Tracking

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2014-09-29


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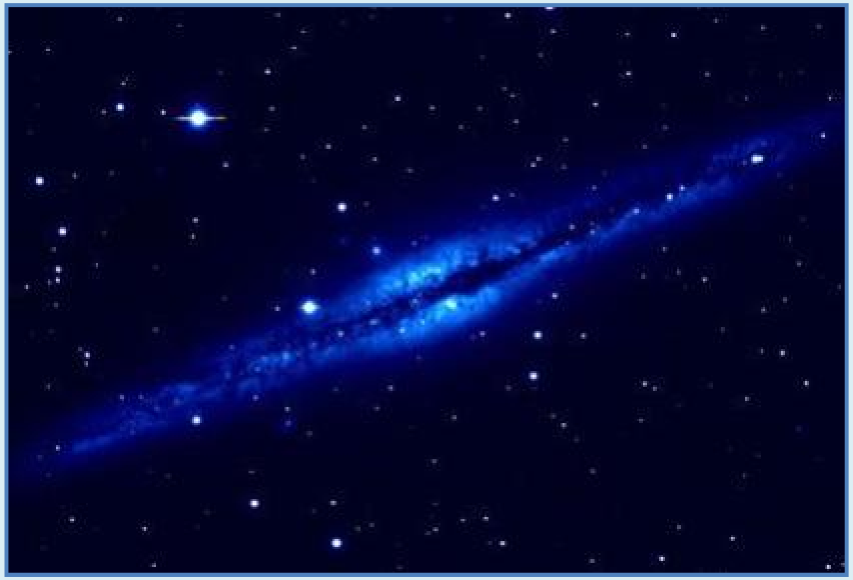


Tracking in Multimedia

Multimedia

- Video
- Audio

Video Tracking

- Use your eyes

Audio Tracking

- Use your ears

Visual Tracking

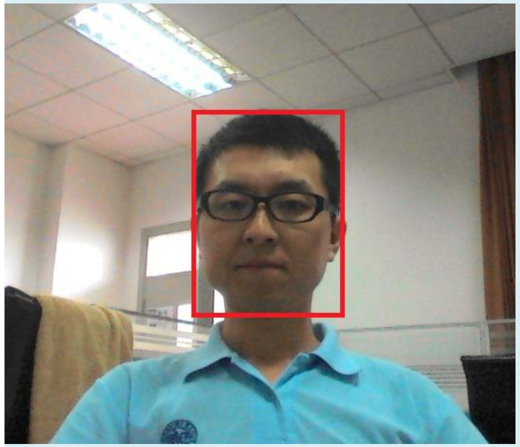
Object Tracking

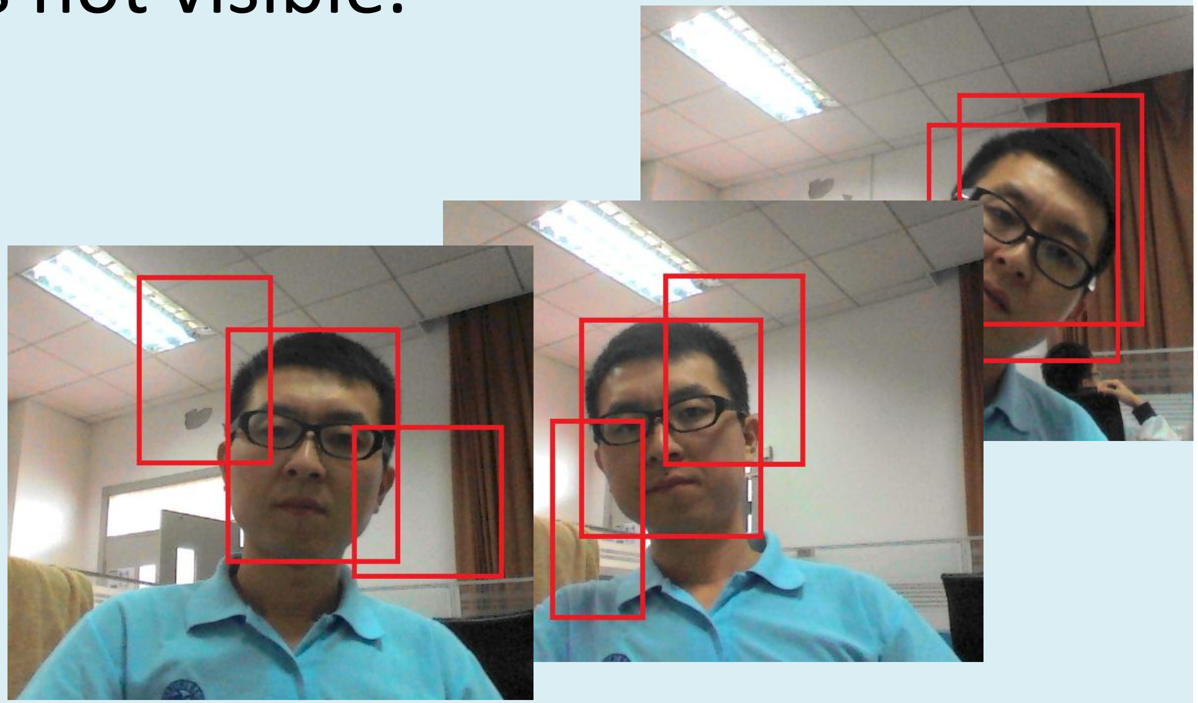
Tracking

Video Tracking

Definition

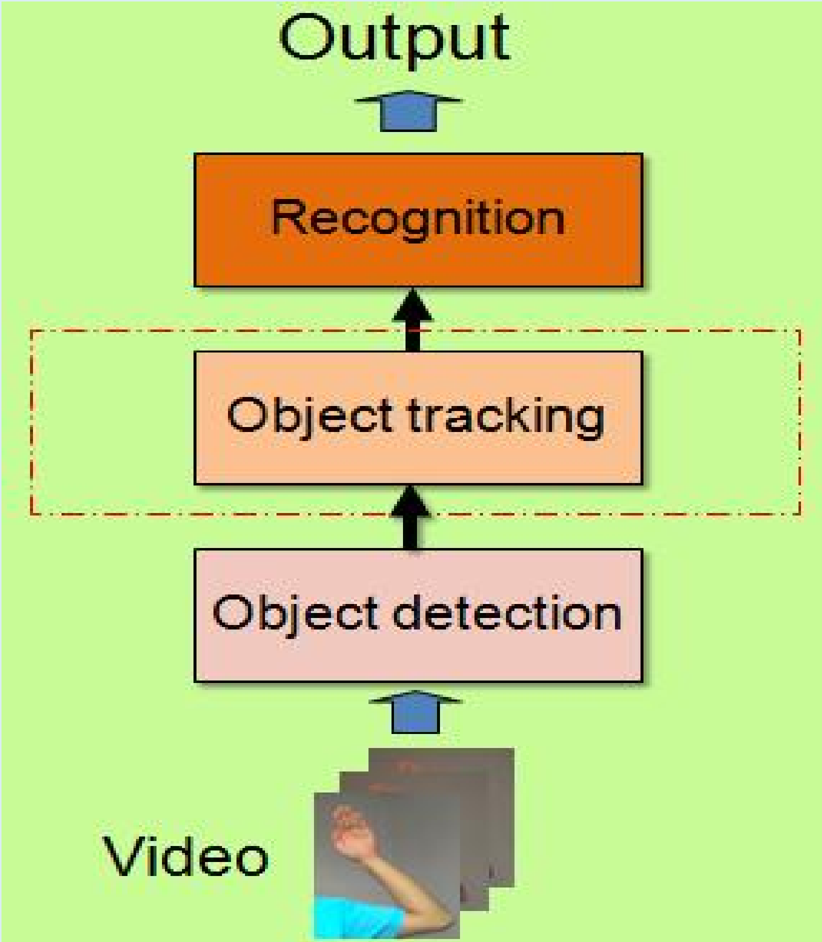
Given a bounding box defining the initial position of an object in a single frame, automatically determine the object's bounding box in the following frames or indicate the object is not visible.





Why important?

- An important Mid-level of a vision system



Why important?

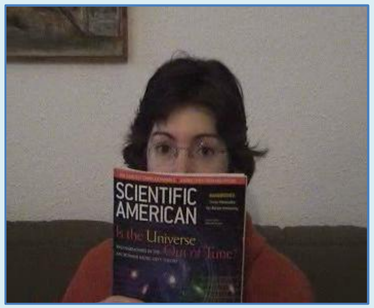
- One of the most practical areas of CV

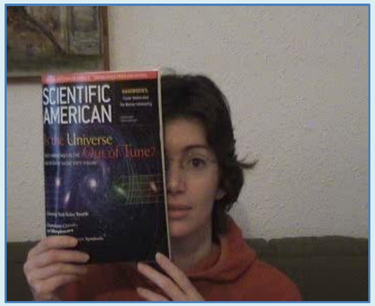
Why difficult?

- Illumination



- Occlusion

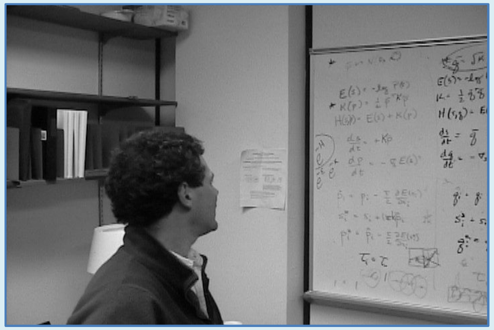




Why difficult?

- Pose variants





- Clutter

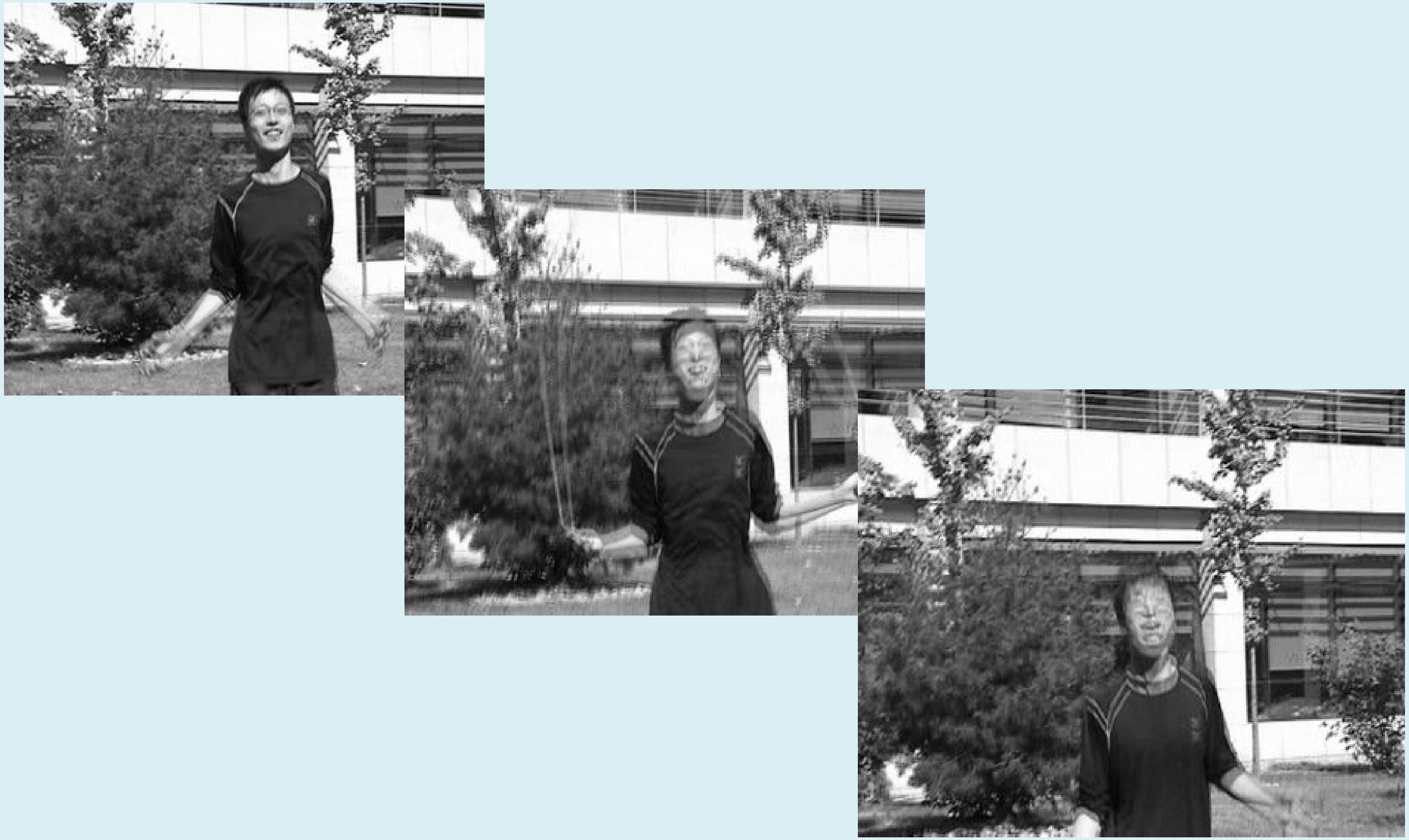


Why difficult?

