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A robust object tracking framework based on a reliable point assignment algorithm

Key words: Local maximal wavelet coefficients; Reliable point assignment; Object tracking; Tracking learning detection (TLD); Kalman filter

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Motivation

- Visual tracking has been one of the hot research topics in computer vision in recent years. It has been widely used in traffic surveillance, anti-terrorism, etc.
- There are still challenges for visual tracking: illumination change, object occlusion, appearance deformation, image noise, etc.
- **The motivation** of this paper is to improve the performance of object tracking in illumination change, object occlusion, appearance deformation and real-time processing with an improved TLD framework.

Main idea

1. RPA (reliable point assignment) is proposed: The reliable points are located by searching the points that possess local maximal wavelet coefficients. Due to the fact that the wavelet coefficient denotes image variation, the reliable points are rich with discriminant information for tracking, which makes the points robust against image noise, illumination change, and change in target size.

2. To reduce the processing time and false detections, a Kalman filter is applied to the tracking and detection model, which can greatly reduce the search space of the detection model. By cutting down the search space, false detection results from the detector in TLD decrease because background interference is reduced.

Owing to RPA and the fusion of the Kalman filter, the learning step is improved. Consequently, the method proposed is faster and more robust against image noise, illumination change, and tracking target size than the original TLD.

Related works (I)

TLD

Promising performances

toward

Object occlusion

Scale change

Background clutter

The algorithm includes mainly three steps:
tracking, detection, and feedback learning

Tracking step:

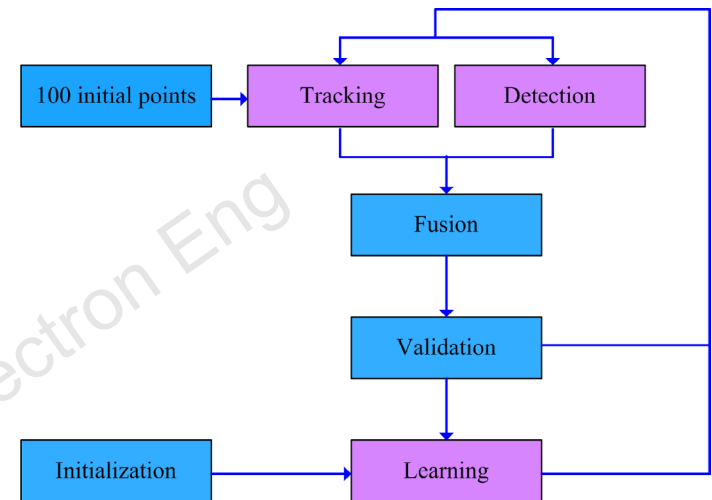
- Draw a bounding box, construct an equally spaced set of points
- Based on Median-Flow tracker

Detection step:

- Based on sliding sub-windows
- Sub-windows are tested by a cascade procedure.

Learning step:

- Generate positive (P) and negative (N) examples
- Produce stable outputs



Procedure for the TLD framework

Related works (II)



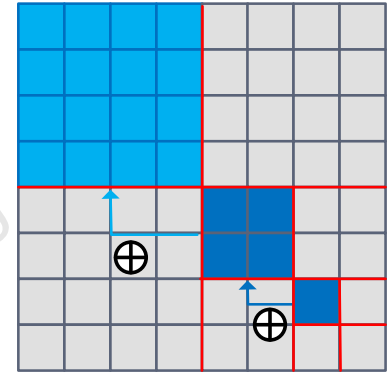
- ❑ In the tracking step, an **equally spaced set of points** (10-by-10) is constructed in the bounding box for tracking.
- ❑ **Disadvantage:** The position of the point may coincidentally locate on an image noise or an image area that **is sensitive to the illumination**

Proposed method (I)

■ How to overcome it?

A wavelet based robust point detection approach

- ✓ The wavelet transform is a multi-resolution representation that can be applied to study the signal at different scales by using the scaling functions and wavelet functions.
- ✓ Search the summation coefficients of each tile, the point in a tile that **corresponds to the local maximum** is defined as the ‘robust point’.



Summation of wavelet coefficients of a point at each scale



Robust points

How to overcome it?

