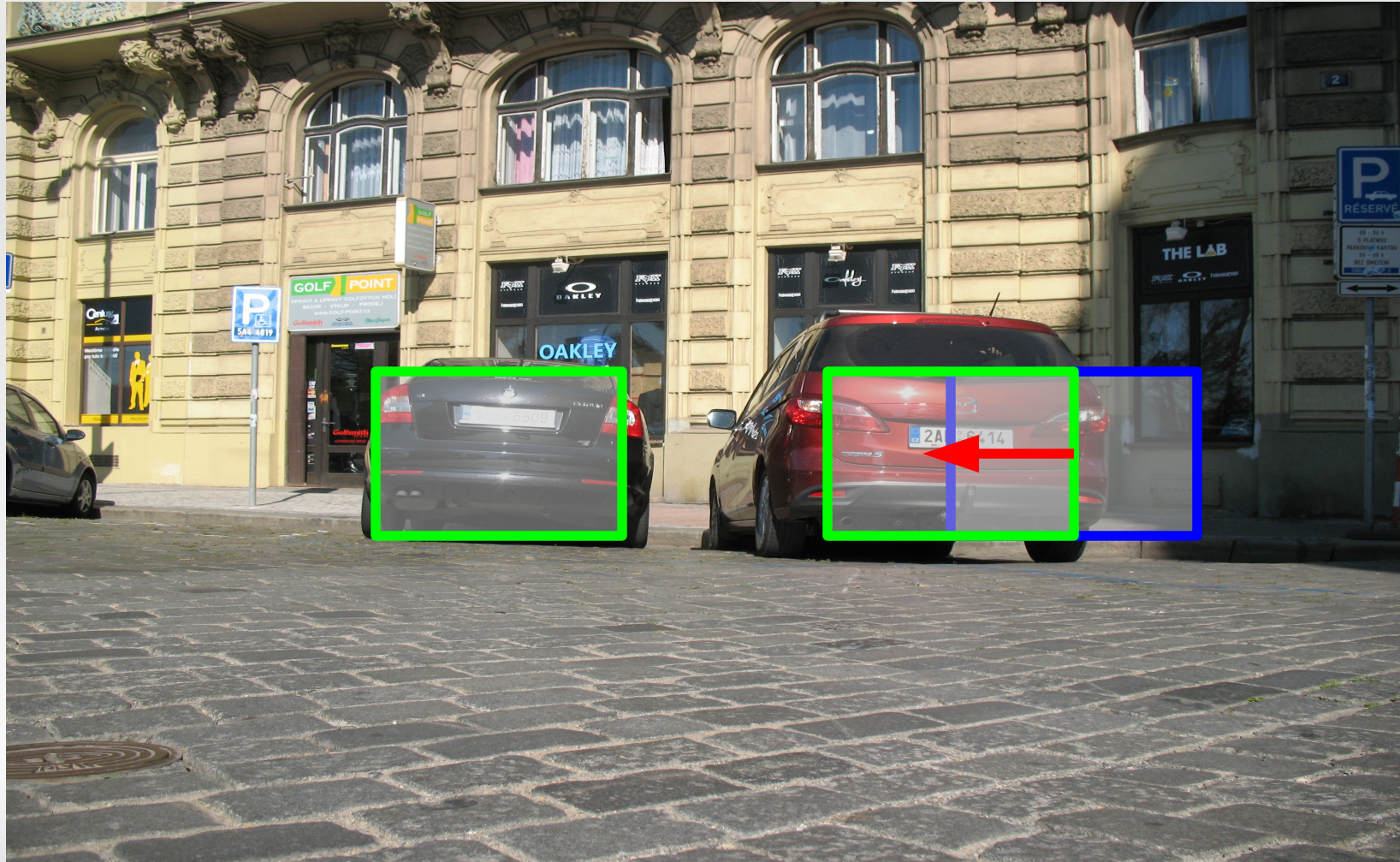
Overview



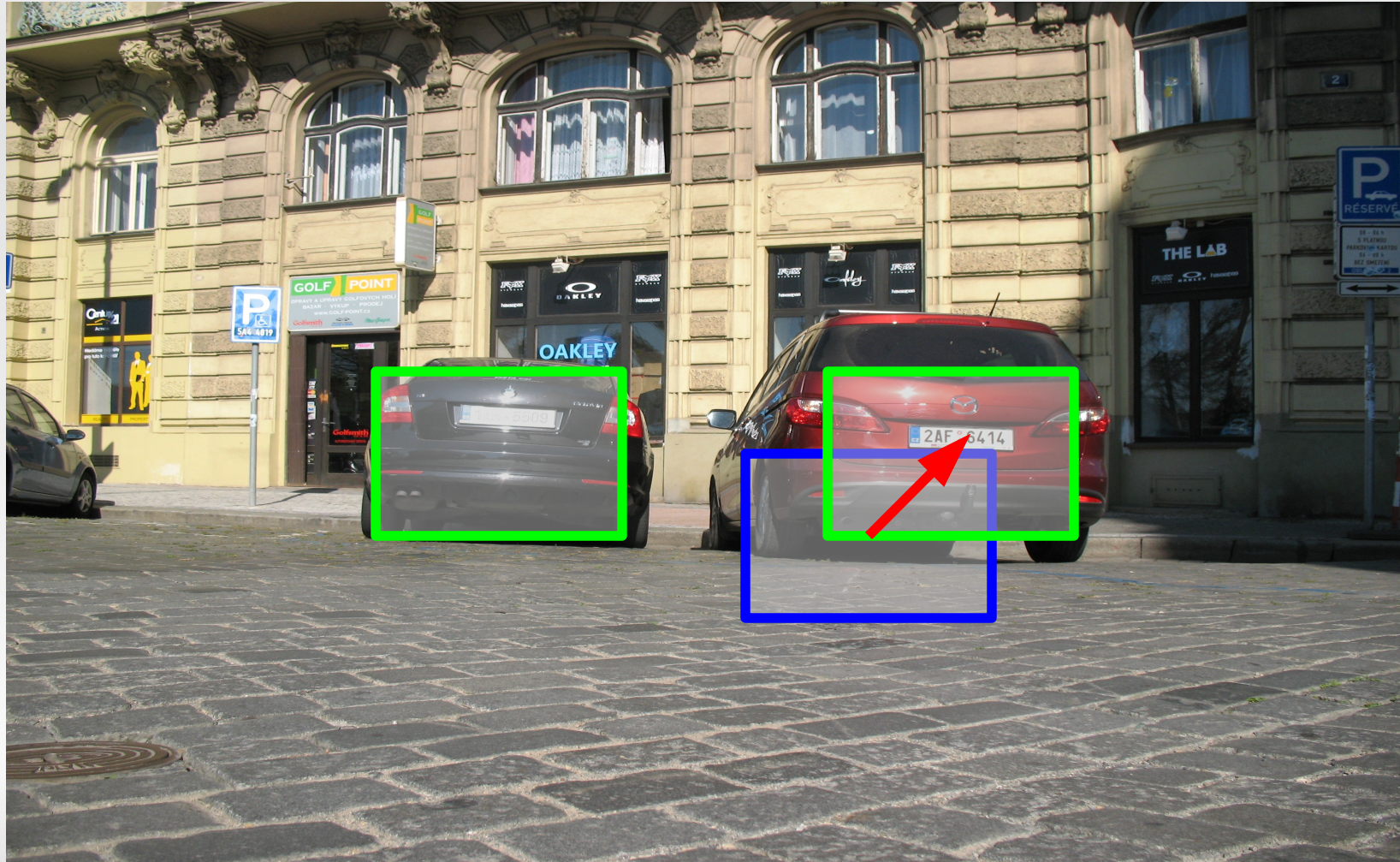
Overview



Overview

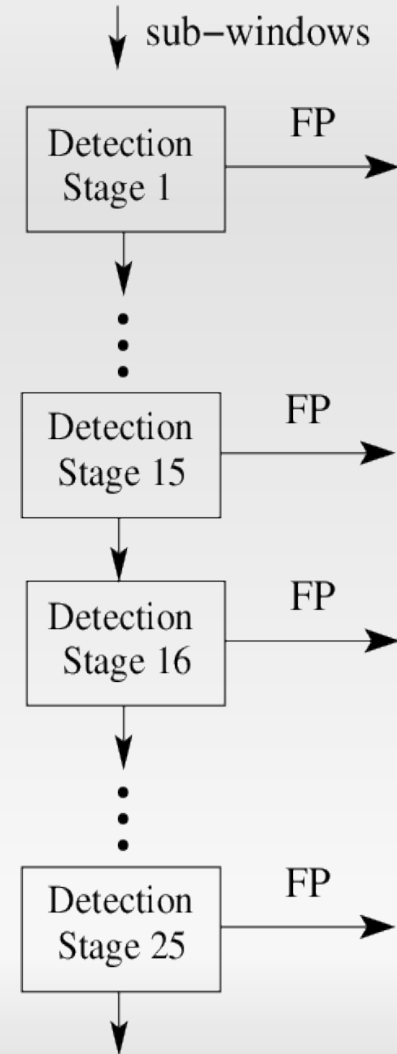


Overview



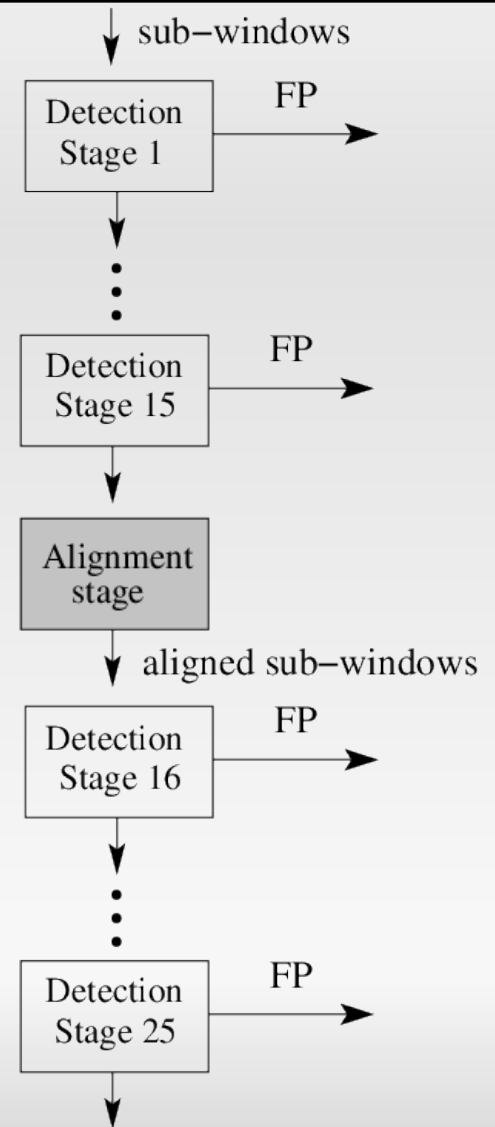
Overview

- Cascade of Gentle-Boost classifiers (on Haar features).
- Each Detection stage rejects 40% of background sub-windows.