- Scale variant

Why difficult?

- Fast Motion



Categories

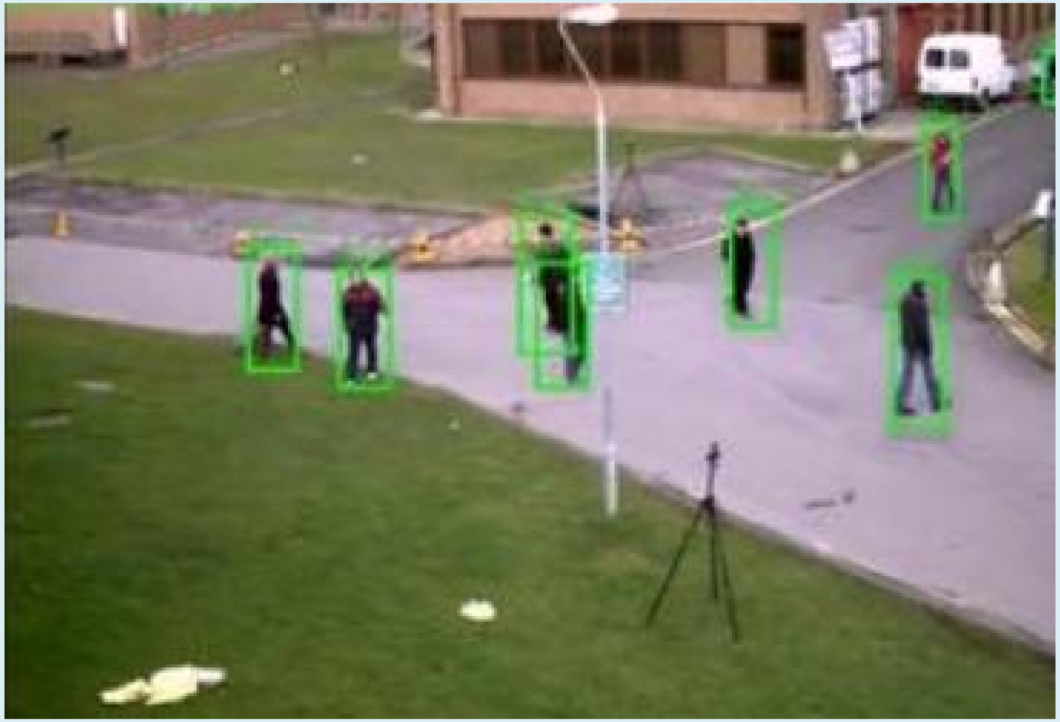
- Single camera
- Multiple camera
- Re -identification

Categories

- Static camera
- moving camera

Categories

- Single Object
- Multiple Object



Categories

- Visible
- Infrared

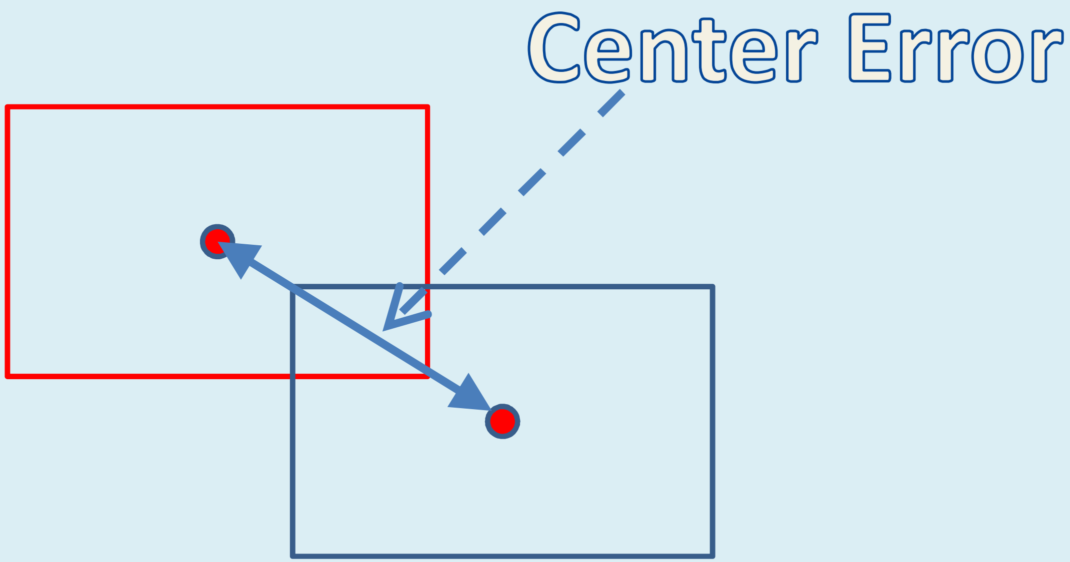
Categories

- Rigid Object
- Non-rigid Object

Evaluation

- Center Location Error

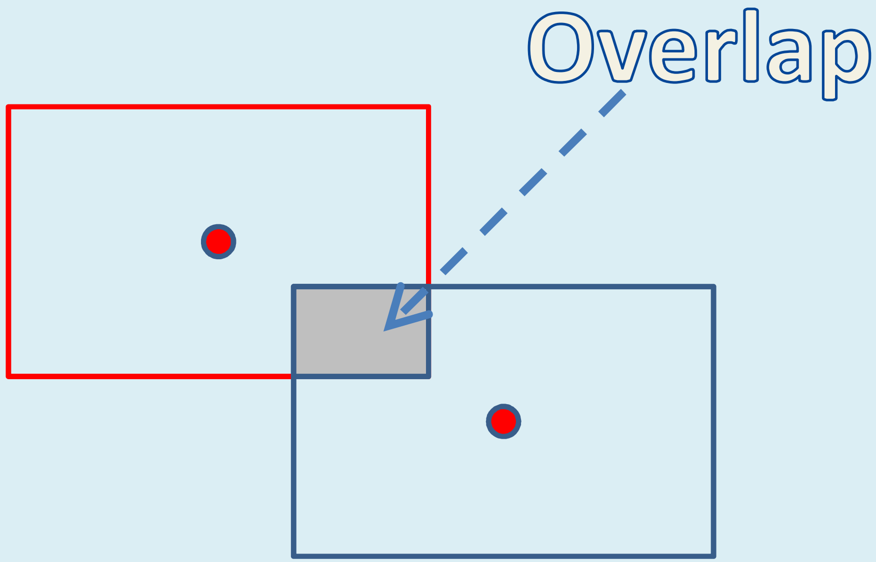
average Euclidean distance between the center of the tracked target and the ground truth in all the frames of one video.



Evaluation

- Success Rate

The success rate is the radio of the frames whose scores are larger than a given threshold.



$$score = \frac{R_t \cap R_g}{R_t \cup R_g}$$

The State-of-the-art trackers

- Tracking by detection is becoming popular.

This stems directly from the development of powerful discriminative methods in machine learning and their application to detection with offline training.

The discriminative trackers try to differentiate the target from the background by taking tracking as a binary classification problem.

Real-Time Compressive Tracking(CT)

- Core idea

Facilitate an efficient project from the image feature space to a low-dimensional compressed space.

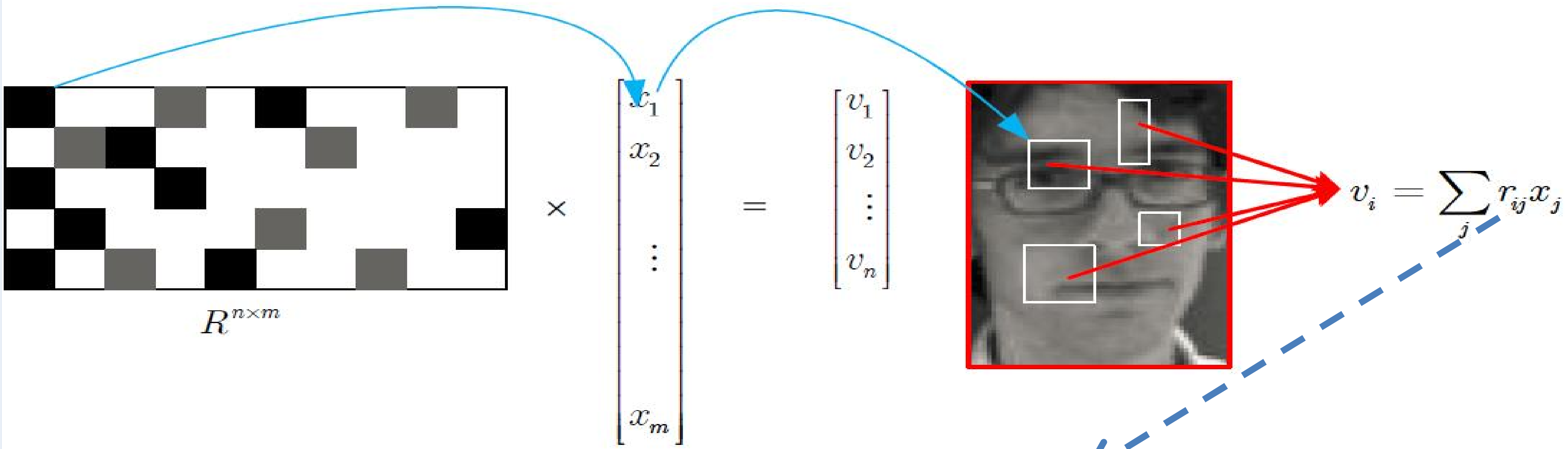
- Theoretical basis

Compressive sensing theories

A small number of randomly generated linear measurements can preserve most of the salient information and almost perfect reconstruct the signal

