A Probabilistic Shape Filter for Online Contour Tracking

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Abstract

- Online contour-based tracking is considered through the estimation perspective. We propose a recursive dynamic filtering solution to the tracking problem.
- The state of the target is described by a pose state which represents the ensemble movement and a shape state which represents the local deformations. The filtering procedure decouples the pose and shape estimation.
- To demonstrate improved performance, tracking experiments are conducted with recorded imagery and objective measures of quality.

Problem statement - Background

Consider the problem of faithful contour-based target tracking under imaging noise and approximate target/background models.

- Detection over individual frames of the image sequence fails to exploit the underlying natural coherence and consistency of the target.
- Batch processing techniques can successfully recover a solution that guarantees global coherence by processing the entire sequence at once. However, by requiring access to future frames, such methods fall outside the context of online, recursive tracking.
- Alternatively, the tracking problem can be conceived as an estimation problem given temporally correlated measurements. A Markovian assumption simplifies the problem to one of recursive estimation, for which one solution is given by recursive filters. In this formulation, the visual tracking problem is expressed as recursive filter design.

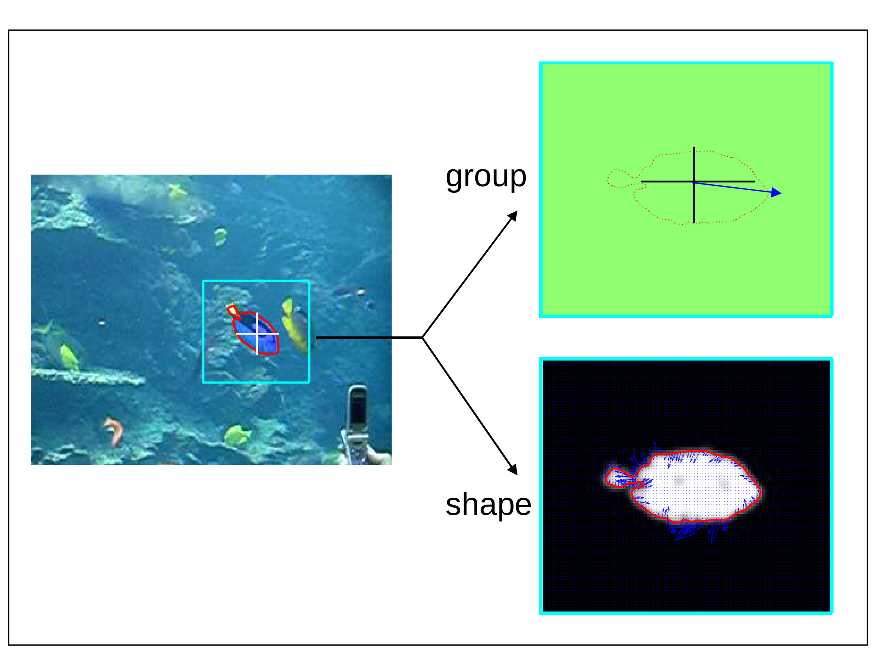
Contributions

The principal contributions of the paper include:

