Fast Keypoint Detection in Video Sequences

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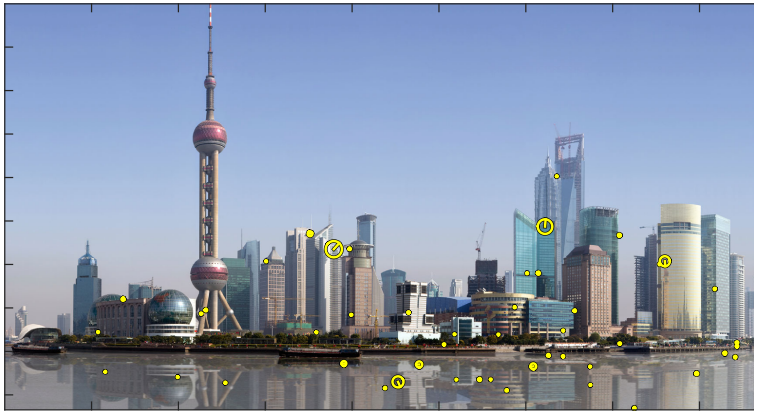
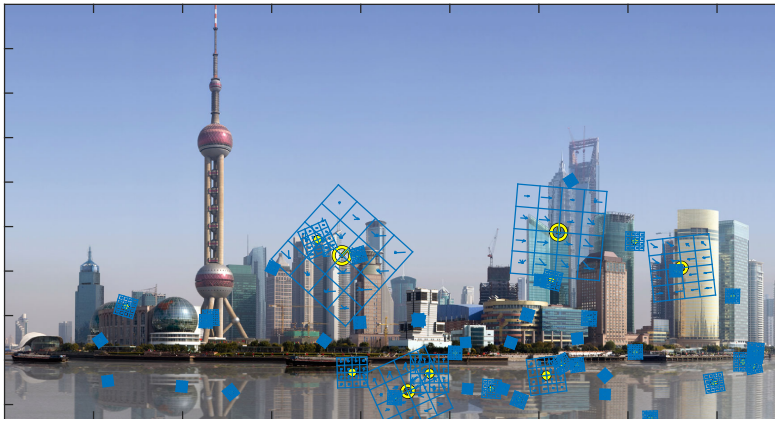
Local Visual Features

- Starting point for many computer vision tasks
  - Object recognition
  - Content-based retrieval
  - Image registration
- Two-steps approach:
  - First step: keypoint detection (corners, blobs, etc.)
  - Second step: descriptor extraction (SIFT, SURF, BRISK, etc.)





Local features detection in video

- Most algorithms are tailored to still images
- For video, past literature targets the identification of keypoints that are **stable across time**
  - Stable features are key to object tracking, event identification and video calibration (main goal: application accuracy)
  - Stable features improve the efficiency of coding architectures exploiting the temporal redundancy (main goal: minimize bandwidth)
- We target computational complexity
  - Low power devices (smartphones, embedded systems, Visual Sensor Networks) require the process of features detection to be both **fast** and **accurate**

Fast extraction from video

- Baseline approach: apply a feature detector on each frame $\mathcal{I}_n$ of a video sequence
  - Inefficient from a computational point of view!
  - Temporal redundancy is not exploited!

- Our approach: apply the feature detector only in regions of $\mathcal{I}_n$ that are sufficiently different from $\mathcal{I}_{n-1}$
  - Compute a **detection mask** to identify such regions
  - **Reuse** keypoints from $\mathcal{I}_{n-1}$ outside those regions (keypoint propagation from $\mathcal{I}_{n-1}$ to $\mathcal{I}_n$)

Fast extraction from video

- Formally:
  - Let $\mathcal{D}_n$ be the set of features extracted from frame $\mathcal{I}_n$ (size $N_x \times N_y$)
  - Let $d_{n,i} \in \mathcal{D}_n$ be the i-th features of the set, computed in keypoint location $\mathbf{p}_{n,i}$
  - Let $\mathcal{M}_n \in \{0,1\}^{N_x \times N_y}$ be a binary detection mask defining the regions of the frame where the detector should be applied

$$\mathcal{D}_n = \{ d_{n,i} : \mathcal{M}_n(\mathbf{p}_{n,i}) = 1 \cup d_{n-1,j} : \mathcal{M}_n(\mathbf{p}_{n-1,j}) = 0 \}$$