Feature Extraction

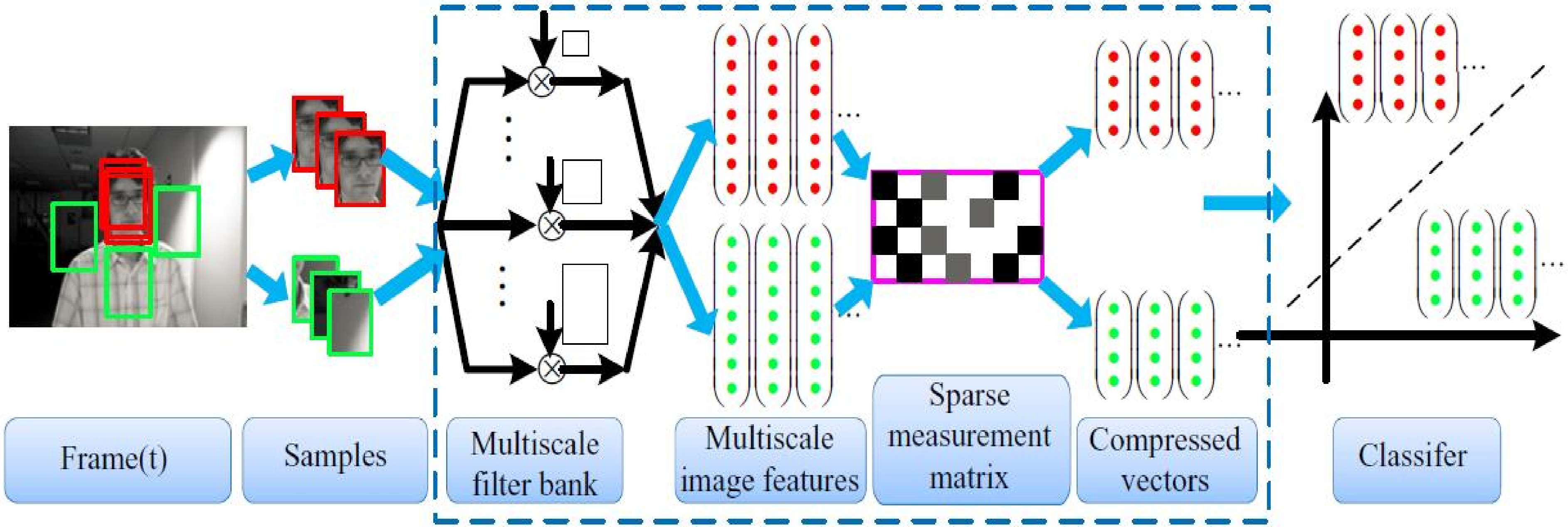
- Dimension reduction



$$r_{ij} = \sqrt{s} \times \begin{cases} 1 & \text{with probability } \frac{1}{2s} \\ 0 & \text{with probability } 1 - \frac{1}{s} \\ -1 & \text{with probability } \frac{1}{2s}. \end{cases}$$

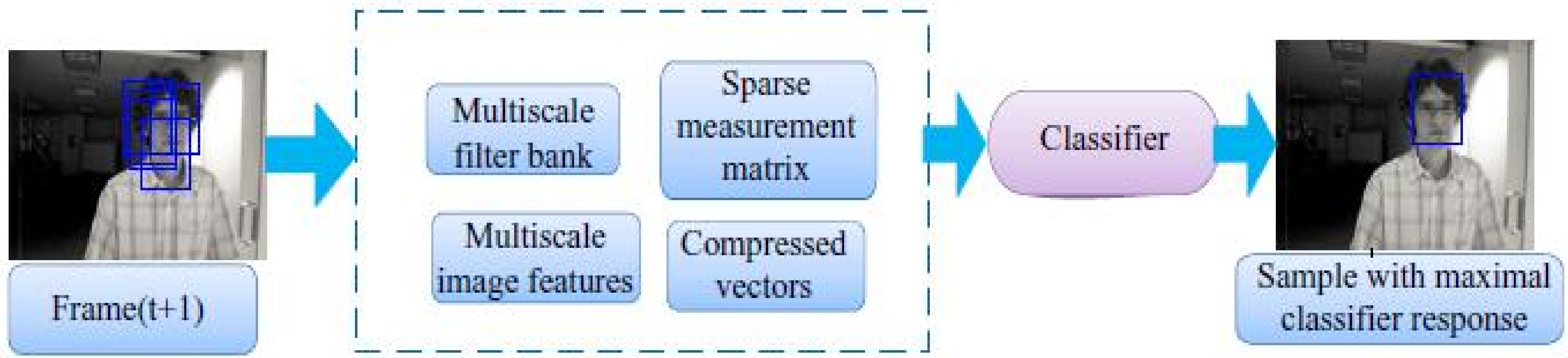
Updating the classifier at the *t*-th frame

Positive and negative samples are used to train a Naïve Bayes Classifier



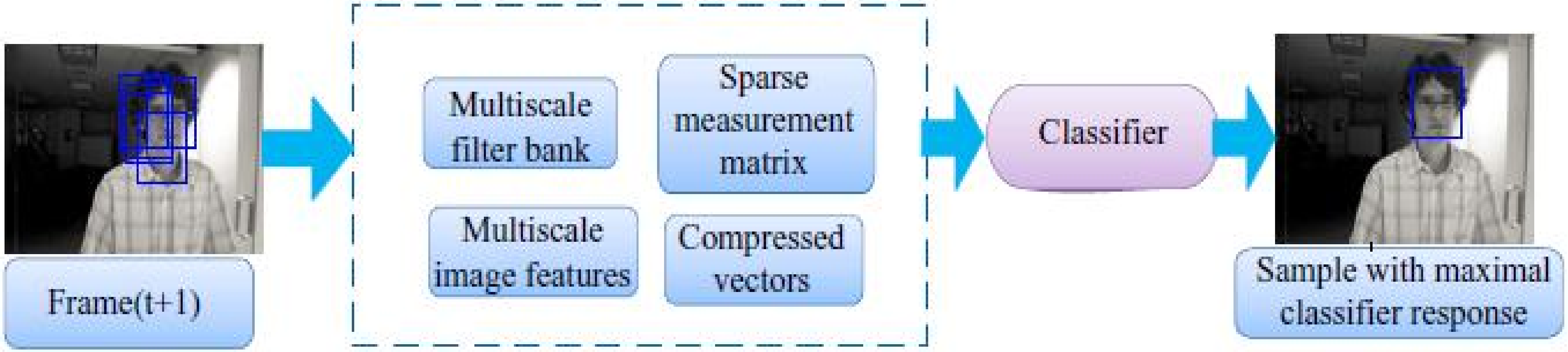
Tracking at the (t+1)-th frame

The sample which has the highest score will be the tracked position.



$$H(\mathbf{v}) = \log\left(\frac{\prod_{i=1}^{n} p(v_i|y=1)p(y=1)}{\prod_{i=1}^{n} p(v_i|y=0)p(y=0)}\right) = \sum_{i=1}^{n} \log\left(\frac{p(v_i|y=1)}{p(v_i|y=0)}\right)$$

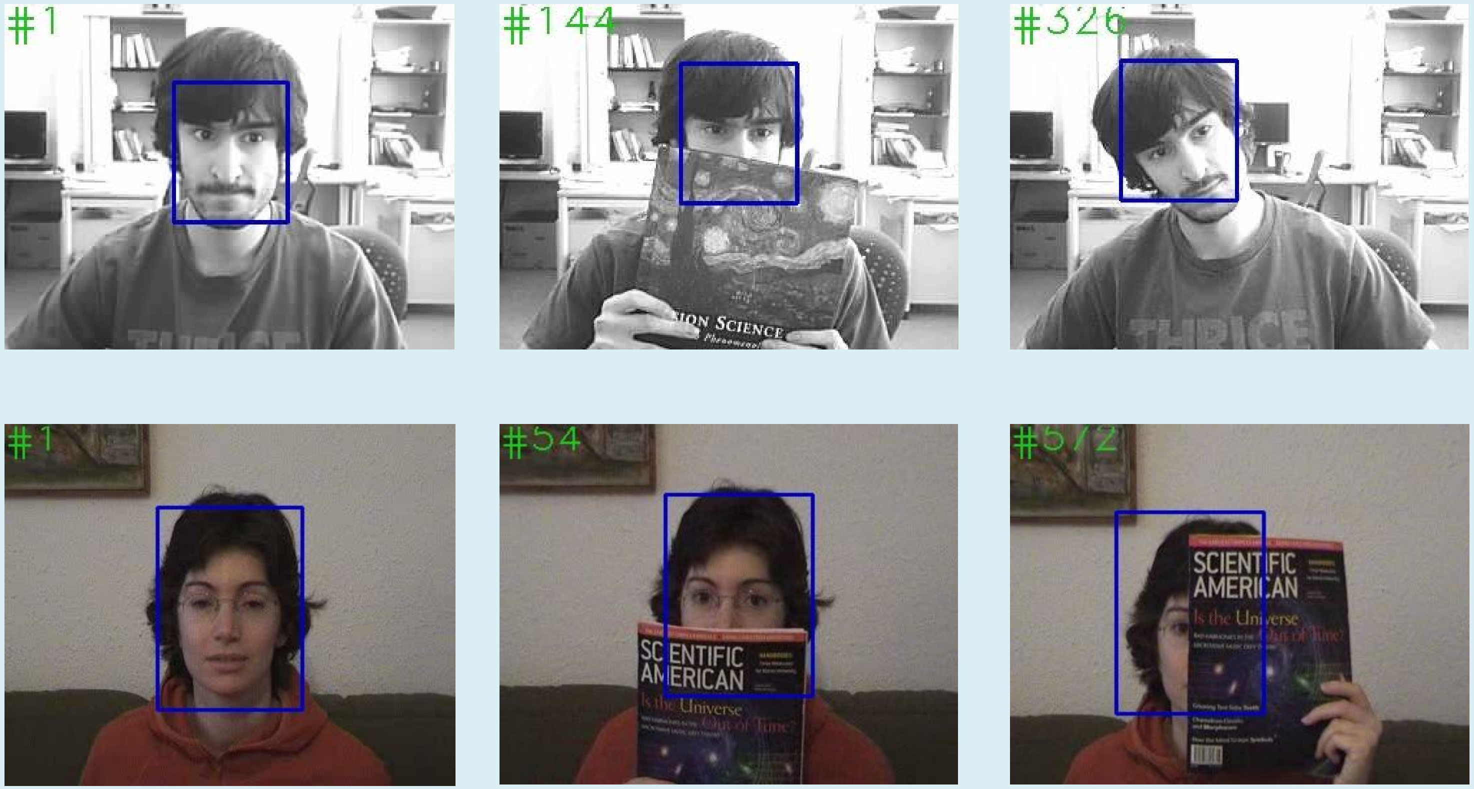
Tracking at the (t+1)-th frame



$$H(\mathbf{v}) = \log\left(\frac{\prod_{i=1}^{n} p(v_i|y=1)p(y=1)}{\prod_{i=1}^{n} p(v_i|y=0)p(y=0)}\right) = \sum_{i=1}^{n} \log\left(\frac{p(v_i|y=1)}{p(v_i|y=0)}\right)$$

$$p(v_i|y=1) \sim N(\mu_i^1, \sigma_i^1), \qquad p(v_i|y=0) \sim N(\mu_i^0, \sigma_i^0).$$