- Each detection stage preserve 99.5% positive samples



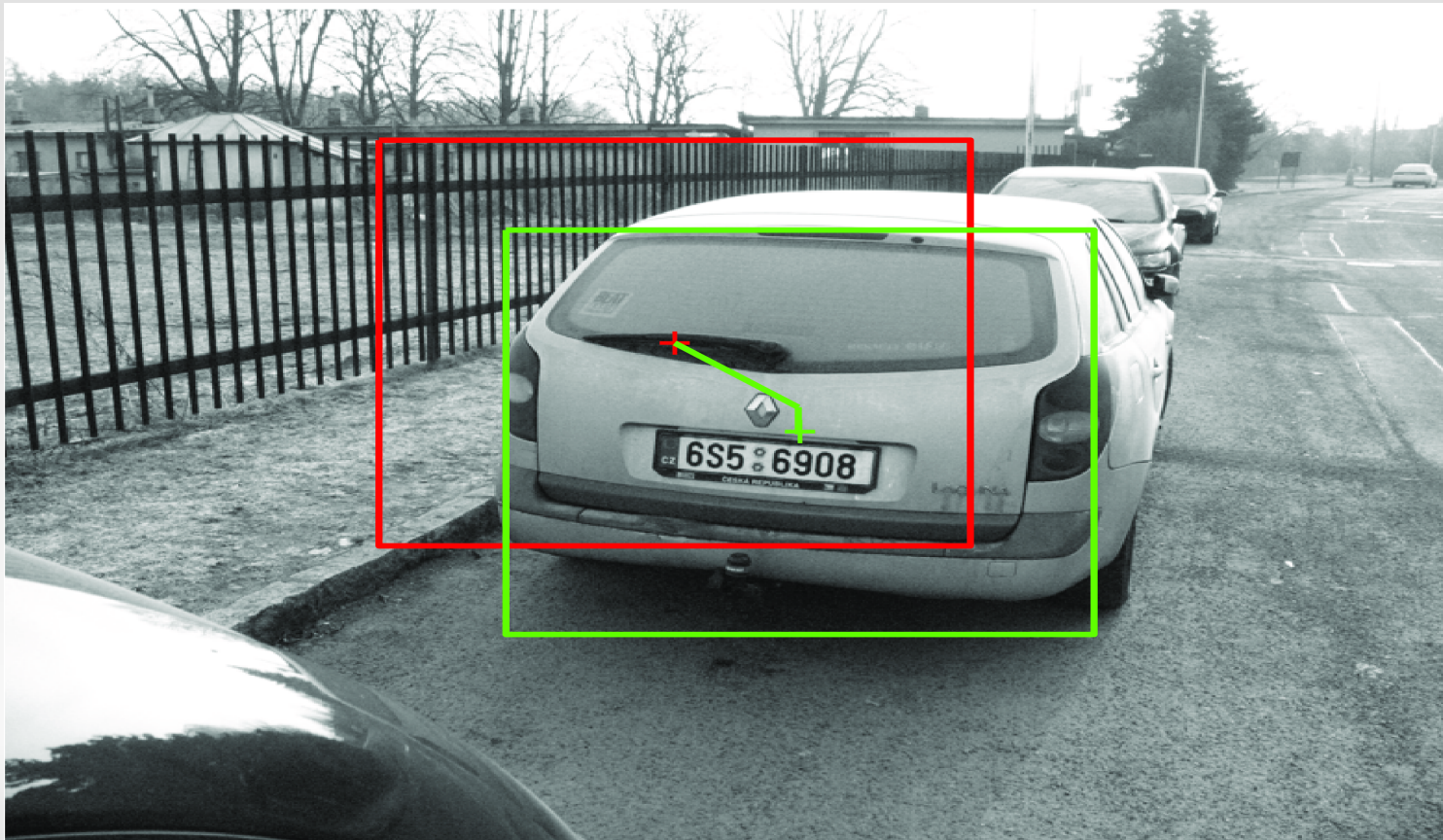
Overview

- Sliding window detection with a cascade extended by alignment.
- The **alignment** is invoked iff the sub-window survives up to a certain detection stage.
- Well aligned sub-window is more likely to be detected.