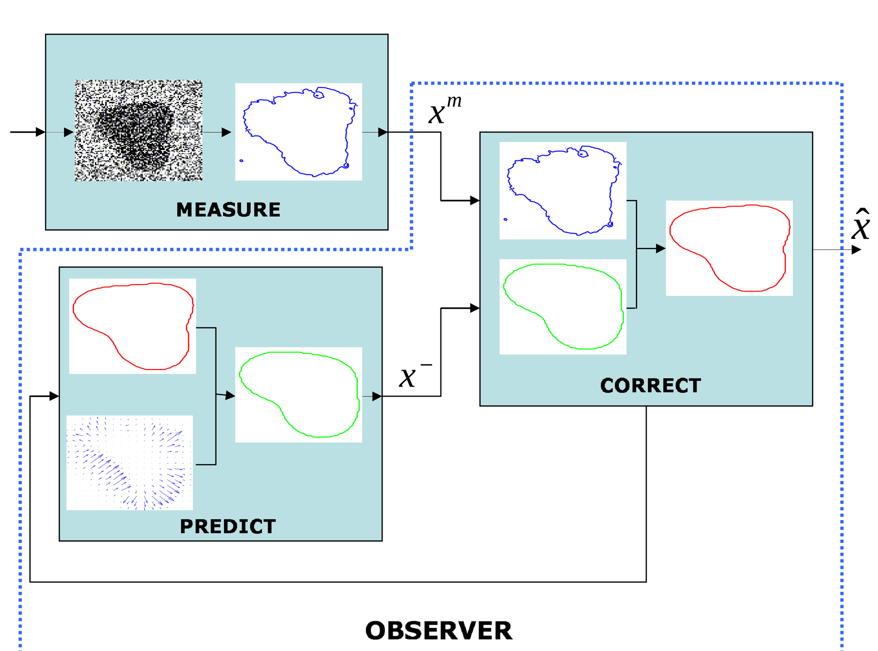
- the reformulation of the tracking problem as filter design on a dynamic target state
- the decoupling of the filtering on the group and shape components
- the incorporation of a second-order dynamical prediction model to handle non-rigid shape deformations
- the definition of a novel correction method suited to the shape space description
- the quantitative validation of the filter's performance

State description - Filter structure

The state-space representation is based on a *deformotion* decomposition. The structure of the recursive filter is proposed below. It reflects the fact that filtering will be performed on the output of a visual tracking strategy rather than on the raw visual sensor data:



(a) State representation



(b) Recursive filter structure

Components of the filter

- Prediction

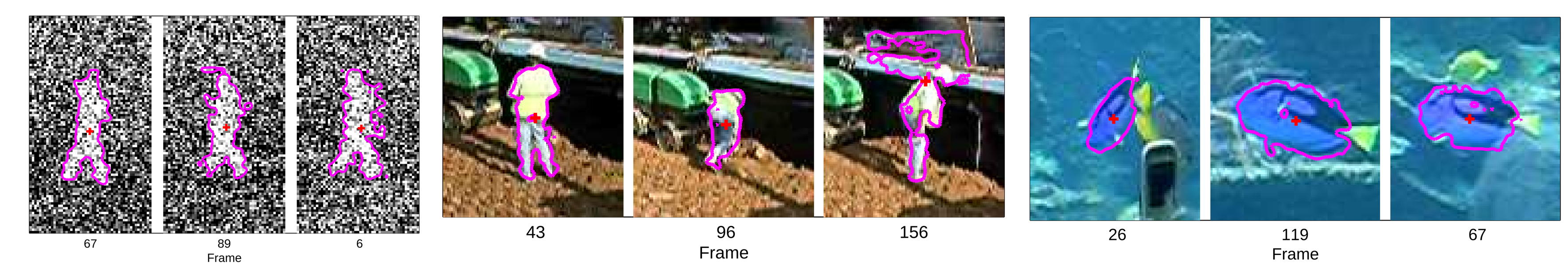
$$\dot{g} = \xi, \qquad \dot{\xi} = 0,$$
$$\dot{P} = \nabla P \cdot \Theta, \qquad \dot{\Theta} = 0.$$

- Measurement
  It involves the determination of the four sub-states (g, ξ, P, Θ). Application of a segmentation algorithm preceded by localization (or succeeded by registration) provide the group and shape components. The optical flow between two consecutive frames provides measurement for the shape velocity.
- Correction