Experiments



Experiments

Experiments

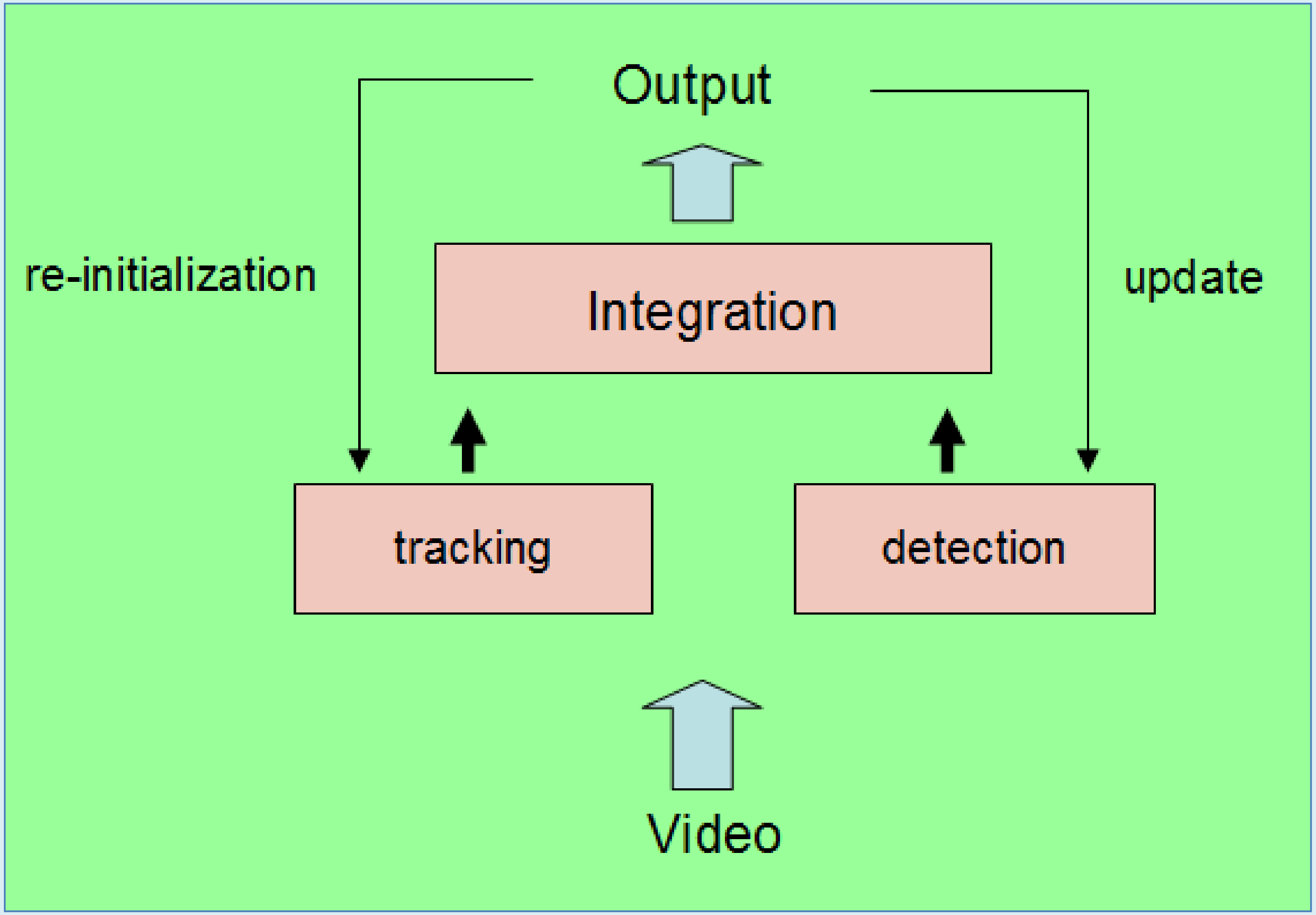
Tracking-Learning-Detection(TLD)

- Core idea

Combination of motion tracking and object detection.
Focused on long-term tracking.

Use detector to relocate the tracker.

Framework Overview

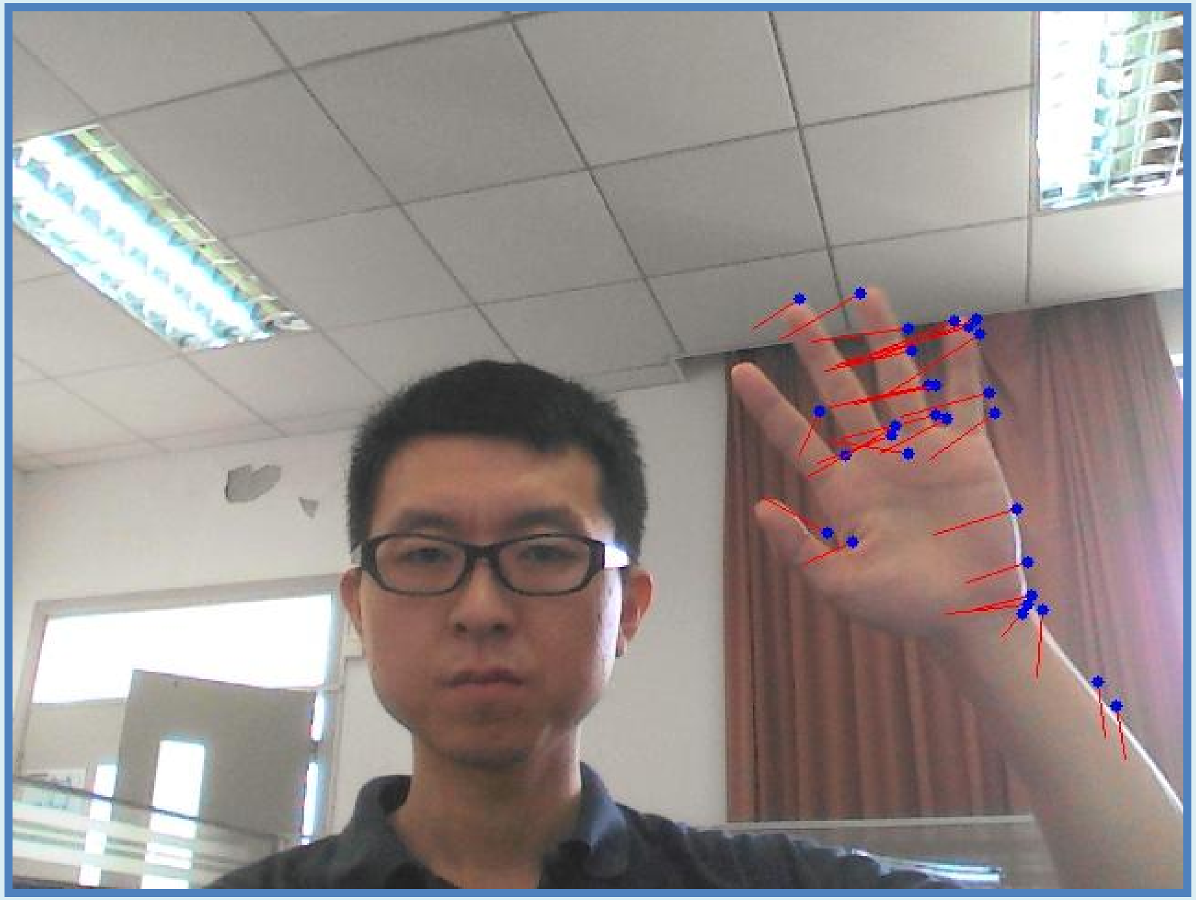


Tracking Module of TLD

- Frame difference
- Background subtraction
- Optical flow

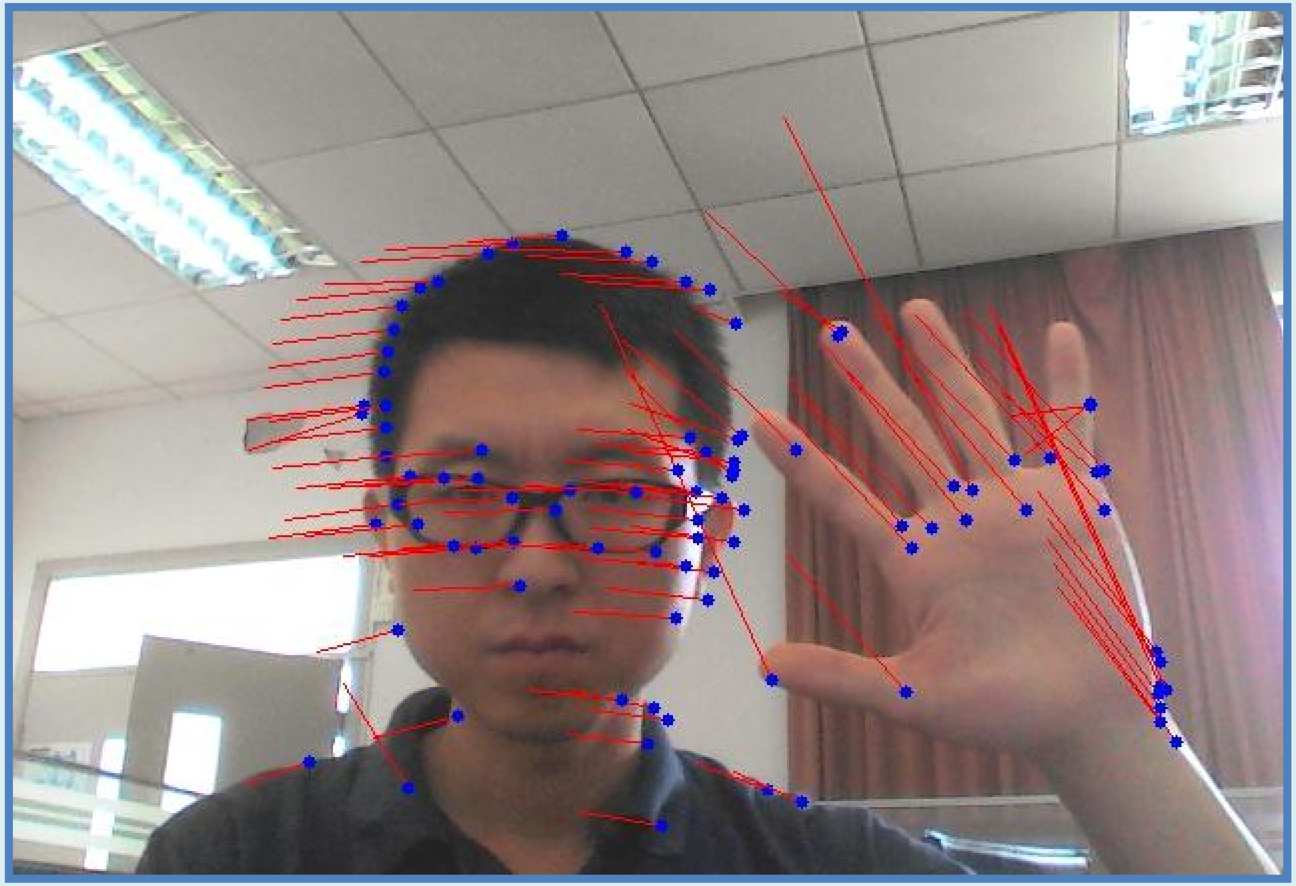
Optical Flow

- A classical, common, successful method



Optical Flow

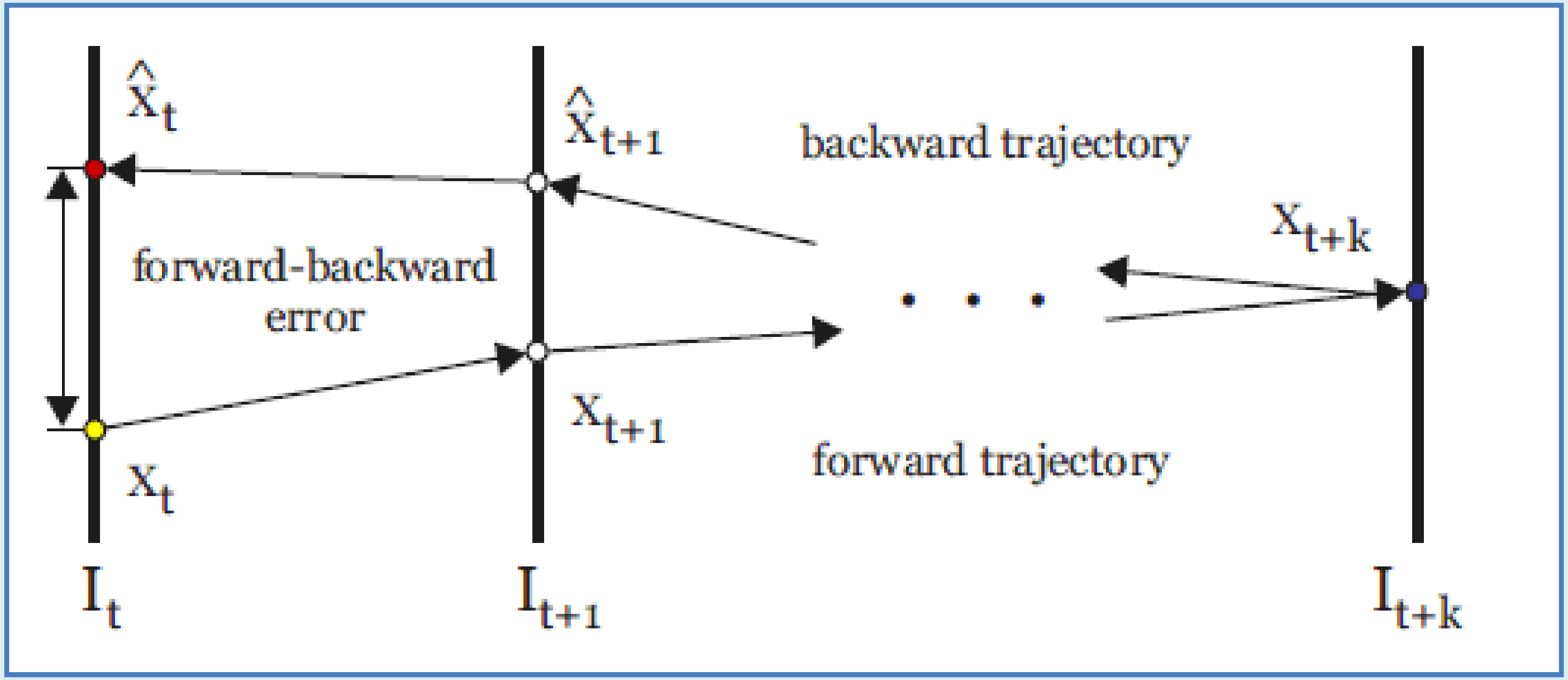
- A classical, common, successful method



Median Flow for TLD

- Assumption

A good tracker should have forward-backward consistency.