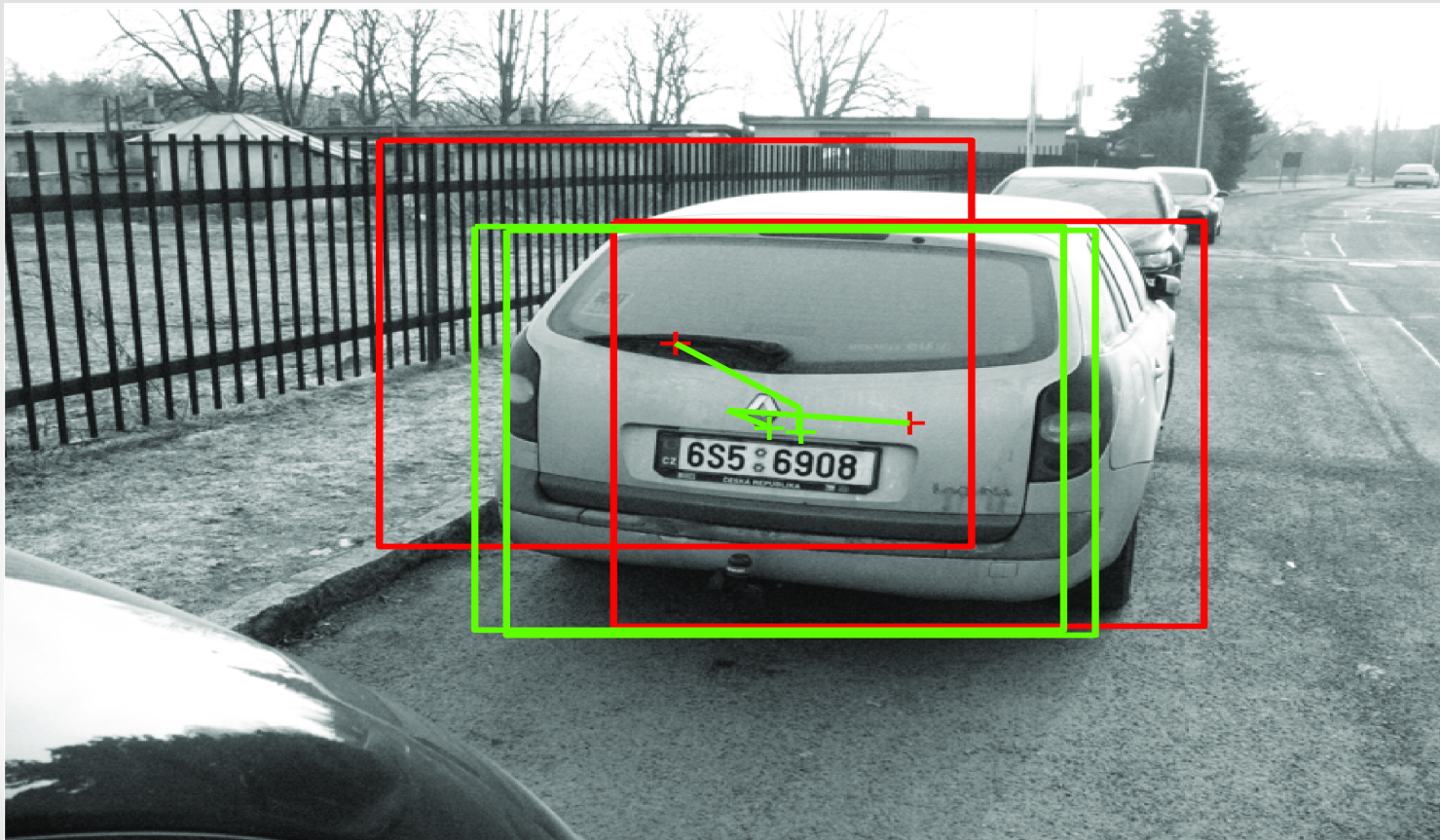
Detection with aligned cascade

- Alignment method assigns translation to sub-windows



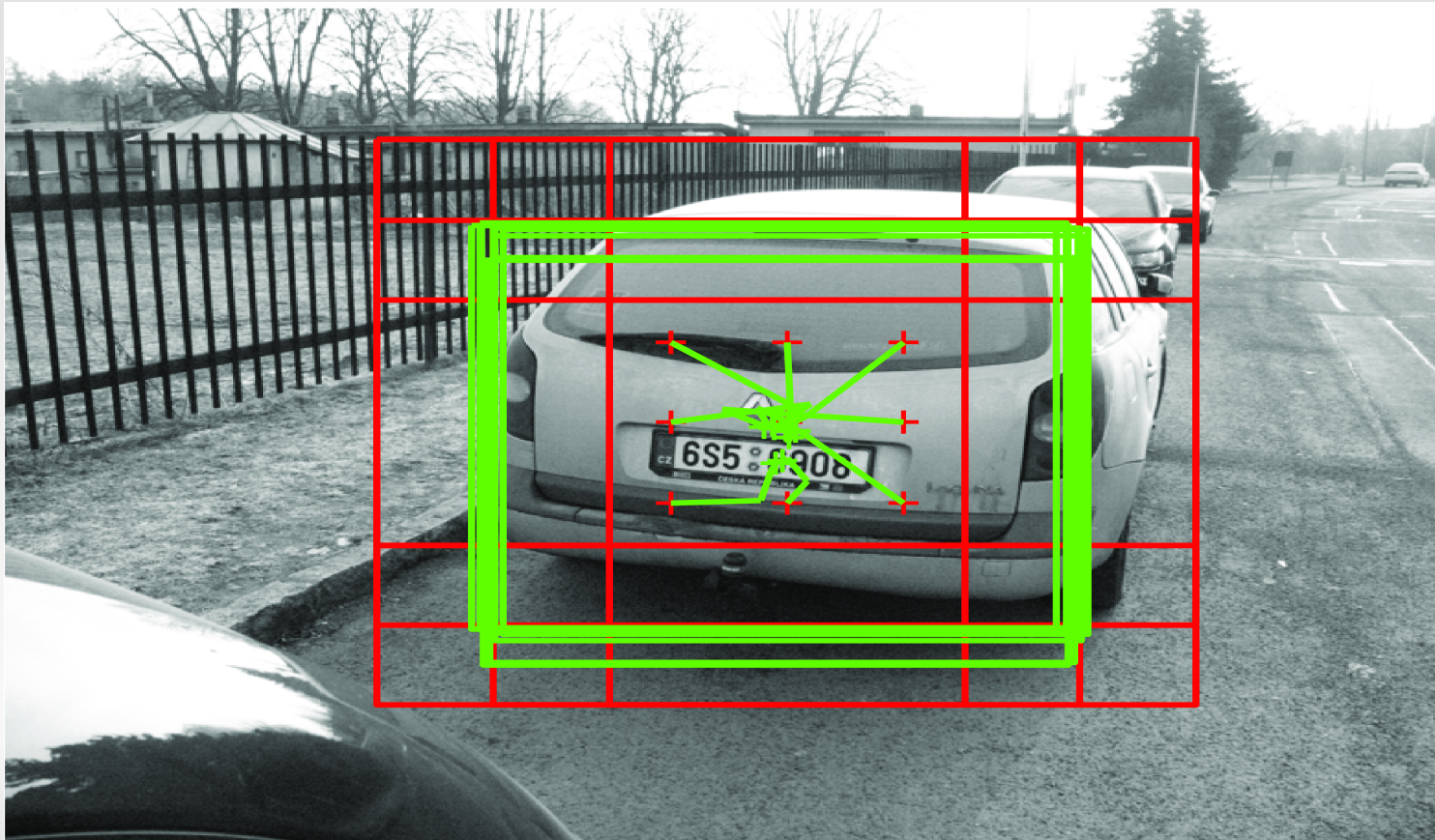
Detection with aligned cascade

- Sub-windows close to the object are aligned on the object



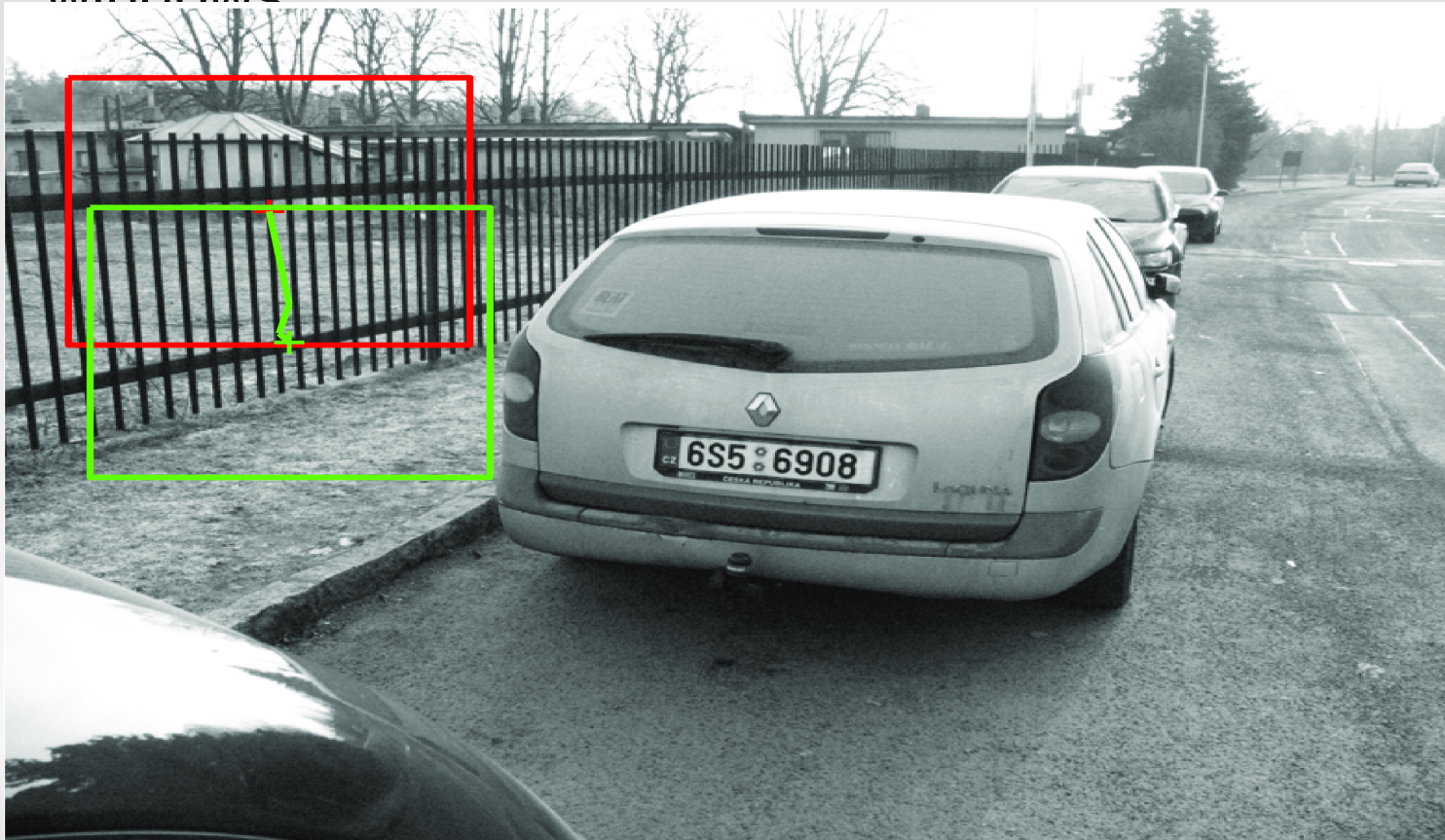
Detection with aligned cascade

- Sub-windows close to the object are aligned on the object



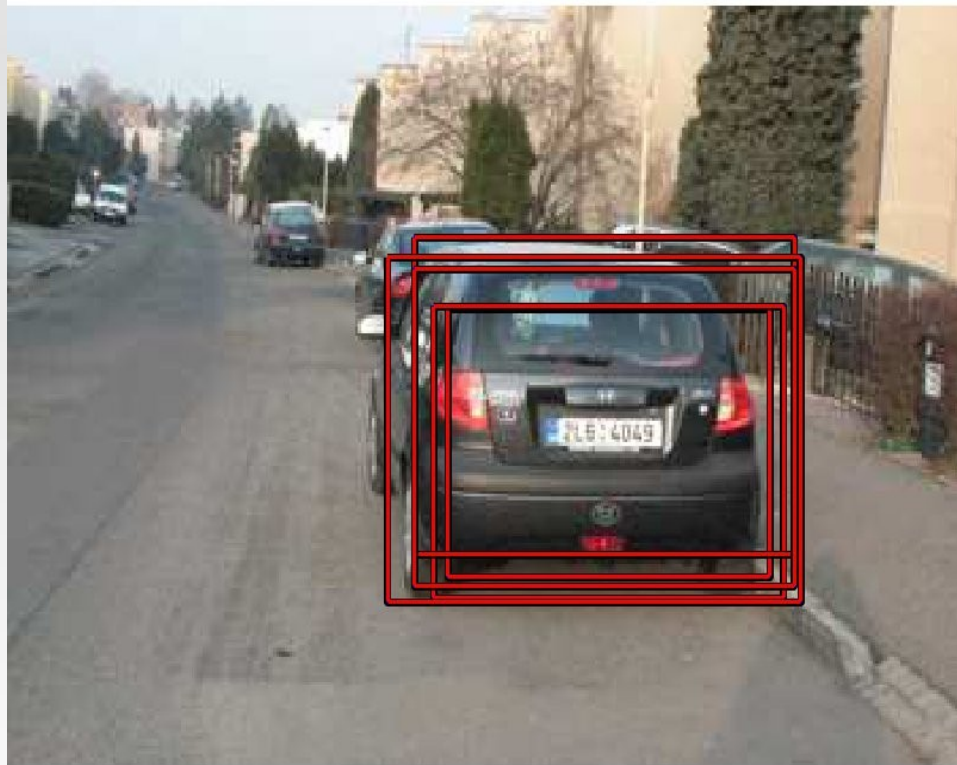
Detection with aligned cascade

- Alignment method *randomly* shifts background sub-windows

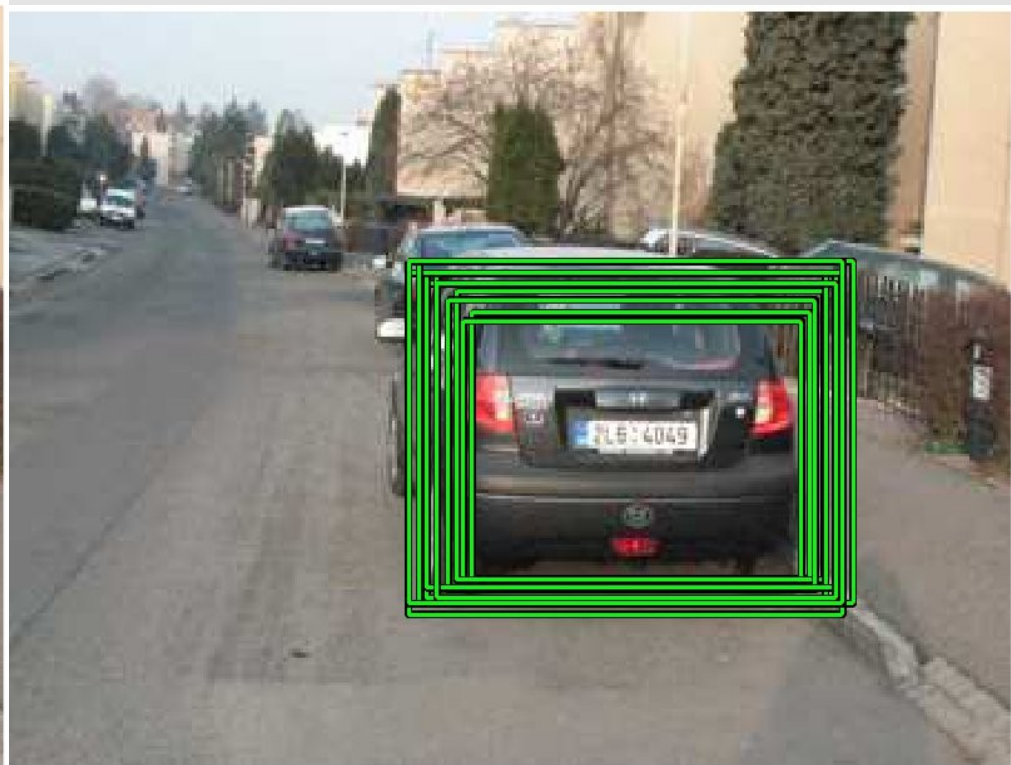


Detection with aligned cascade

Detector

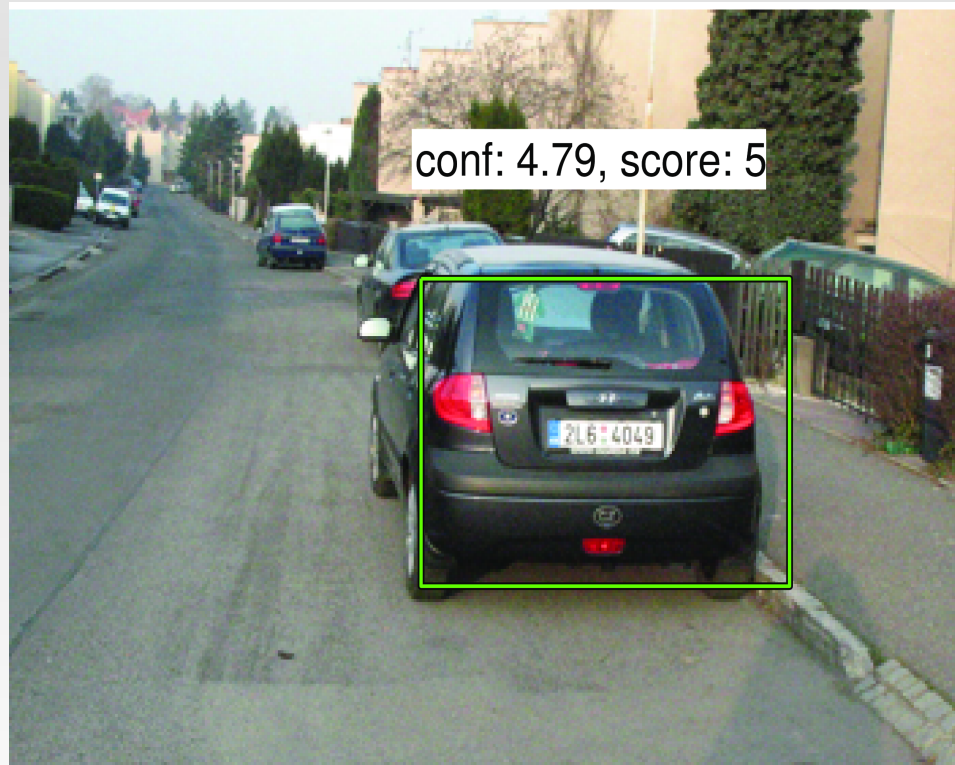


Detector + Alignment

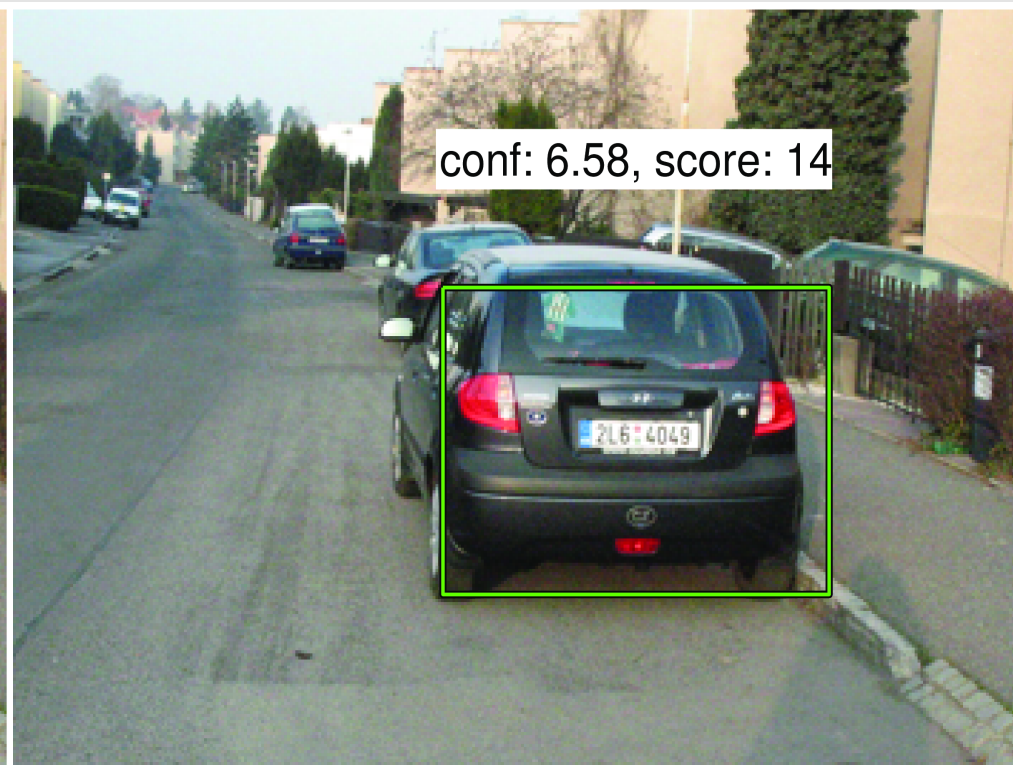


Detection with aligned cascade

Detector



Detector + Alignment



Sequential linear predictor

- Two different alignment methods were studied:
 - Linear predictor
 - Fern

Alignment with linear predictor

- Linear predictor maps features (f) from the evaluated sub-window to local displacement (t)

$$t = H \cdot f$$

where f is absolute value of Haar-like features.

Alignment with linear predictor

- Linear predictor maps features (f) from the evaluated sub-window to local translation (t)

$$t = H \cdot f$$

where f is absolute value of Haar-like features.

- Linear regression function (H) learned by the Least-Squares method on the training set.

Alignment with linear predictor



...



■
■
■

■
■
■

■
■
■



...