New features

Propagated features

Detection Mask

- How to compute the detection mask $\mathcal{M}_n$?
  - Need for a computationally efficient algorithm!
- We propose two alternatives:
  - Intensity Difference Detection mask
  - Keypoint Binning Detection Mask

Intensity Difference Detection Mask

- Idea: apply a detection only to regions that **vary sufficiently** across contiguous frames
- To this end, compute the absolute difference between **downsampled** representations of two consecutive frames
  - Already computed by the scale-space pyramid!
- If the difference in a given region **is greater than a threshold**, perform detection in such a region

$$\mathcal{M}'_{n,o}(k,l) = \begin{cases} 1 & \text{if } |\mathcal{L}_{n,o}(k,l) - \mathcal{L}_{n-1,o}(k,l)| \leq \mathcal{T}_I \\ 0 & \text{if } |\mathcal{L}_{n,o}(k,l) - \mathcal{L}_{n-1,o}(k,l)| > \mathcal{T}_I, \end{cases}$$

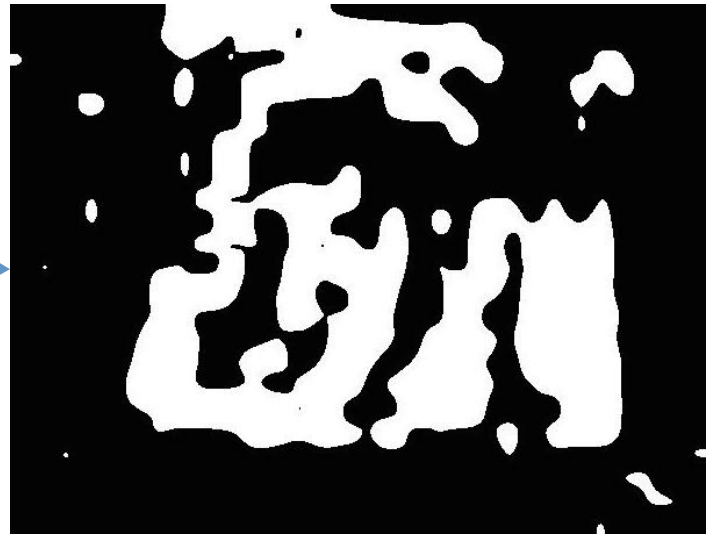
- Final mask obtained through upsampling

Intensity Difference Detection Mask

Idea: apply a detector only to regions of the image that **sufficiently vary across contiguous frames**.

Absolute difference

threshold



Keypoint Binning Detection Mask

- Idea: apply a detection only to regions where features have been found in previous frames
- To this end, compute a 2D spatial histogram of keypoints location
- If the number of keypoints in a spatial bin (of the previous frame) is greater than a threshold, perform detection in such a region

$$\mathcal{M}'_n(k,l) = \begin{cases} 1 & \text{if } \mathcal{M}''_n(k,l) \geq \mathcal{T}_H \\ 0 & \text{if } \mathcal{M}''_n(k,l) < \mathcal{T}_H, \end{cases}$$