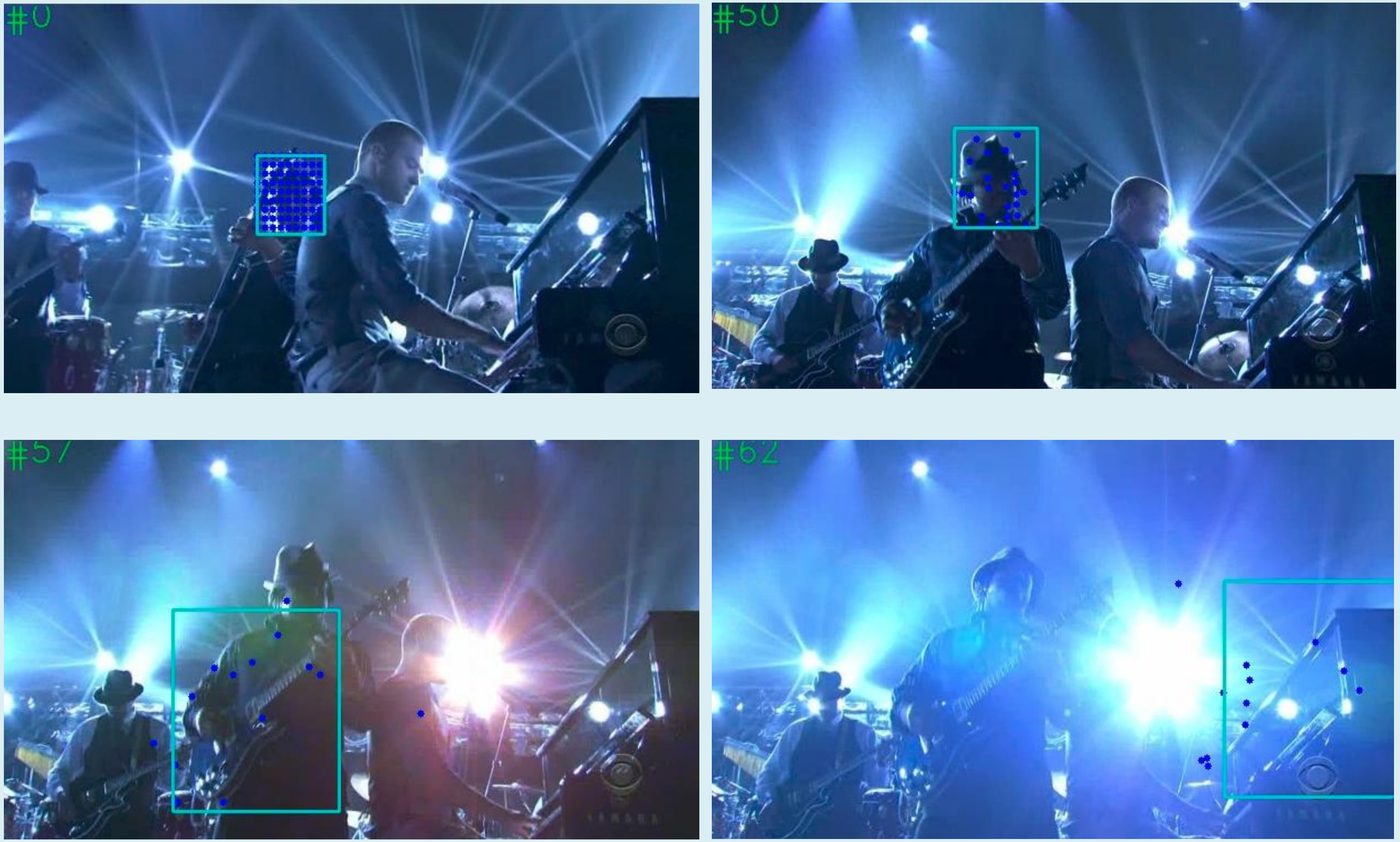
Median Flow for TLD

- Features can be simple
- Handle scale variants
- Simple and efficient

- Sensitive to illumination variants
- Lack of self-learning and update

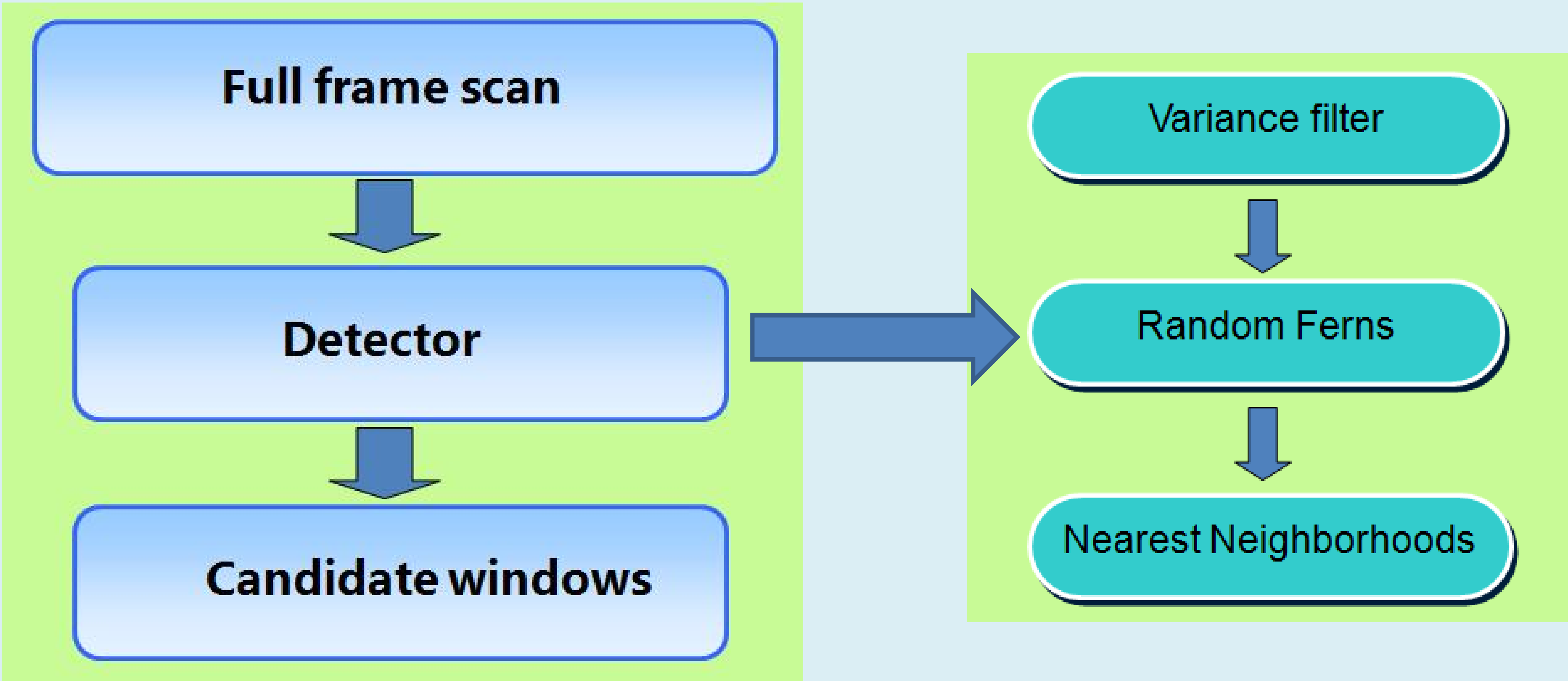
Median Flow for TLD

Median Flow for TLD



Median Flow for TLD

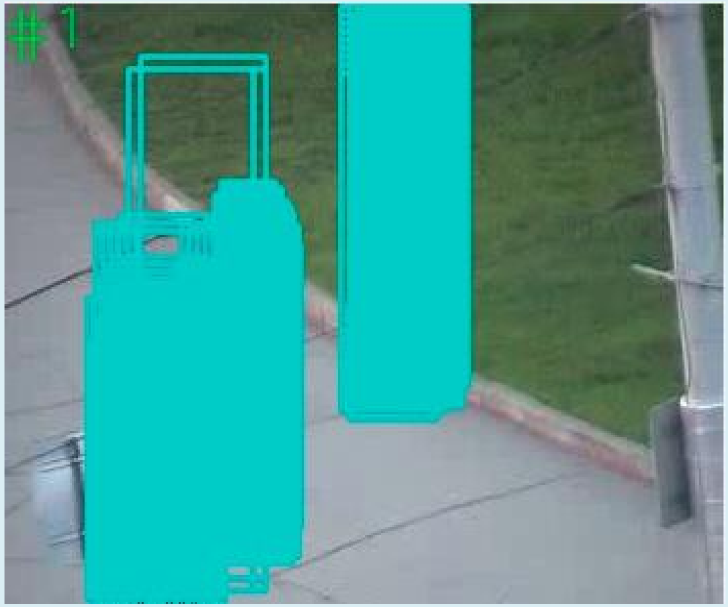
Detection Module of TLD



Variance Filter

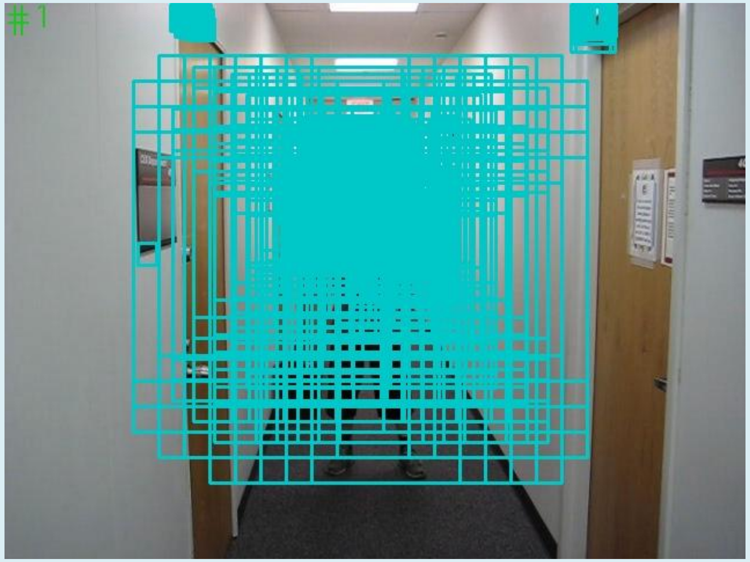
Remove patches that are smooth.