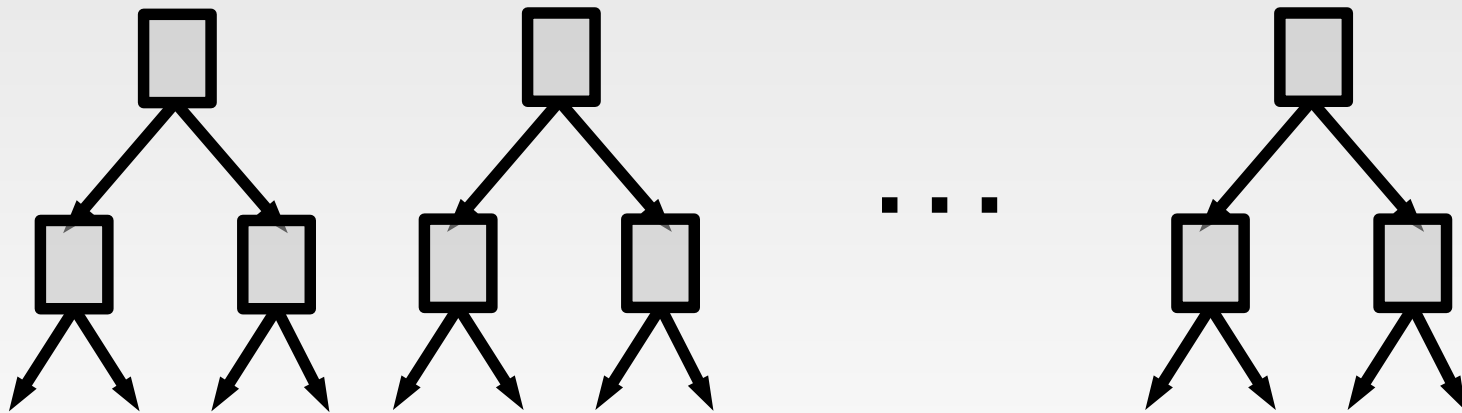


Alignment with linear predictor

- Single linear predictor has a low accuracy.
- Train a sequence of linear predictors.
- Each predictor is trained on the range of translation errors of its predecessor.

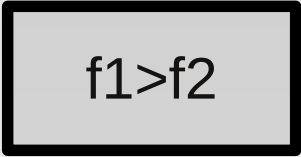
Alignment with ferns

- Ferns: forest of random binary decisions trees.



Alignment with ferns

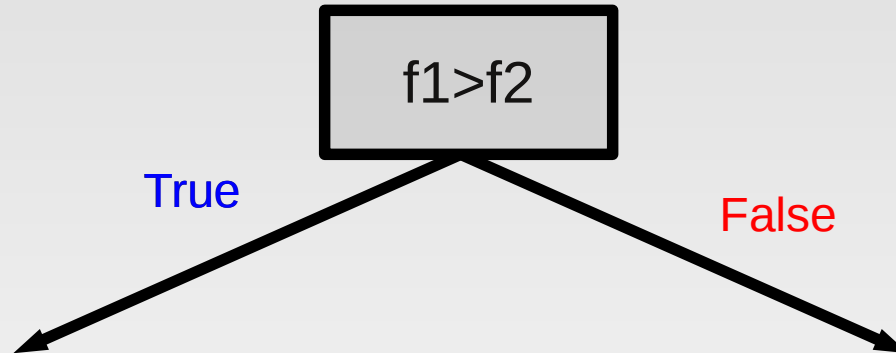
- Each node forms a simple binary condition:



$f1 > f2$

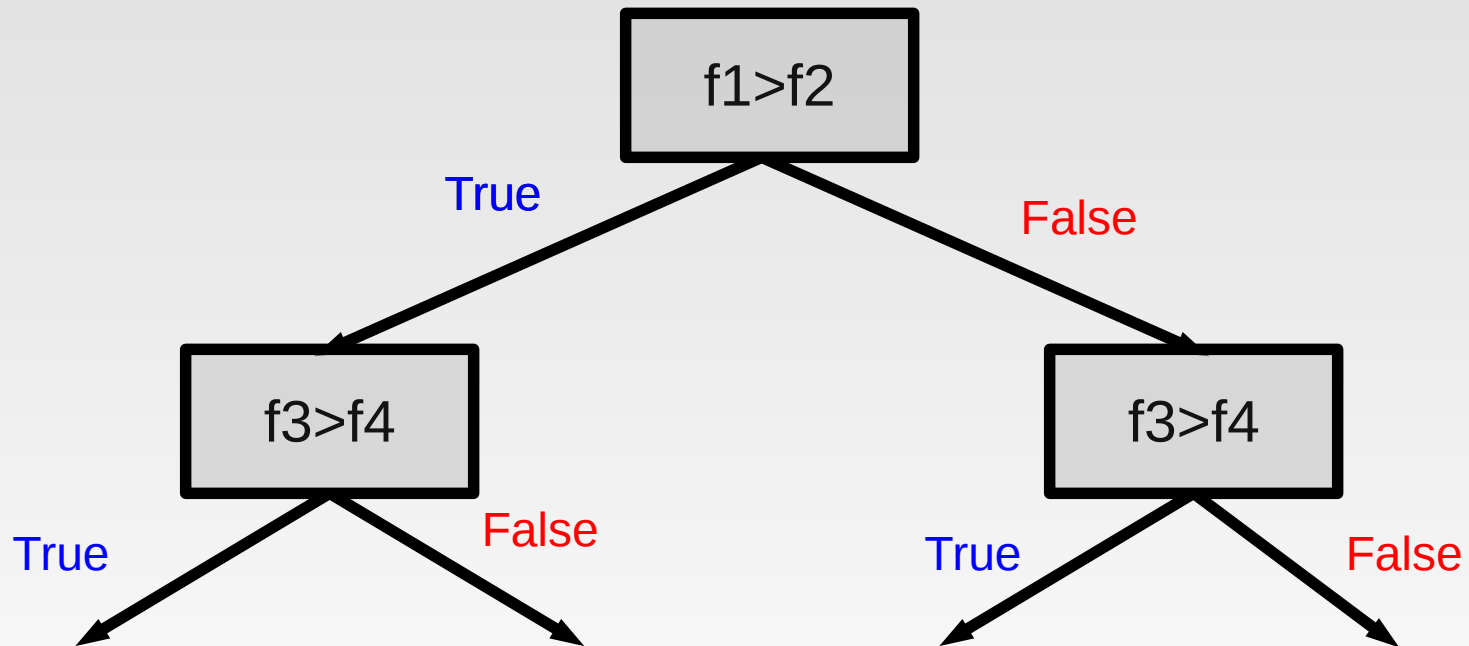
Alignment with ferns

- Result of the condition determines the direction in which the evaluated sub-window continues.