Keypoint Binning Detection Mask

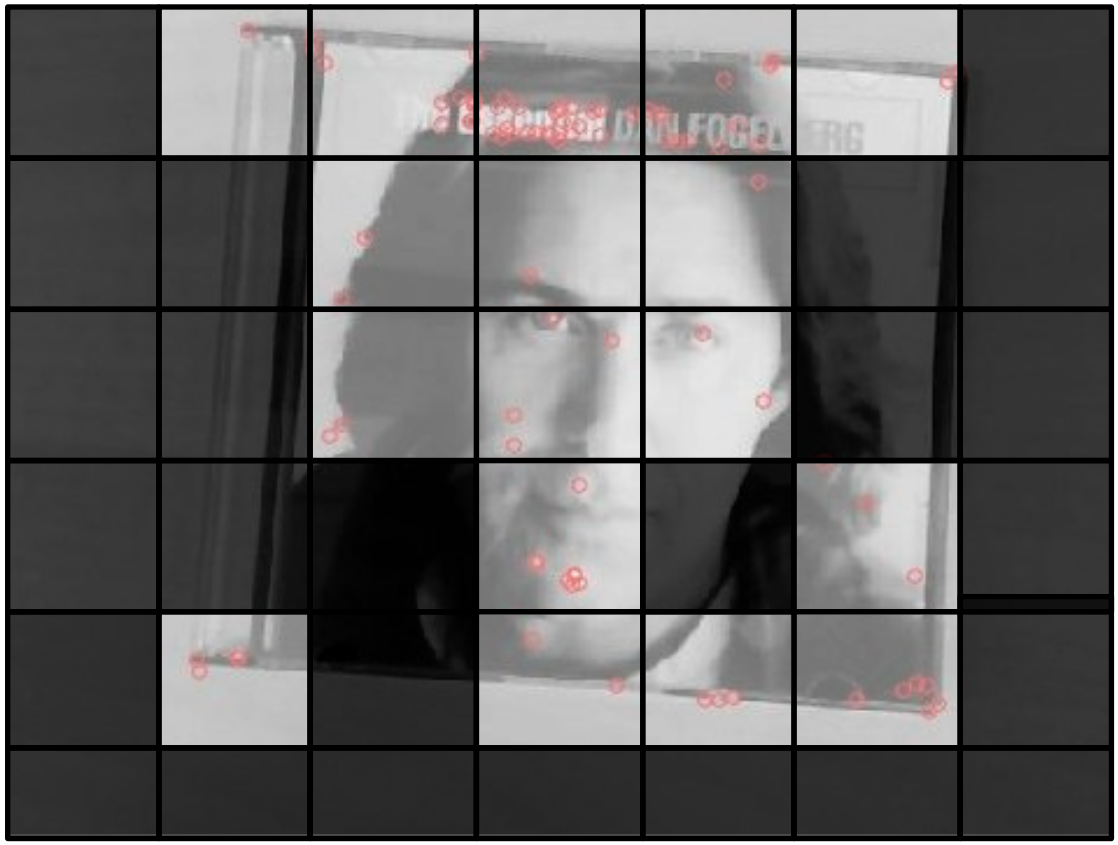
Idea: apply a detector only to regions of the image where features have been found in previous frames.

Keypoint Binning Detection Mask

Idea: apply a detector only to regions of the image where at least N features have been found in previous frames.