Effective for the images that have smooth background



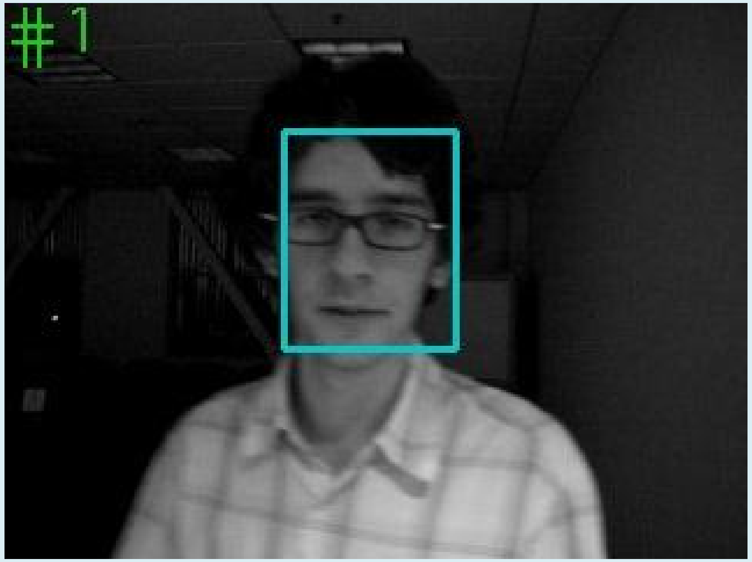
Variance Filter

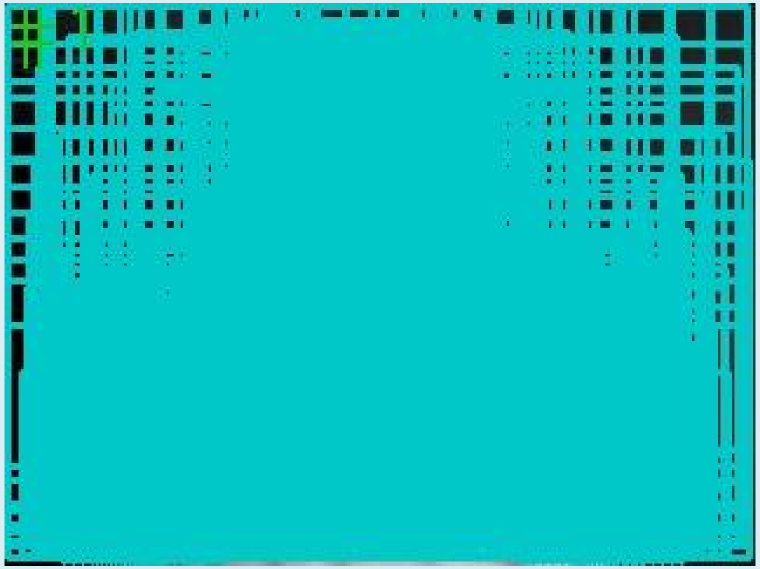
When background is more complicated, the effect will get worse.



Variance Filter

When object is similar to the background , the effect will get worse.

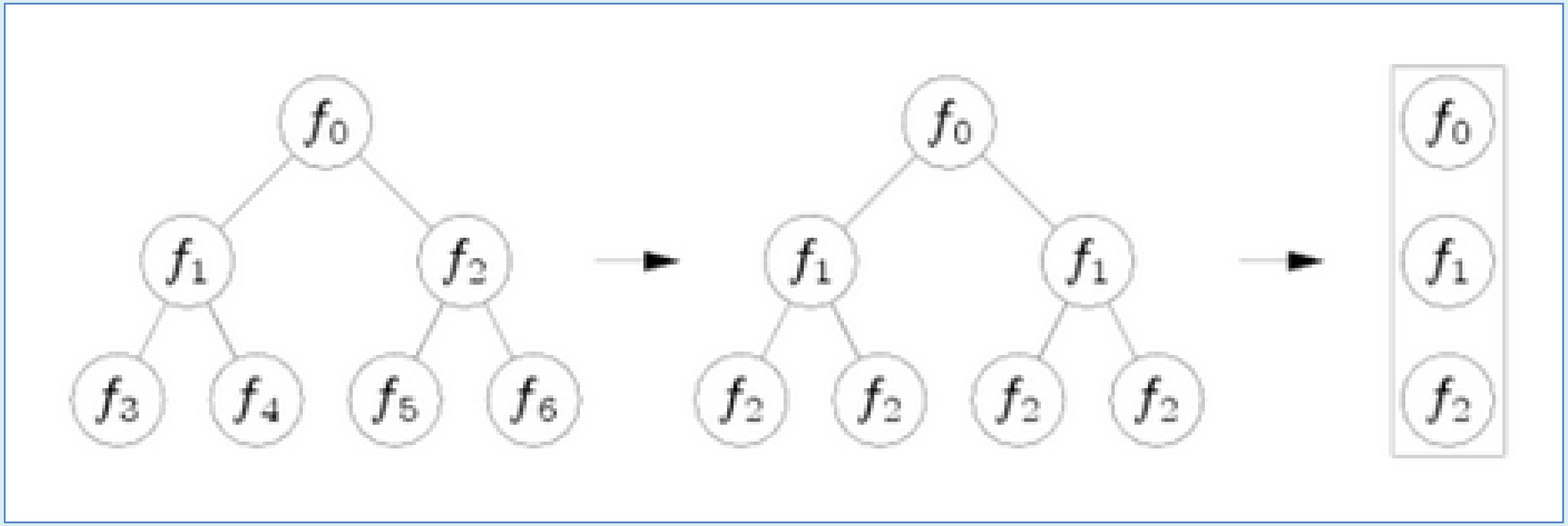




Random Ferns Classifier

- The core part of the detector of TLD.
- Different from Random Forests

  same criterion for every layer, become linear

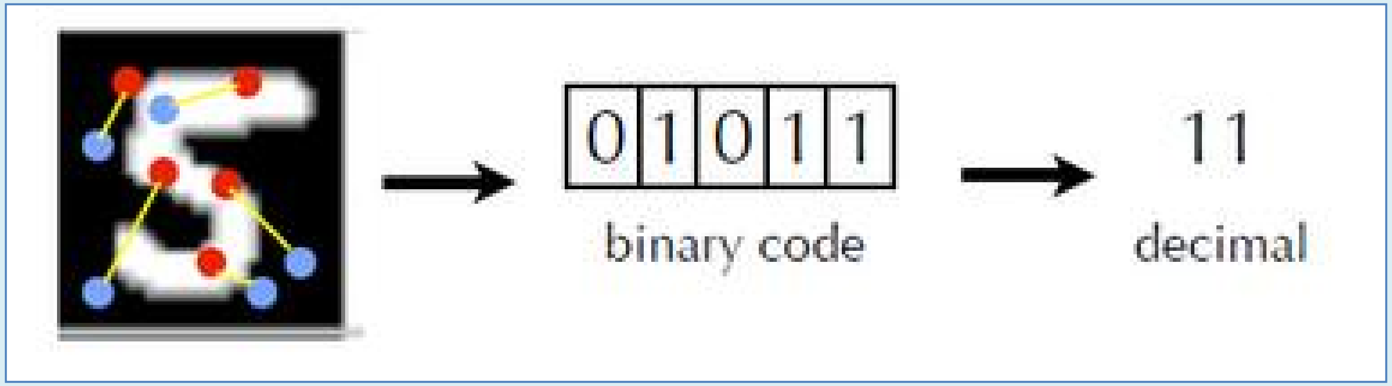


Feature Extraction

LBP features

Select two points A and B randomly from one patch, compare their intensity, if I(A) > I(B), then the feature value is 1, else is 0.

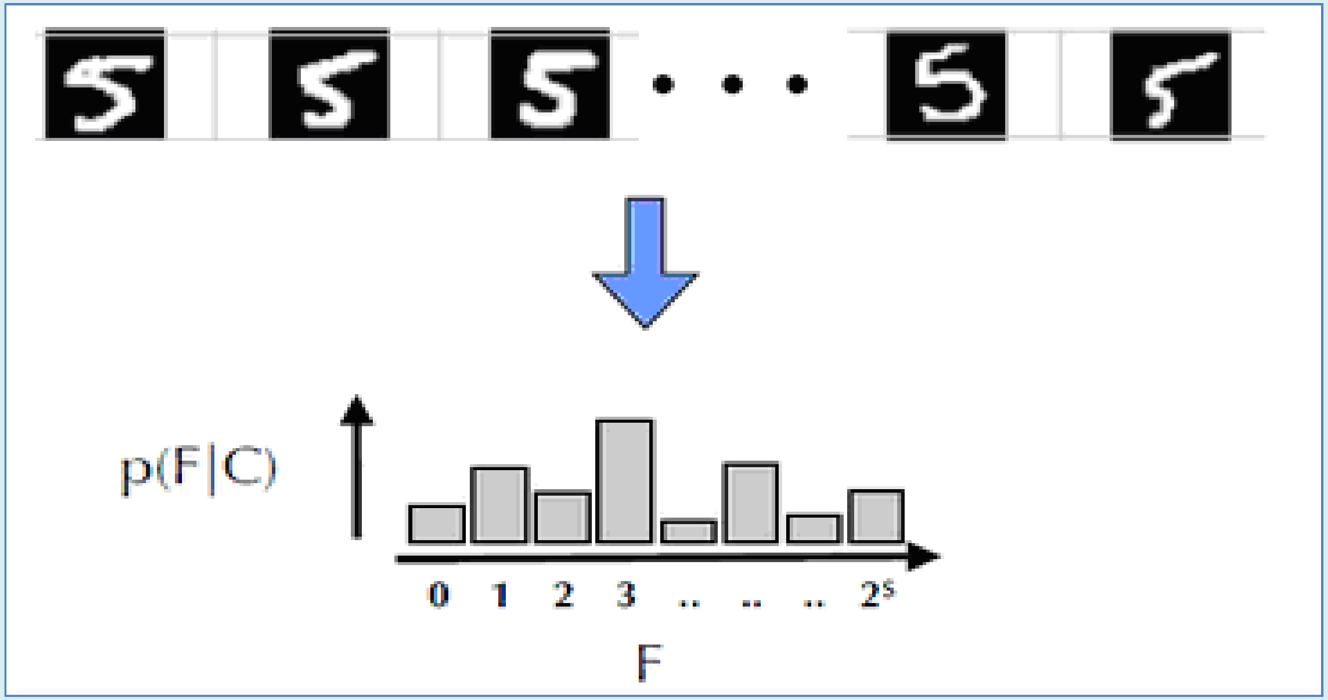
Example: one patch passes a fern with 5 nodes.