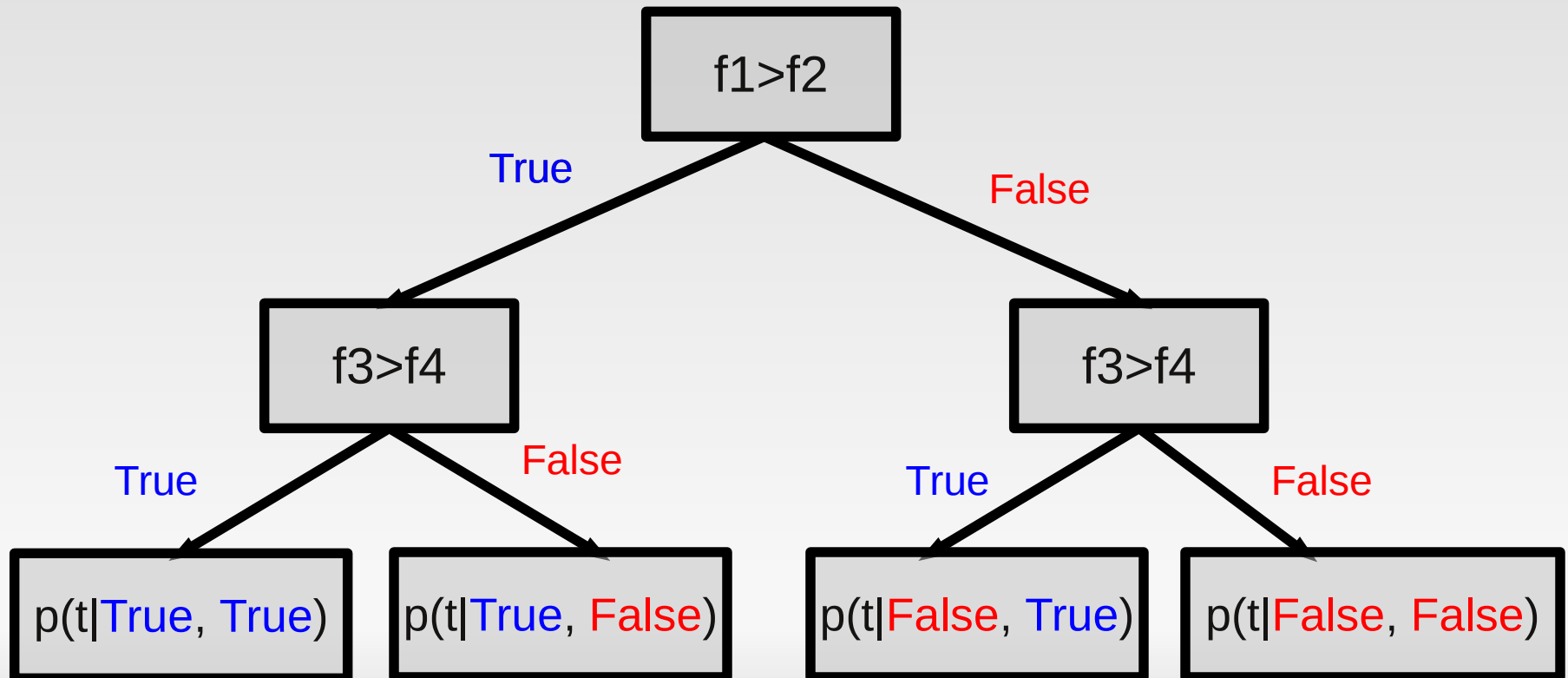
Alignment with ferns

- Then a different features are compared



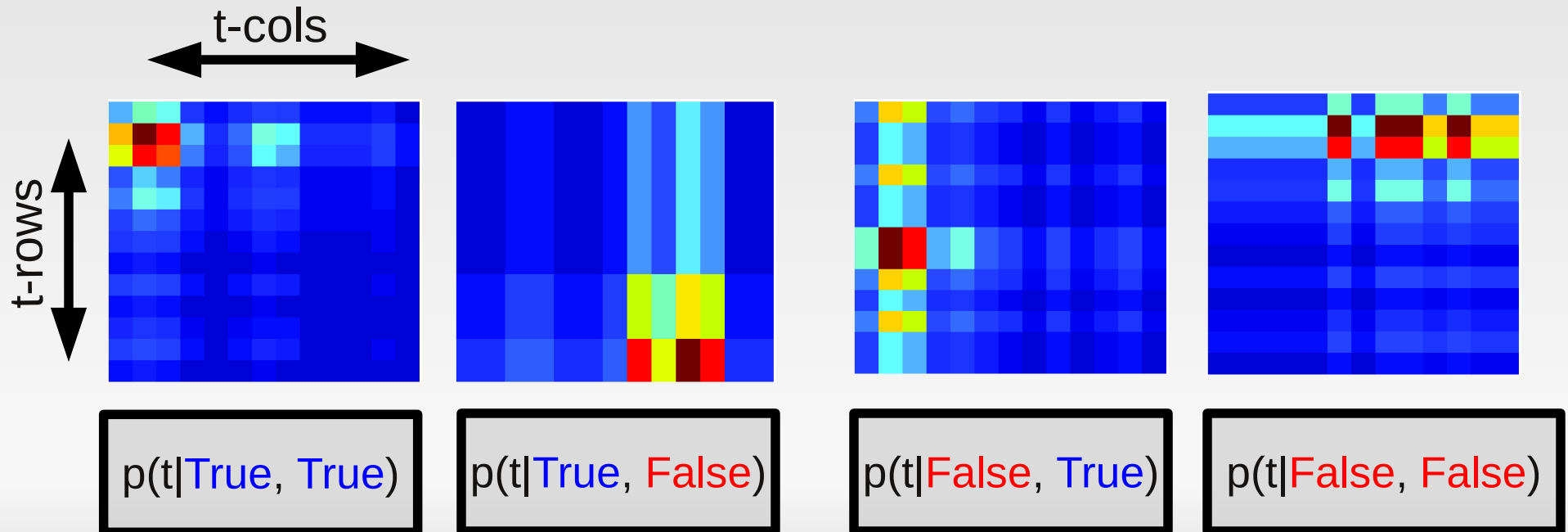
Alignment with ferns

- Leaves contain conditional probability of discretized translations.



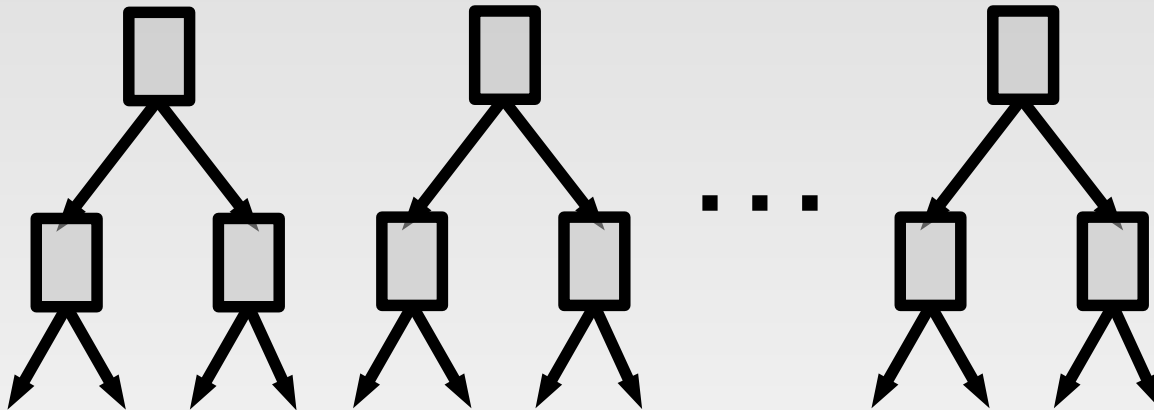
Alignment with ferns

- Probability is learned off-line from the training set.



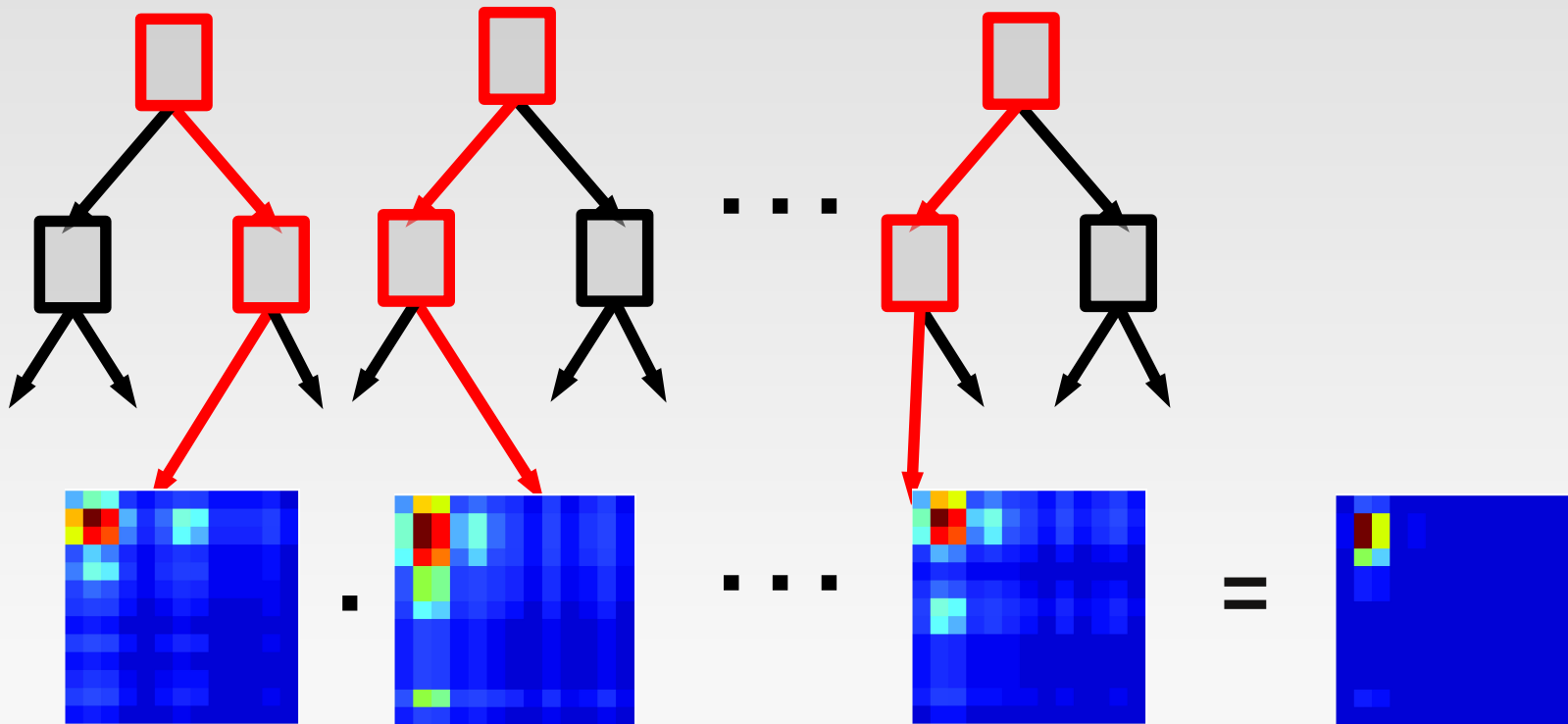
Alignment with ferns

- 50 trees, each with depth 11 (i.e. with 2048 leaves)