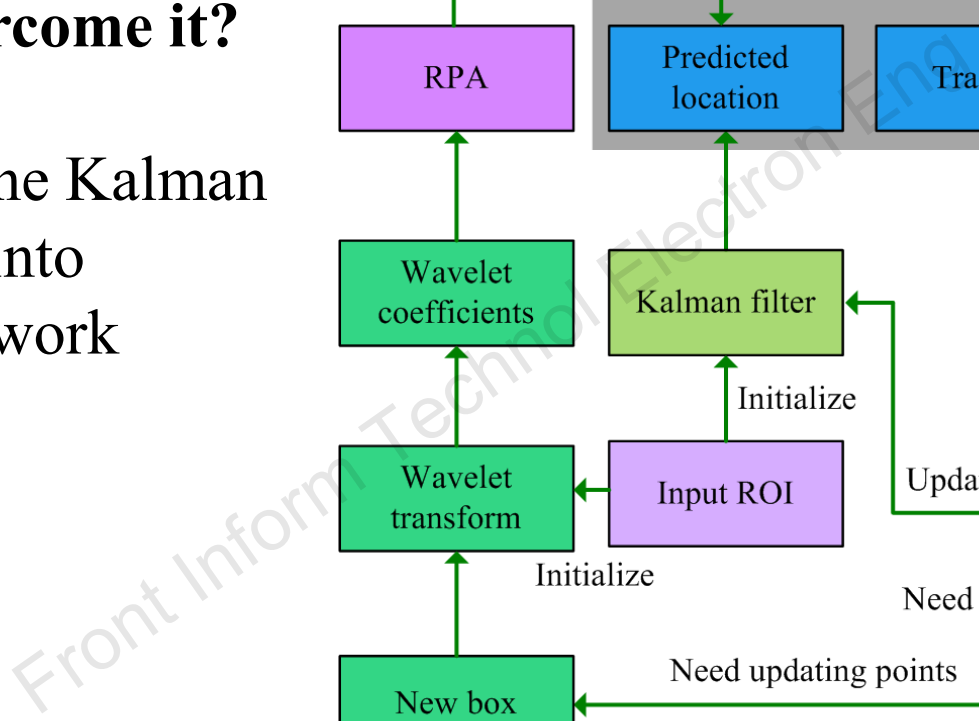
Integrate the Kalman filter into the wavelet network

```
graph TD; NewBox[New box] --> WaveletTransform[Wavelet transform]; WaveletTransform --> WaveletCoeff[Wavelet coefficients]; WaveletCoeff --> RPA[RPA]; RPA --> PredictedLocation[Predicted location]; InputROI[Input ROI] -- Initialize --> WaveletTransform; InputROI -- Initialize --> KalmanFilter[Kalman filter]; KalmanFilter -- Update --> PredictedLocation; KalmanFilter -- Need updating points --> NewBox;
```

The diagram illustrates the integration of a Kalman filter into a wavelet network for target tracking. The process flow is as follows:

- New box** (green box) feeds into the **Wavelet transform** (green box).
- The **Wavelet transform** outputs **Wavelet coefficients** (green box), which are then processed by the **RPA** (purple box) to produce the **Predicted location** (blue box).
- The **Predicted location** is compared with the **True location** (blue box) to calculate the **Tracking error** (blue box).
- The **Tracking error** is used to **Update** the **Kalman filter** (green box).
- The **Kalman filter** outputs the **Predicted location** and also provides **Need updating points** to the **New box**.
- The **Input ROI** (purple box) provides an **Initialize** signal to both the **Wavelet transform** and the **Kalman filter**.

Integration of the Kalman filter and RPA into the TLD framework



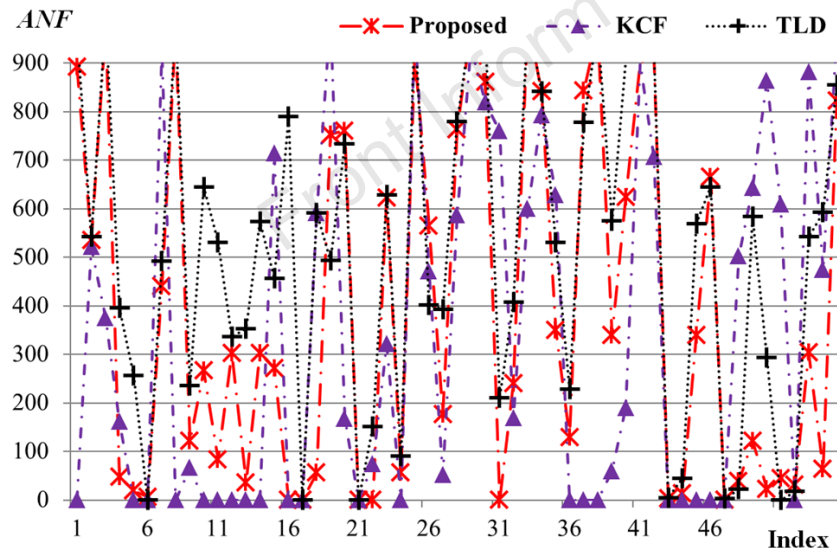
The proposed tracking framework

Major results

- Compared with KCF and TLD

An overall comparison of the proposed method, KCF, and TLD

Method	Response	ON	TP	P	R	F	FR	AOP	ANF
Proposed method	557.31	818.44	483.31	84.63%	58.97%	63.48%	22.94	41.84%	388.90
KCF	720.13	818.44	443.55	62.81%	62.72%	62.69%	46.95	37.34%	336.34
TLD	495.78	818.44	399.44	78.09%	46.94%	52.67%	11.19	37.58%	513.12



ANF for TLD, KCF, and the proposed method

Conclusions

- The proposed method is robust to image illumination change, image noise and object appearance deformation, leading to an improvement in the **tracking step**.
- To speed up the detection step and reduce the false detection, the Kalman filter is applied to be integrated with the TLD framework. RPA improves the tracking precision and the Kalman filter reduces the false **detection**.
- Consequently, the **learning step** is improved by the **tracking and detection step**, which feeds back to the detection step positively.
- As a result, compared with the TLD approach and the KCF approach, the new framework obtains better tracking precision, f-measure, and AOP.