Random Ferns Classifier

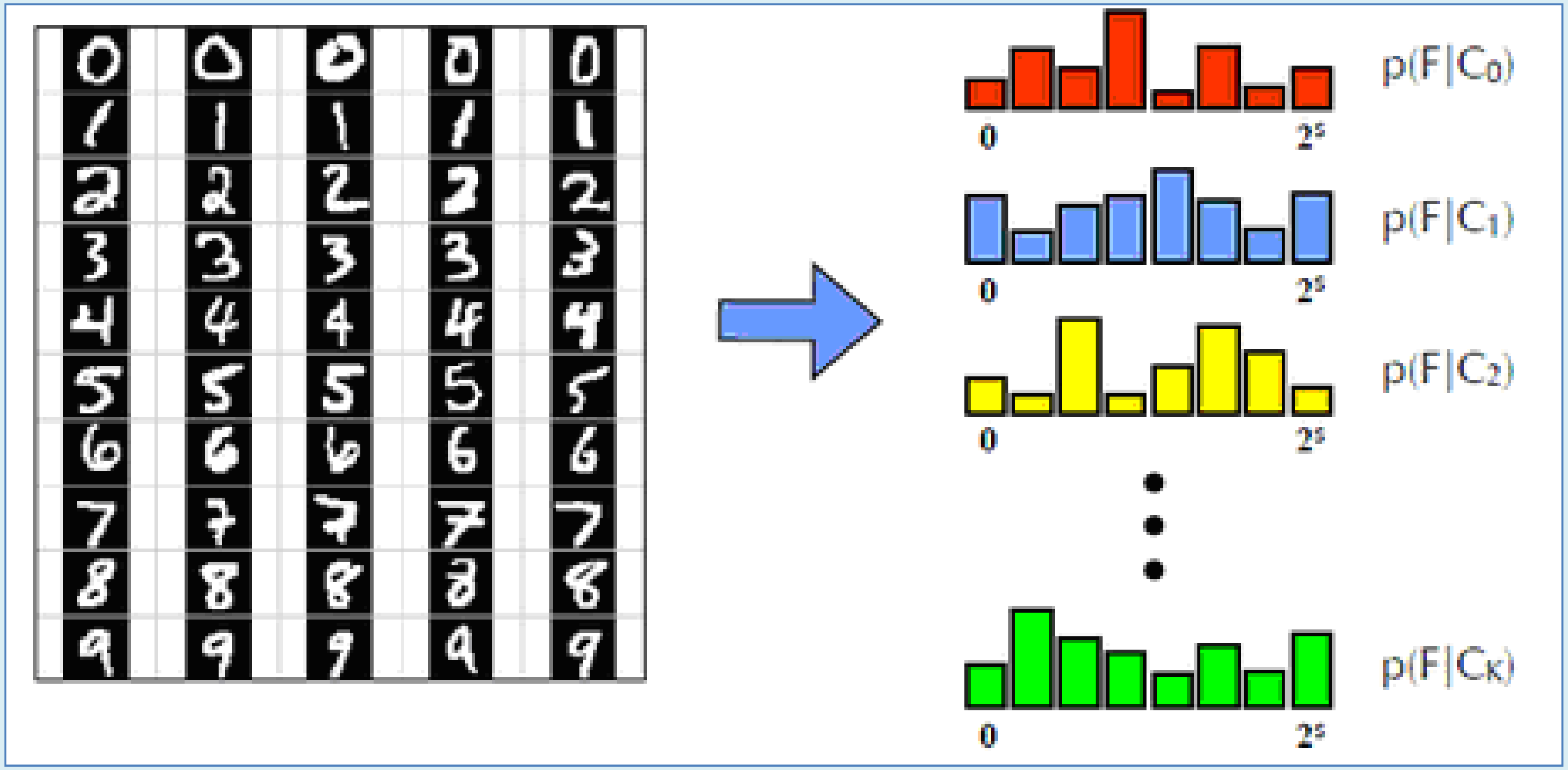
If one fern has *s* nodes, then there will be *$1+2^s$* feature values

The samples of one class pass the fern, we can get the histogram of the prior probability.



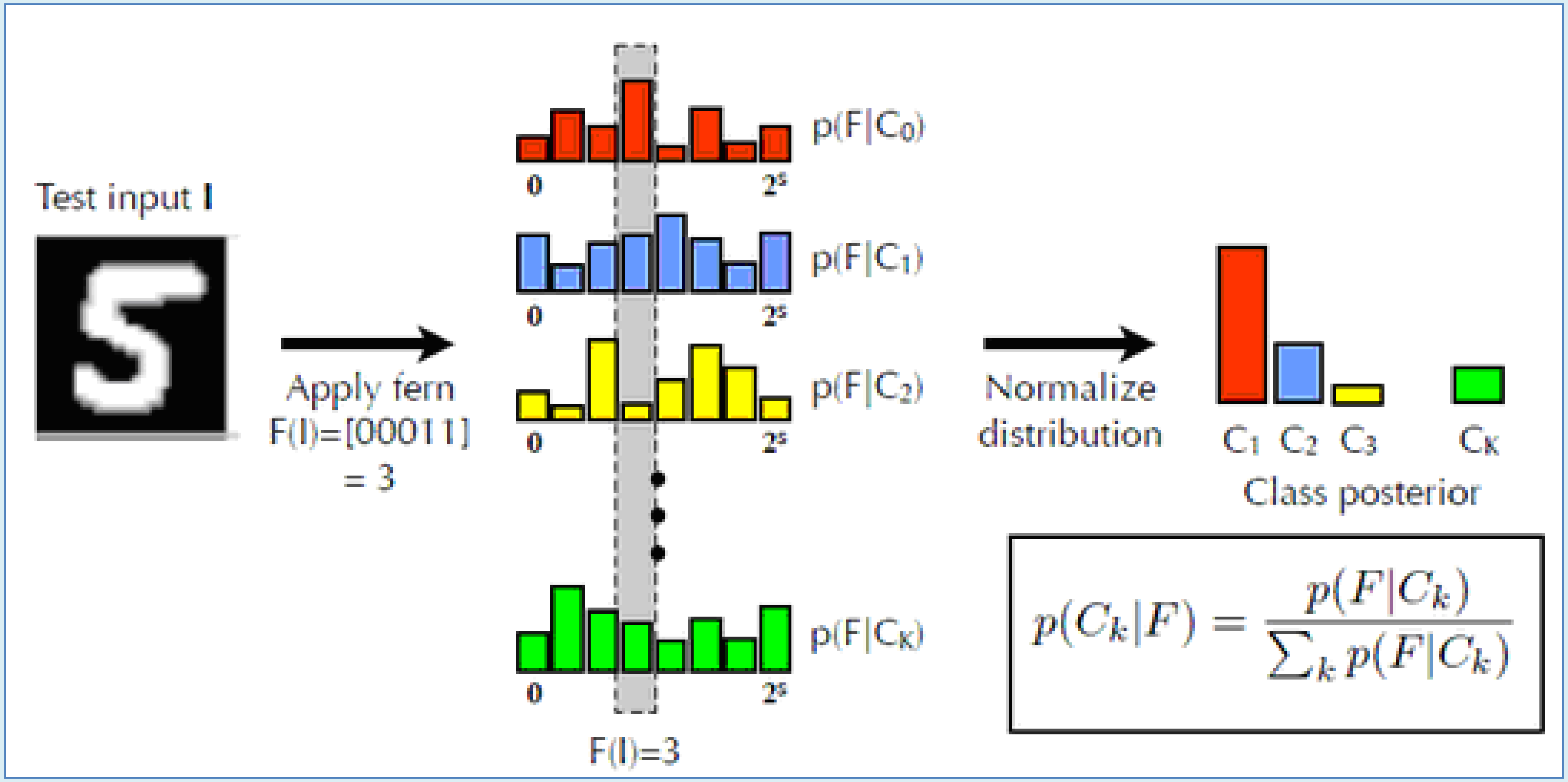
Random Ferns Classifier

Samples of different classes pass the fern, we can get corresponding histograms.



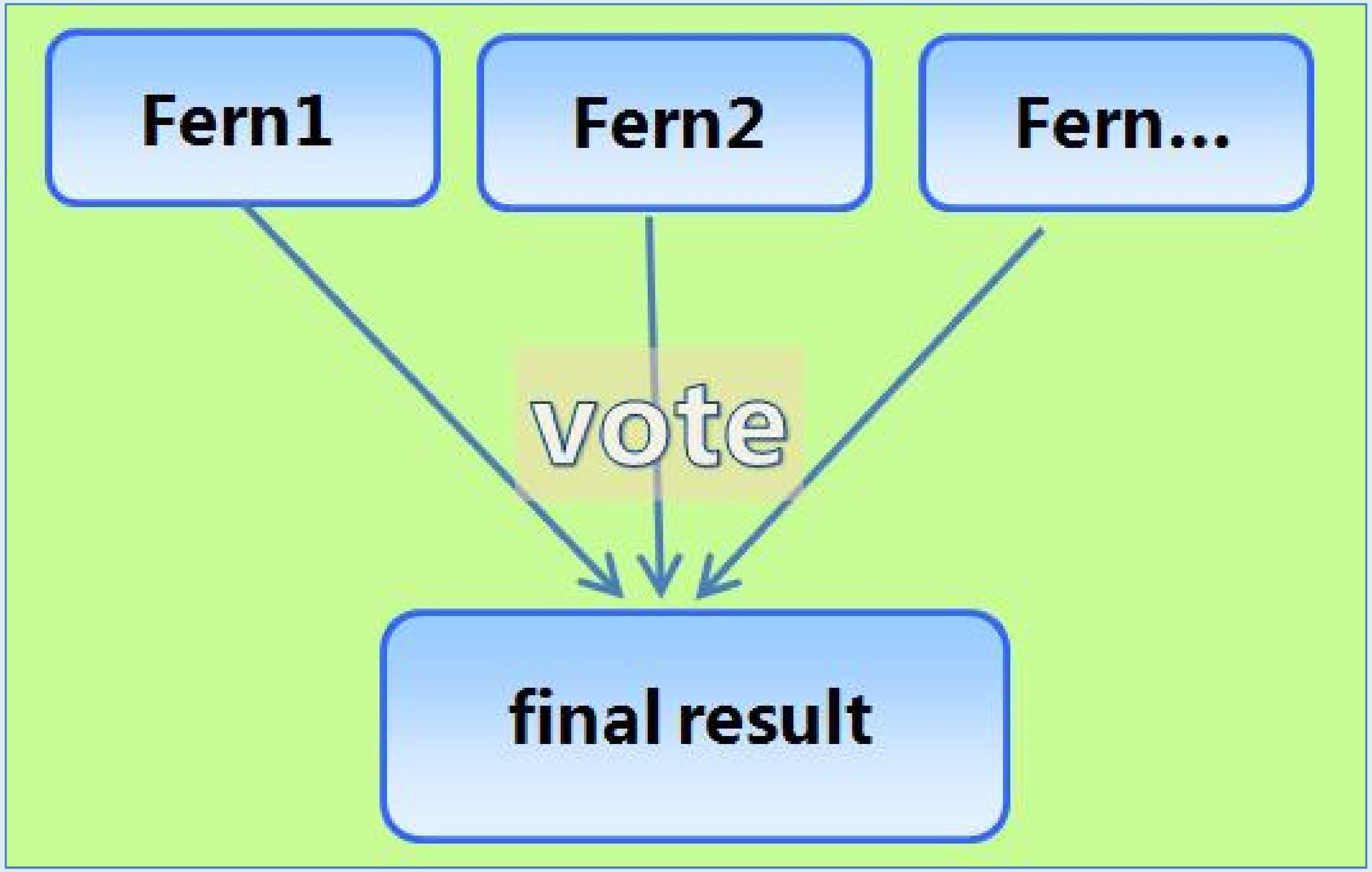
Random Ferns Classifier

When a new patch passes the fern, if its feature is 00011(3) for example, then find the max posterior probability from the given distribution.