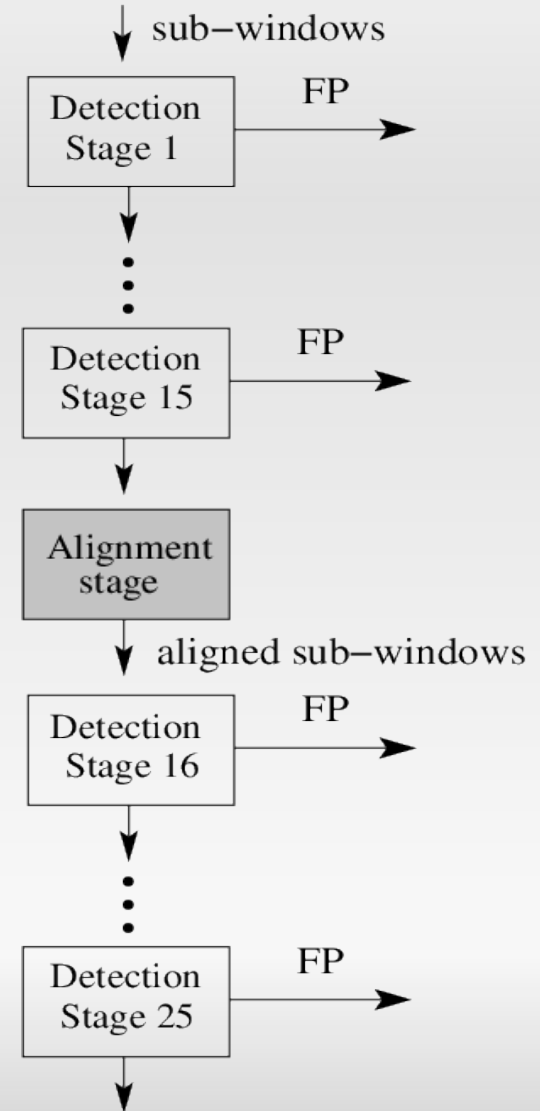
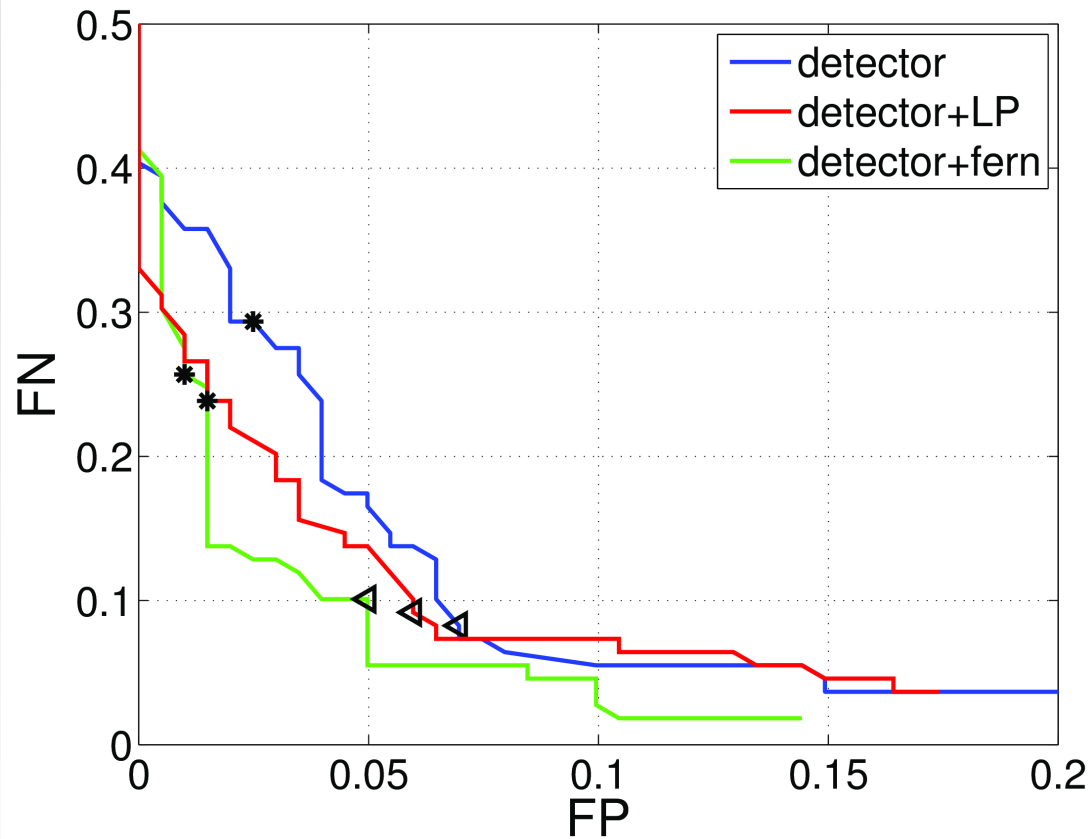


Alignment with ferns

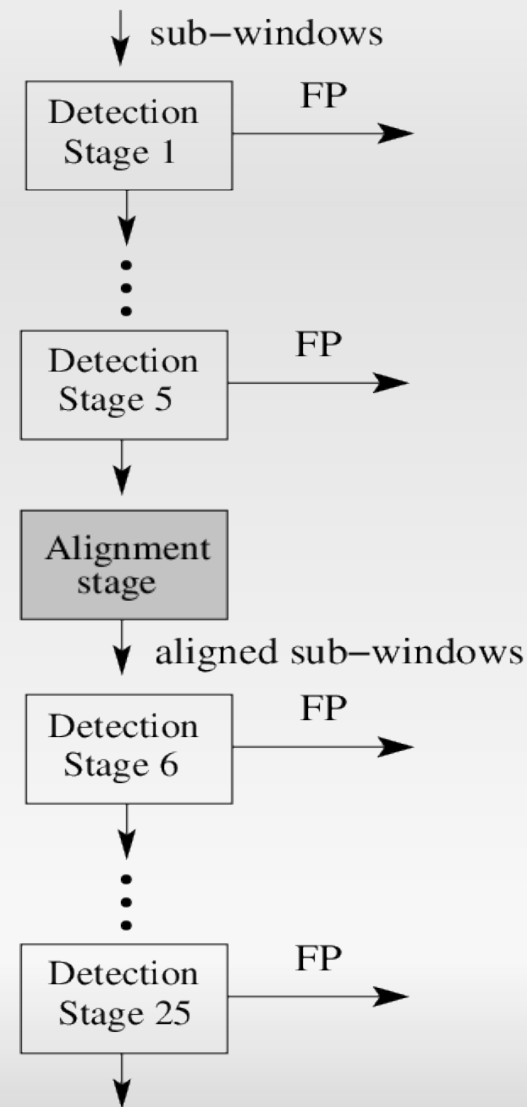
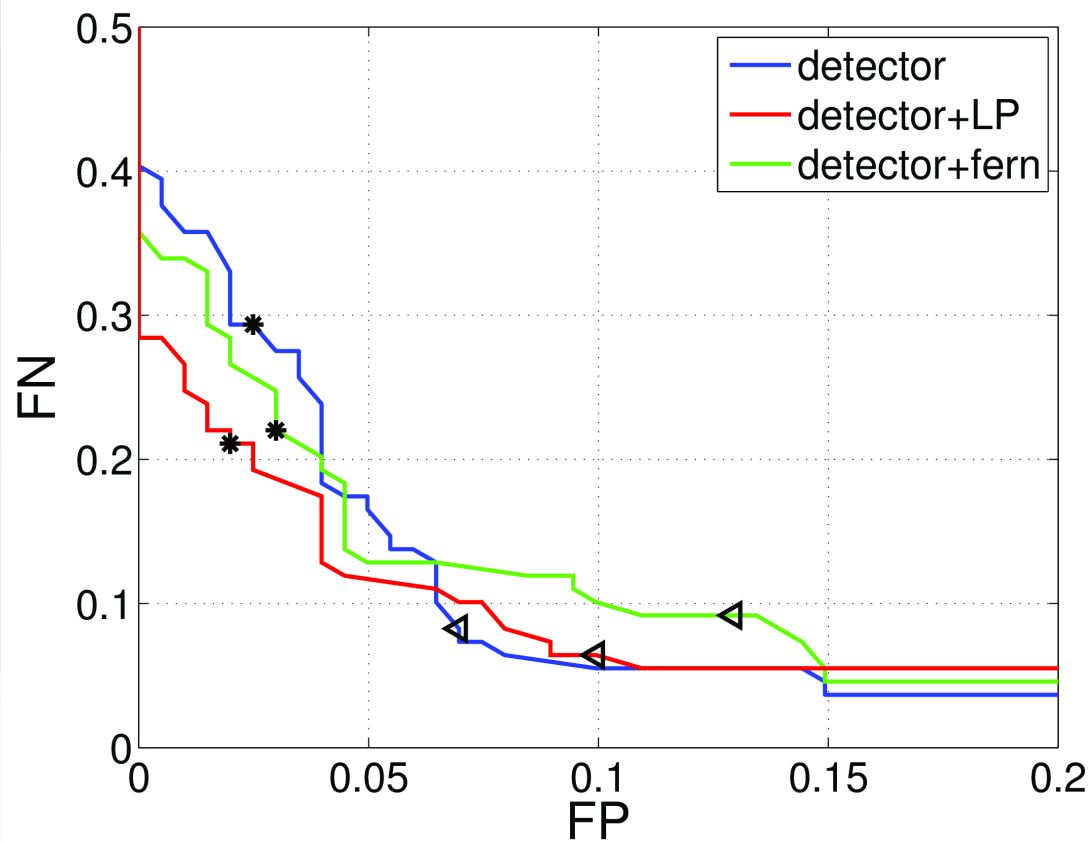
- Final probability estimated as multiplication