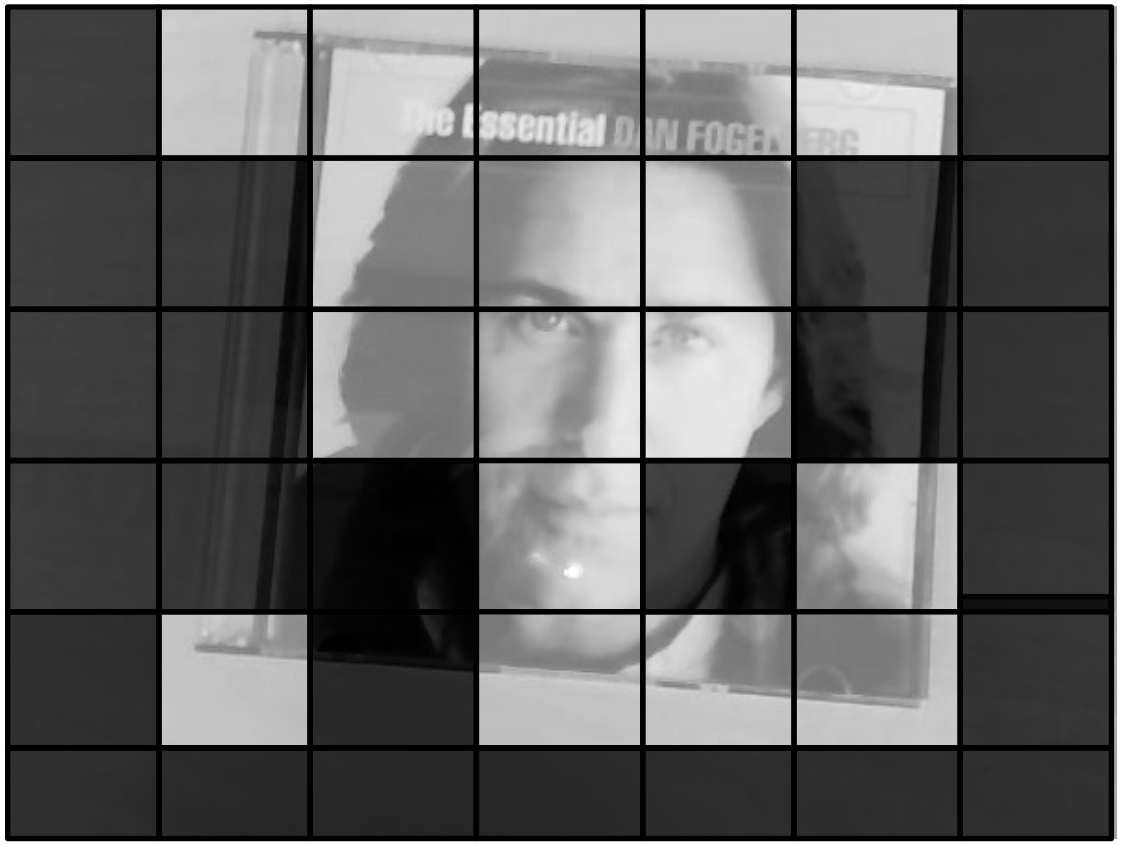
Keypoint Binning Detection Mask

Idea: apply a detector only to regions of the image where features have been found in previous frames.



Keypoint Binning Detection Mask

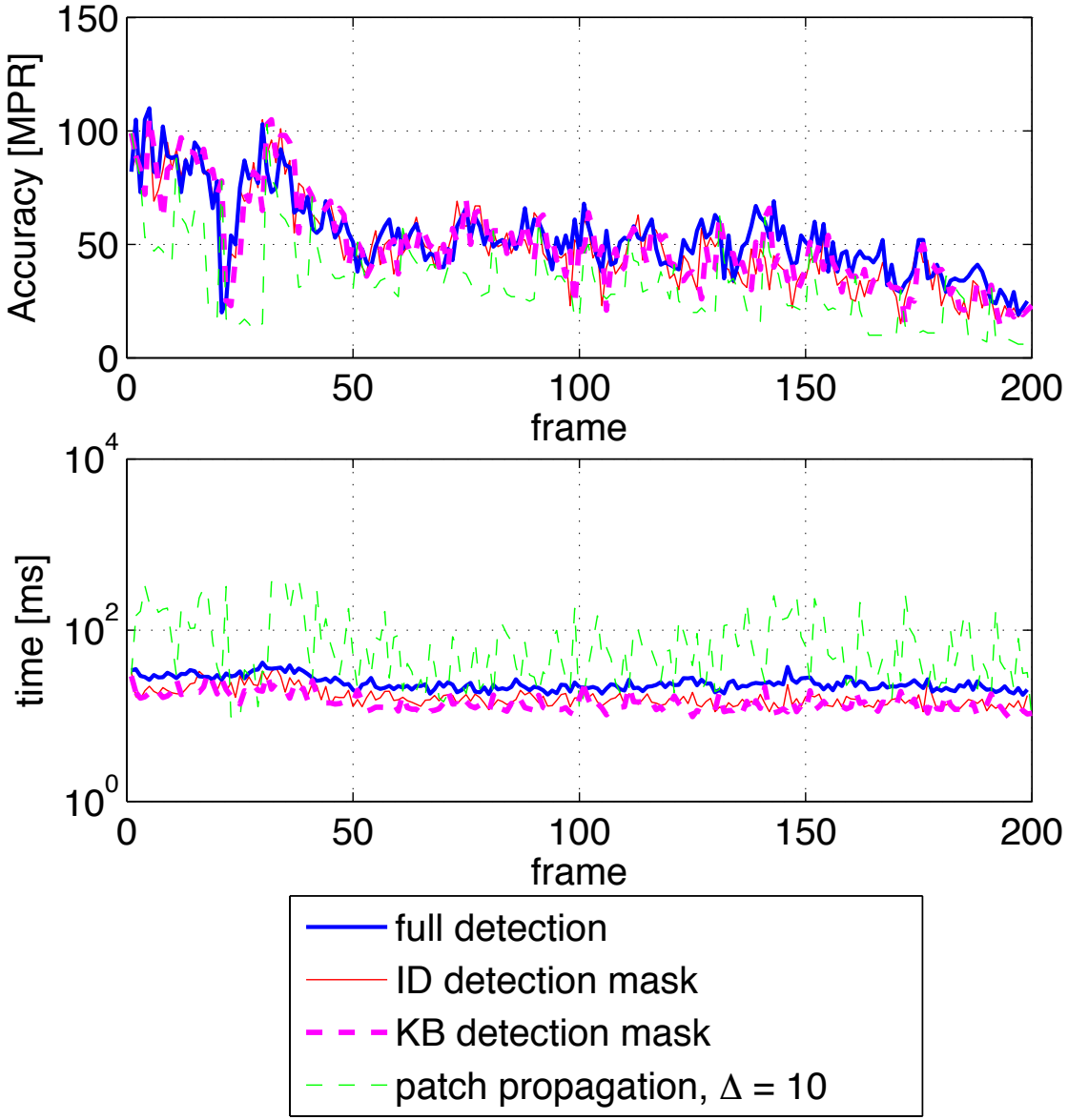
Idea: apply a detector only to regions of the image where features have been found in previous frames.