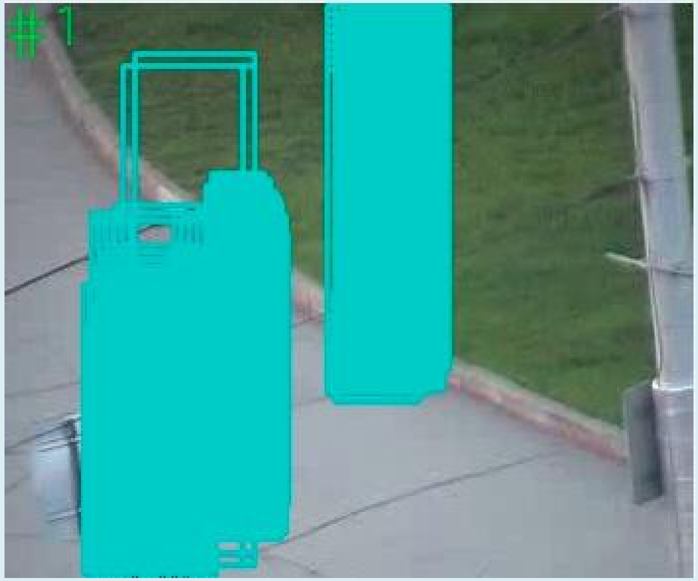
Random Ferns Classifier

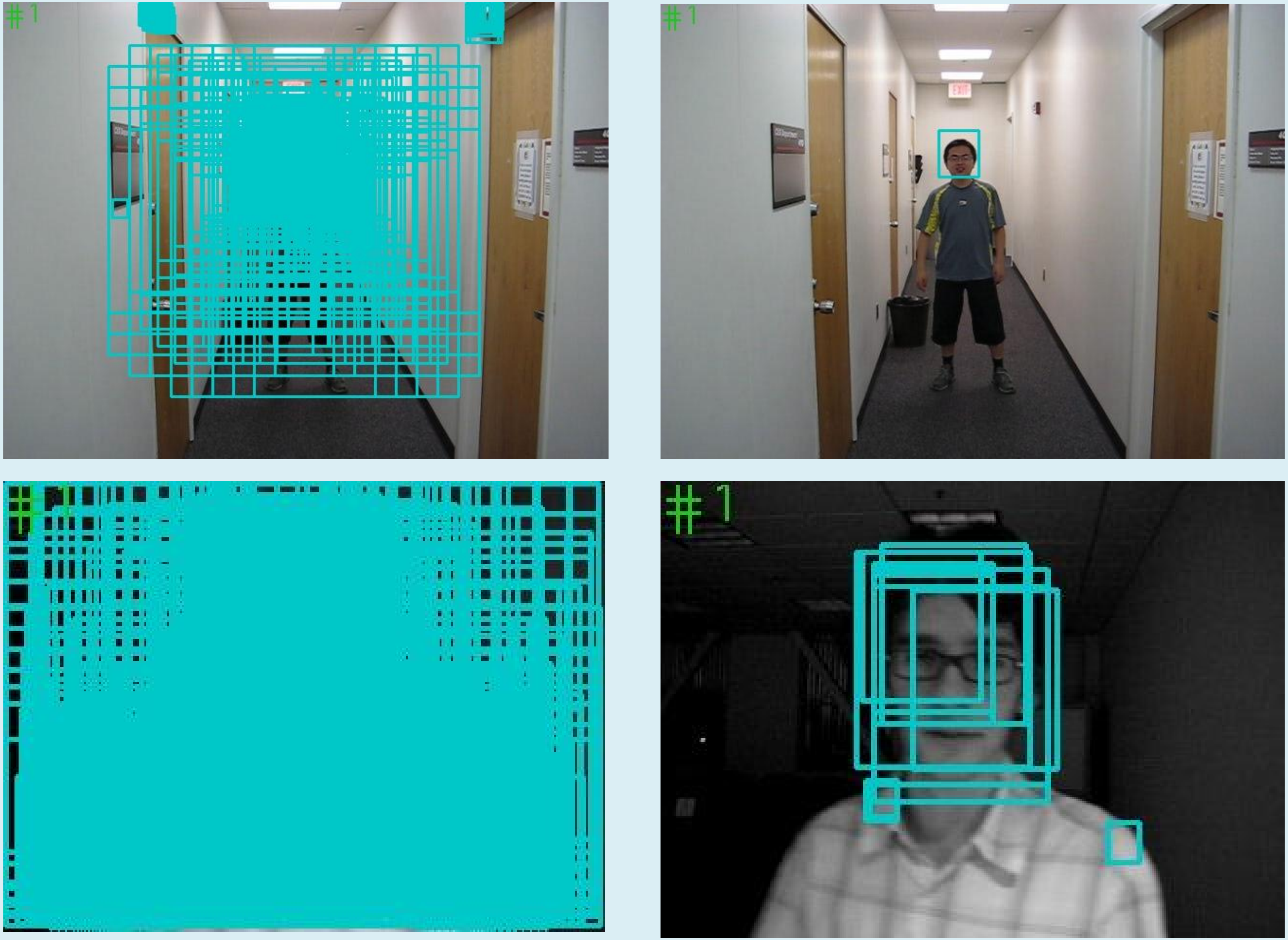
We usually use a few ferns to form a random ferns classifier. Each fern has a vote.



Random Ferns Classifier

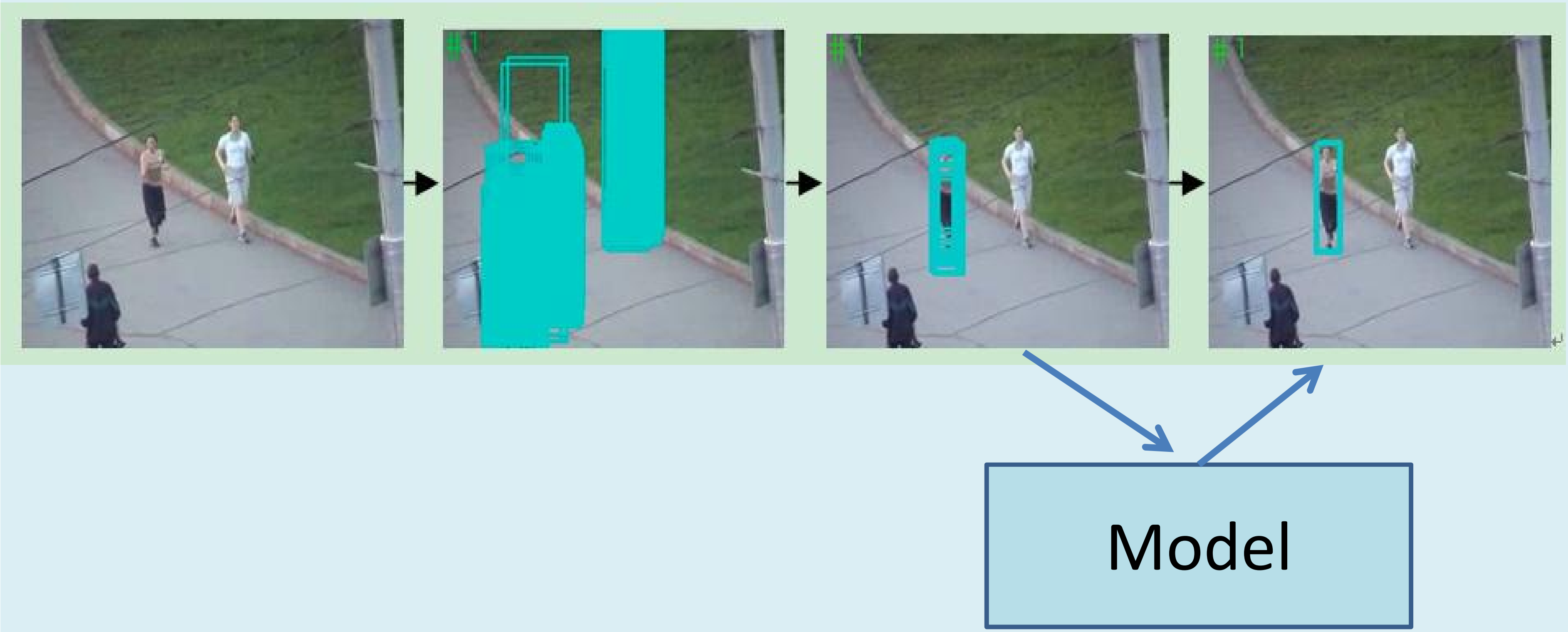
In TLD, 13 nodes each fern, 10 ferns.



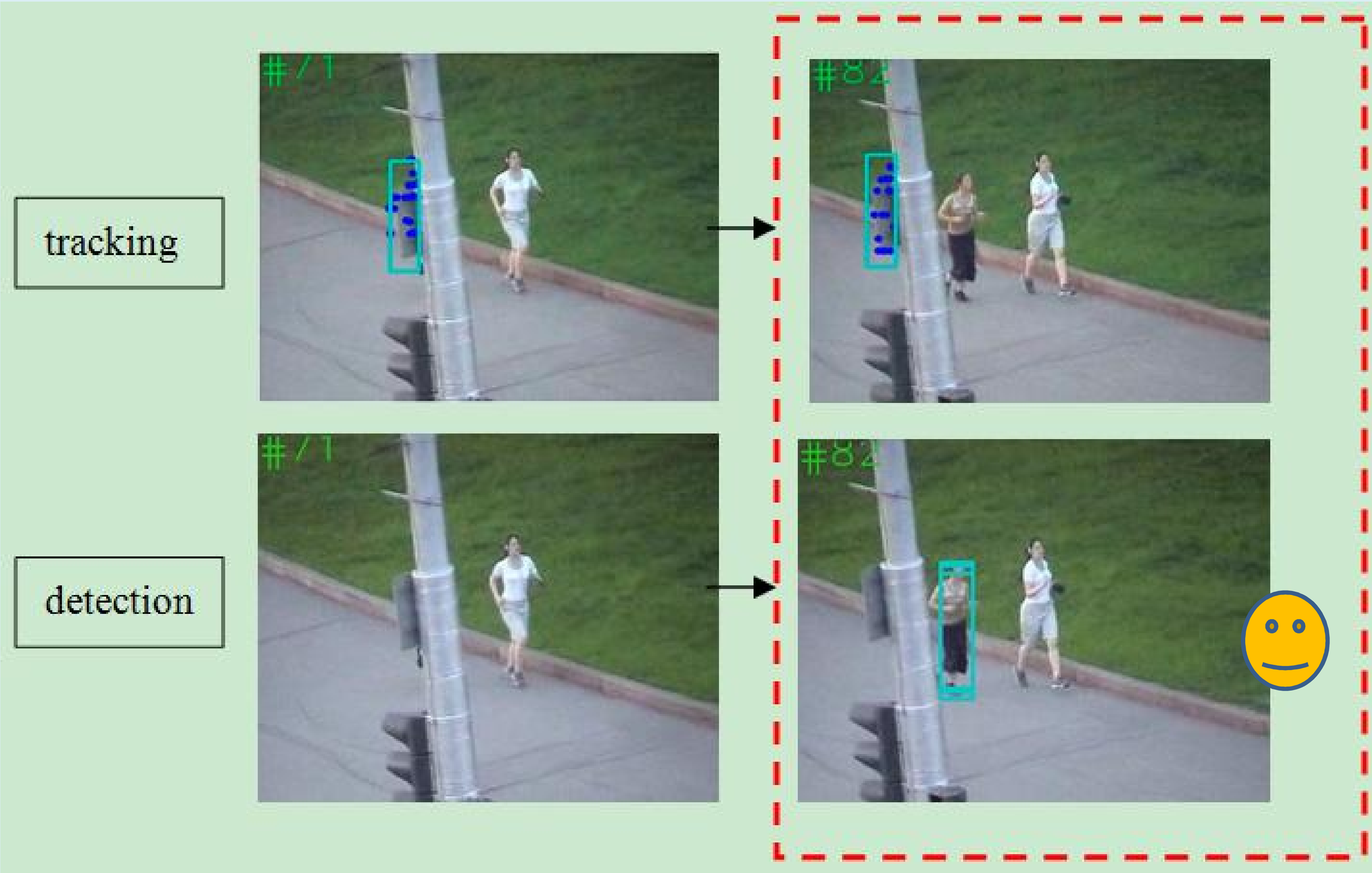

#1
#1
#1
#1

Nearest Neighborhood

- Compute the similarity with object models.



Integration



Conclusions & Future Directions

- There is not a perfect tracker.

  Select the most suitable one according to the application.
- New discriminative features.
- Dynamic and motion analysis.

Conclusions & Future Directions

- Depth information from multi-views.
- Re-identification.
- Integration of Video & Audio tracking

References

- Kaihua Zhang, Lei Zhang, Ming-Hsuan Yang. 20 Real-Time Compressive Tracking. ECCV, 2012.
- Zdenek Kalal, Krystian Mikolajczyk, Jiri Matas. Tracking-Learning-Detection. In PAMI, 2010.
- Kalal Z, Matas J, Mikolajczyk K. P-N learning: Bootstrapping binary classifiers by structural constraints. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2010.

Thank you