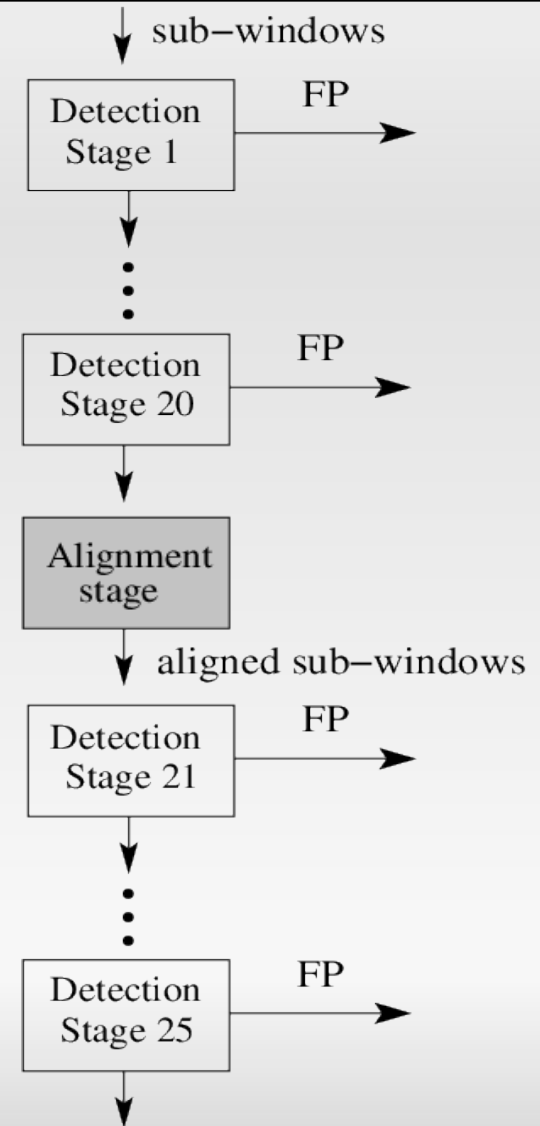
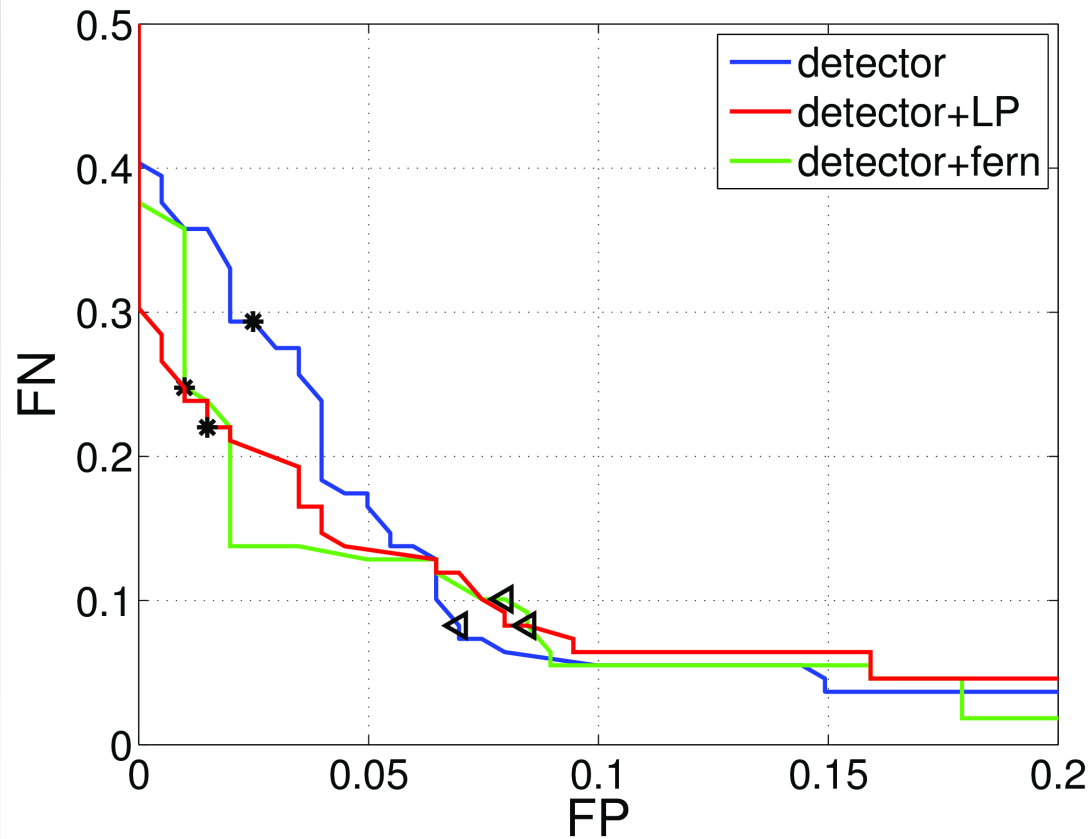
Experiments (alignment stage 15)



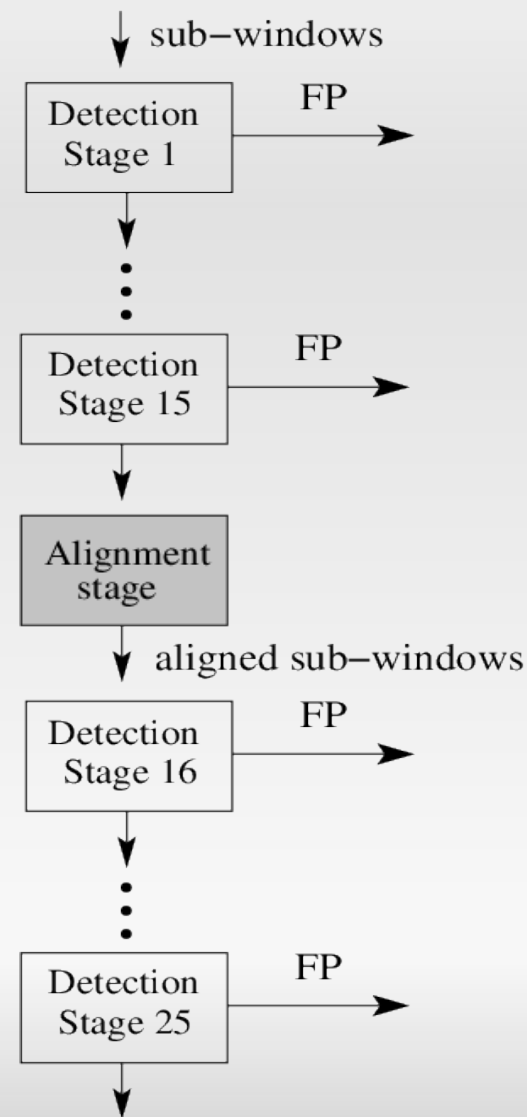
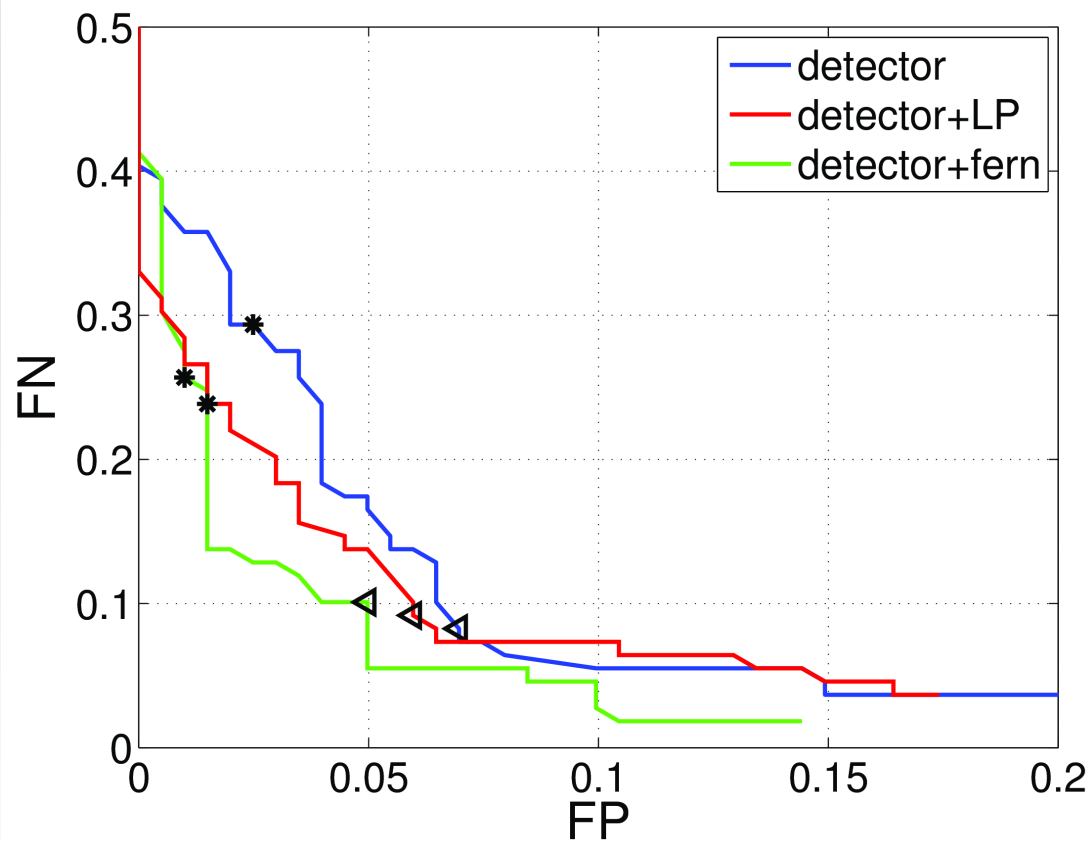
Experiments (alignment stage 5)



Experiments (alignment stage 20)



Experiments (alignment stage 15)



Implementation details

- Cascade of Gentle-Boost detectors trained on Haar features.
- Alignment methods use absolute value of Haar features.
- Less than 0.05% sub-windows survives up to stage 15,
- Ferns: Using the same condition at each level yields speed up (trees-> hash tables).

Future work

- Affine or perspective alignment
- Local gradient-based maximization of the detection function.