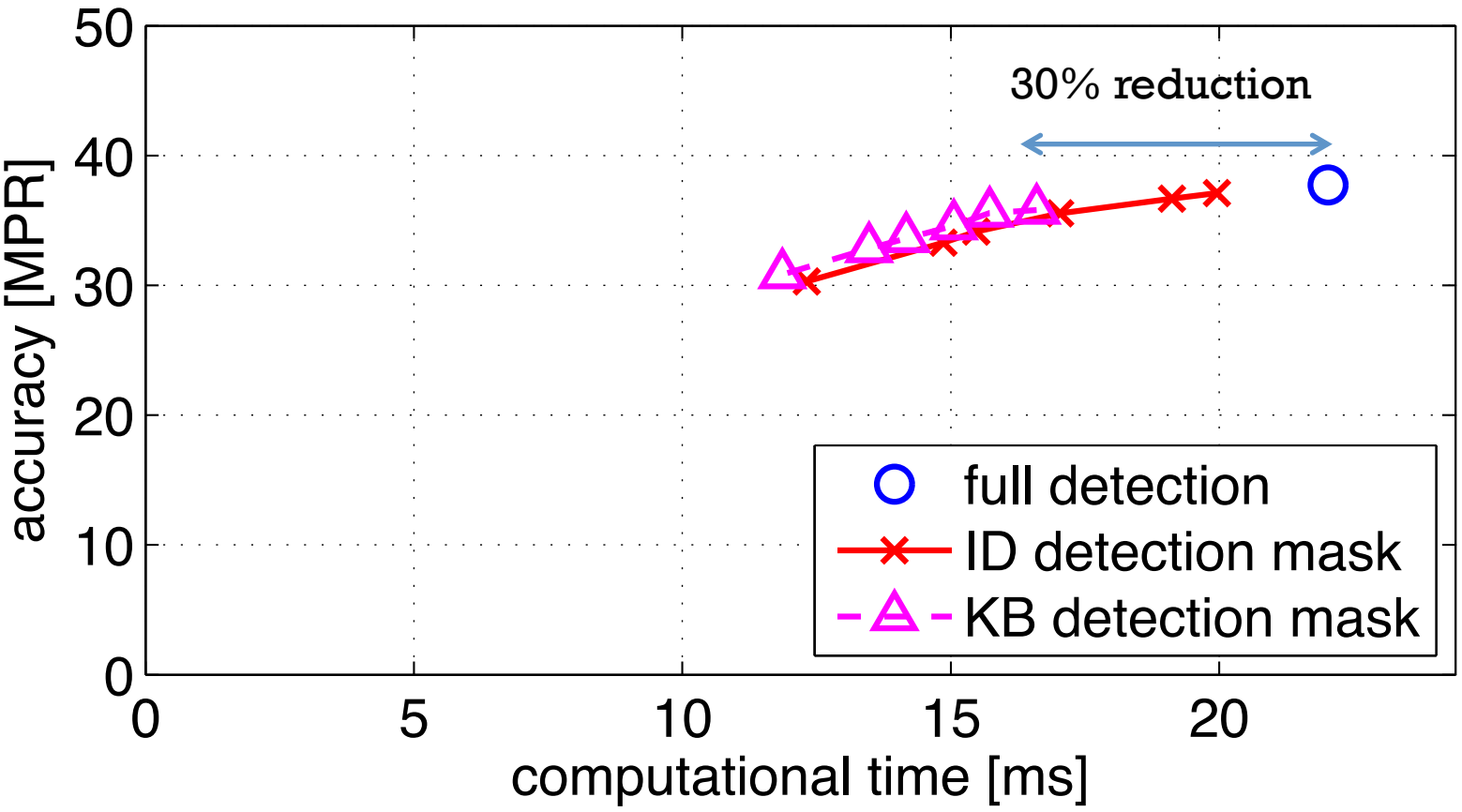
Experiments

- Datasets:
  - Stanford MAR dataset (4 sequences of cd covers under different imaging conditions)
  - Rome Landmark dataset (10 sequences of different landmarks in Rome)
  - Stanford MAR multiple object (4 sequences of different objects)
- Selected local features: BRISK (but our methods is generally appliable)
- Depending on the dataset, different accuracy measures:
  - Matches-post-Ransac (MPR) for Stanford MAR dataset
  - Mean of Average Precision (MAP) for Rome Landmark dataset
  - Combined detection and tracking accuracy for Stanford MAR multiple objects
- Complexity is measured by means of the required CPU time