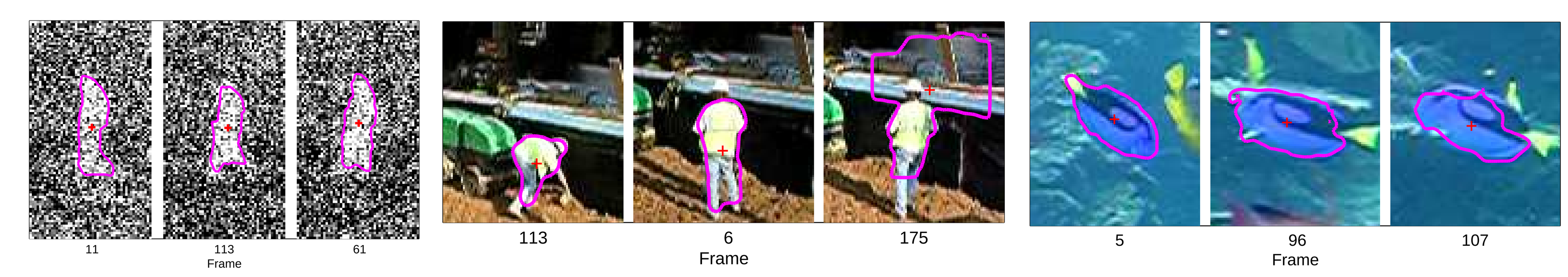
State Component	Correction Description
Group and group velocity (g, ξ)	Correction according to the update equations of the finite-dimensional filter adopted (Kalman, EKF or UKF).
Shape and shape velocity (P, Θ)	$\begin{cases} \widehat{P}^{+} = \left(\widehat{P}^{-}\right)^{1-K_{11}} \cdot \left(P_m\right)^{K_{11}} \\ \widehat{\Theta}^{+} = \widehat{\Theta}^{-} + K_{21} \cdot X_{err}(P_m, \widehat{P}^{-}) + K_{22} \cdot (\Theta_m - \widehat{\Theta}^{-}) \end{cases}$

Experiments and results

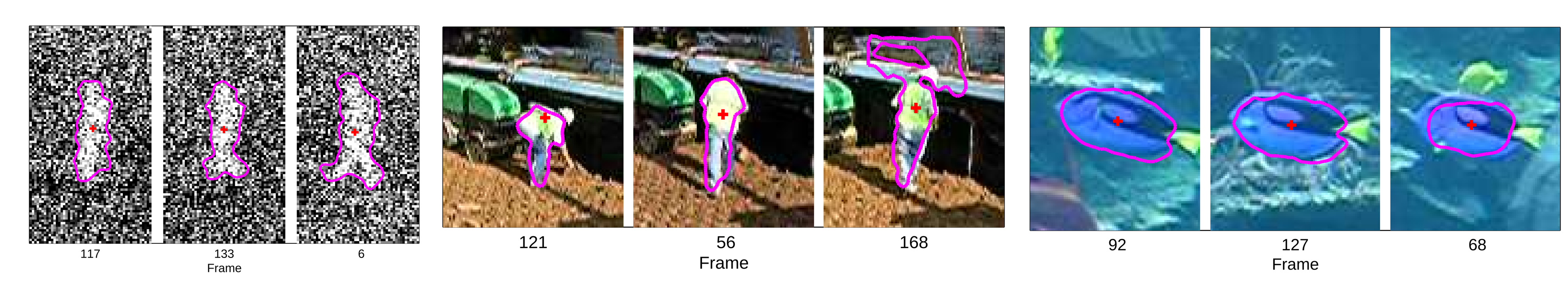
Experiments were conducted to demonstrate the ability of the proposed filter to enhance contour-based trackers and provide consistent tracking under perturbations. Comparison to other visual tracking techniques is also provided. Ground truth for the sequences consists of manual track point determination and manual segmentations. For the group variable, the L_2 error of the pose signal is computed. For the shape variable, frame-wise we compute the number of misclassified pixels and the Hausdorff and Sobolev distances.