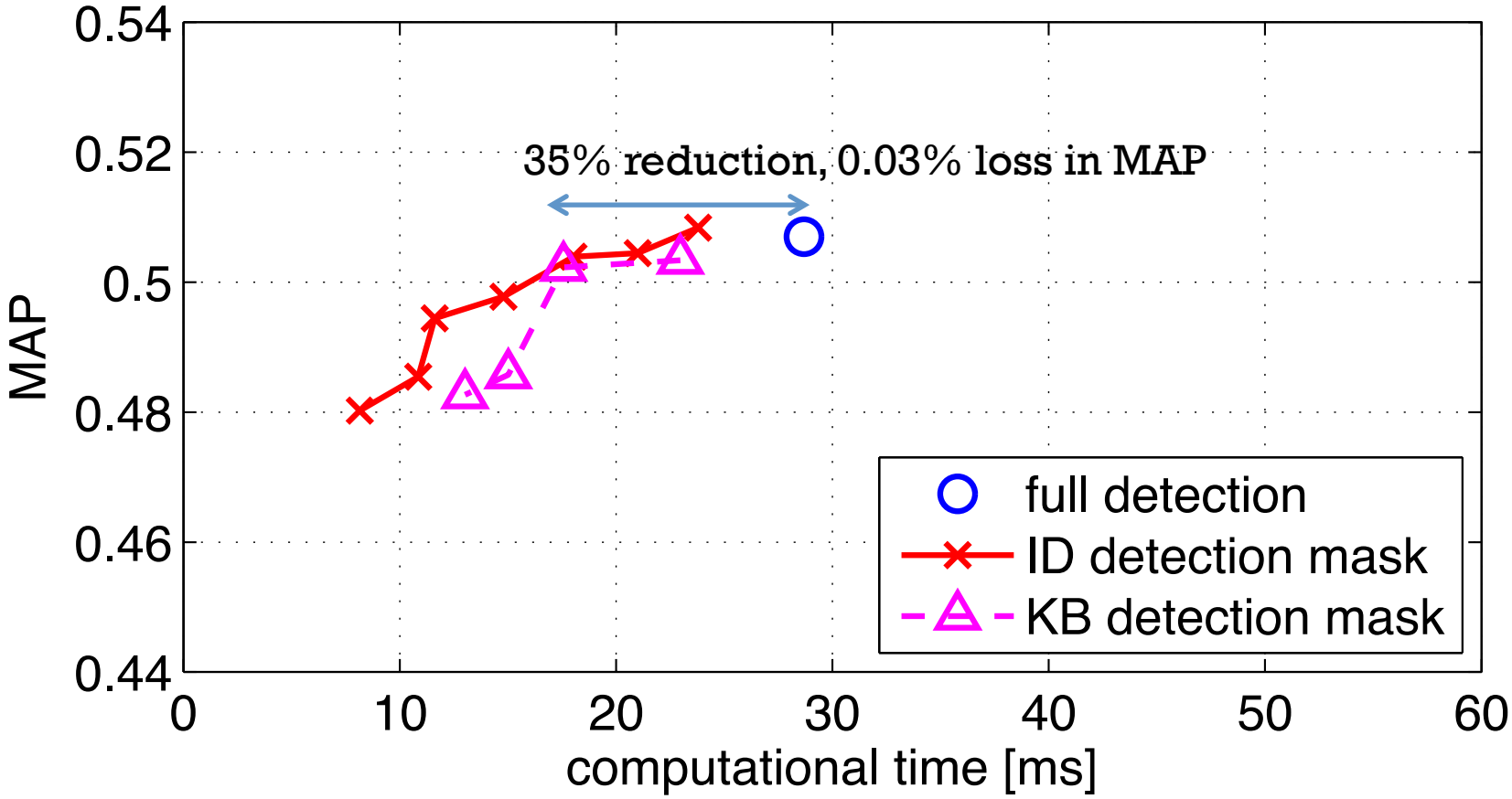
Comparison with baselines



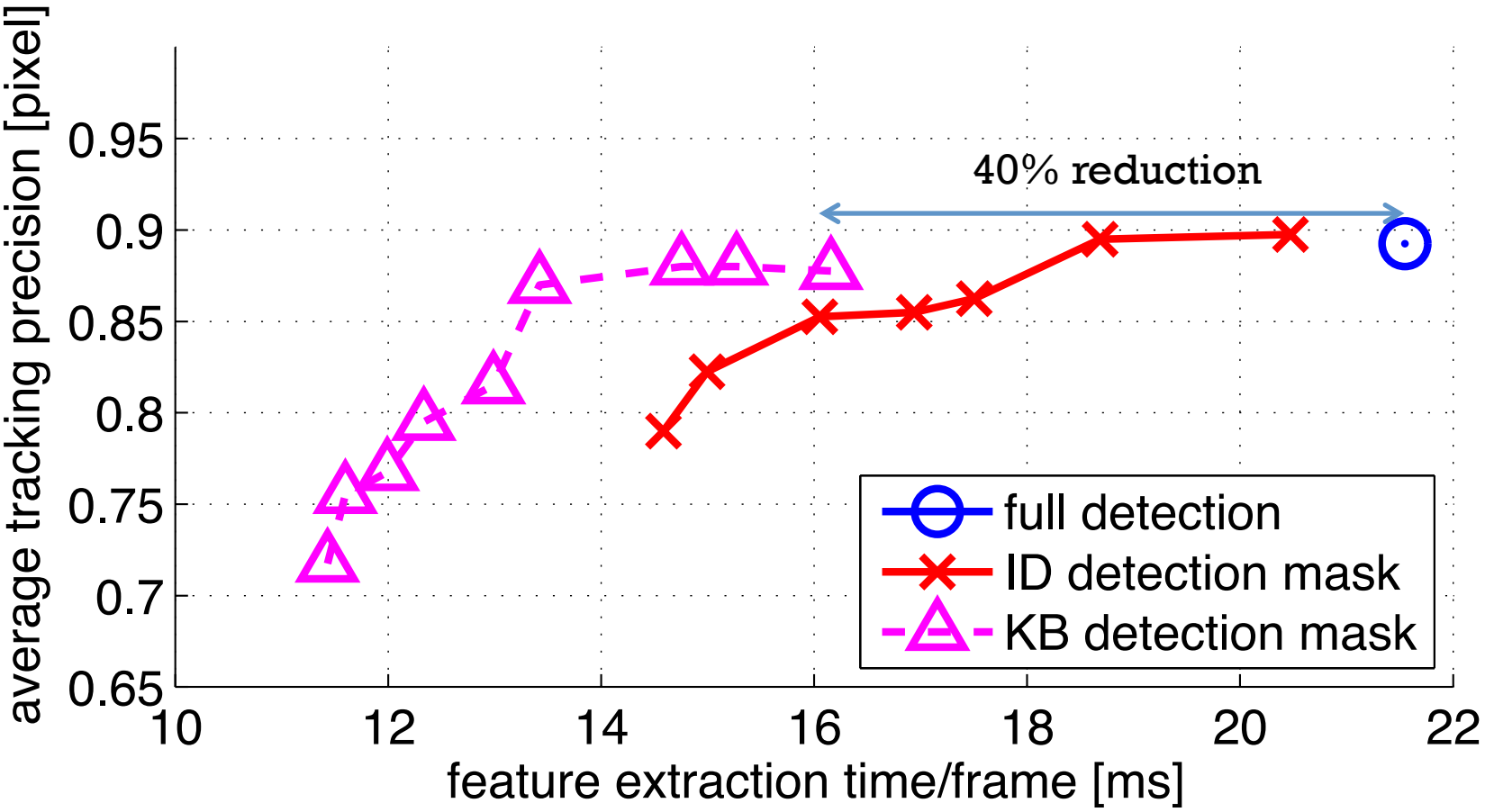
Results – Stanford MAR



Results – Rome Landmark Dataset



Results – Stanford Multiple Object



Conclusions

- Up **to 35/40 % reduction** in terms of computational complexity without significantly reducing visual task accuracy
- Higher frame rates / lower power consumption on low-power devices (smartphones, embedded systems)

Thank you!