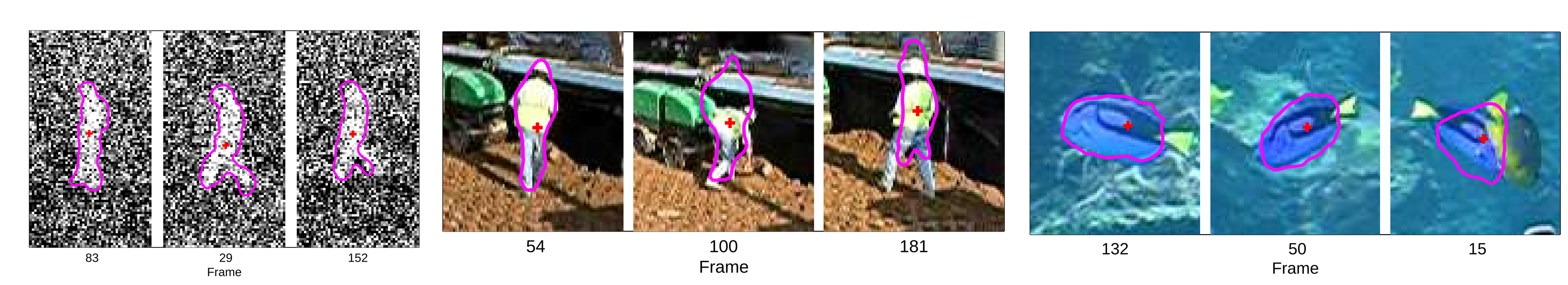
(a) Bayesian (b) Bayesian (c) Bayesian



(d) Active Contour (e) Active Contour (f) Active Contour

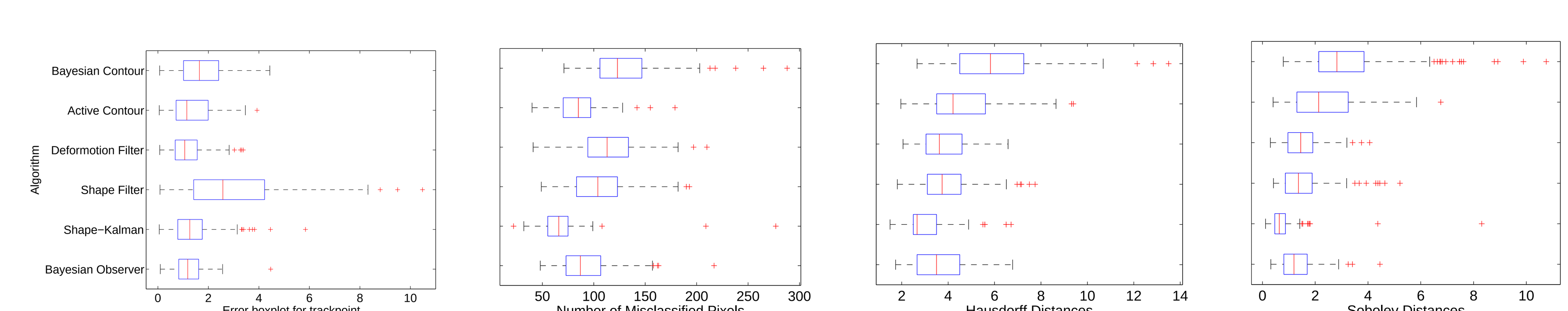


(g) Deformotion Filter (h) Deformotion Filter (i) Deformotion Filter



(j) Shape-constrained (k) Shape-constrained (l) Shape-constrained

(m) Filtered Bayesian (n) Filtered Bayesian (o) Filtered Bayesian



(p) Trackpoint L_2 error (q) NMP (r) Hausdorff error (s) Sobolev error

Conclusion

- We have presented the design of a recursive dynamic filter for the purpose of tracking consistently through imaging perturbations. Objective measures of quality demonstrate that the proposed filter achieves temporal consistency and is equal to or more effective than other tracking algorithms in an online, recursive estimation setting. It does not require any training and has low computational complexity.
- Future work will involve the derivation of an optimal gain strategy for the filtering based on known uncertainty levels associated to the state estimate, the prediction, and the measurement.

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