Noise Estimation and Adaptive Filtering During Visual Tracking

Ibrahima J. Ndiour and Patricio A. Vela
School of Electrical and Computer Engineering,
Georgia Institute of Technology, Atlanta, GA, 30332-0250

IEEE Celebrating 125 Years of Engineering the Future

Georgia Tech

Abstract

This work proposes a procedure to characterize segmentation-based visual tracking performance with respect to imaging noise. We devise a methodology to establish correspondence between a given contrast parameter (Bhattacharyya coefficient) and segmentation errors as measured through local shape metrics (Sobolev and Laplace metrics). The correspondence is used to adaptively filter temporally correlated segmentations.

Motivation

The need for noise models becomes essential when pursuing accurate segmentation-based tracking. Beyond segmentation optimization approaches and shape-constrained methods, filtering schemes constitute an important class of solutions for handling noise. This works aims at characterizing the nominal performance of segmentations algorithms in presence of imaging noise. In the context of recursive filtering, it is then possible to infer a corrective gain to attenuate the expected segmentation error arising from imaging noise.

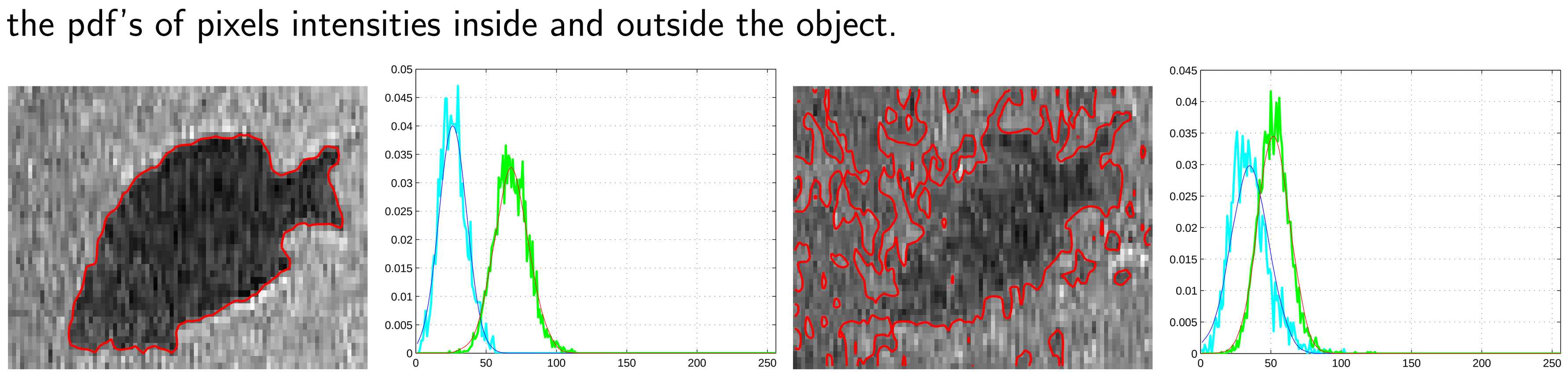
Contributions

The principal contributions of the work include:

- a methodology for utilizing a proven contrast parameter to derive expected segmentation errors that are geometrically relevant
- an empirical procedure for identifying the optimal filter gain given the measured contrast
- the use of the optimal gain for probabilistic shape filtering

Quantification of segmentation error through a contrast parameter

Local to a single connected object in an image, an algorithms ability to segment is directly related to the pdf's of pixels intensities inside and outside the object.



(a) (b) (c) (d)

Distance between pdf's - Distances between curves

- The Bhattacharyya coefficient between two distributions p and q is defined as

$$\beta(p,q) = \int \sqrt{P_{in}(x) \cdot P_{out}(x)}\, dx.$$

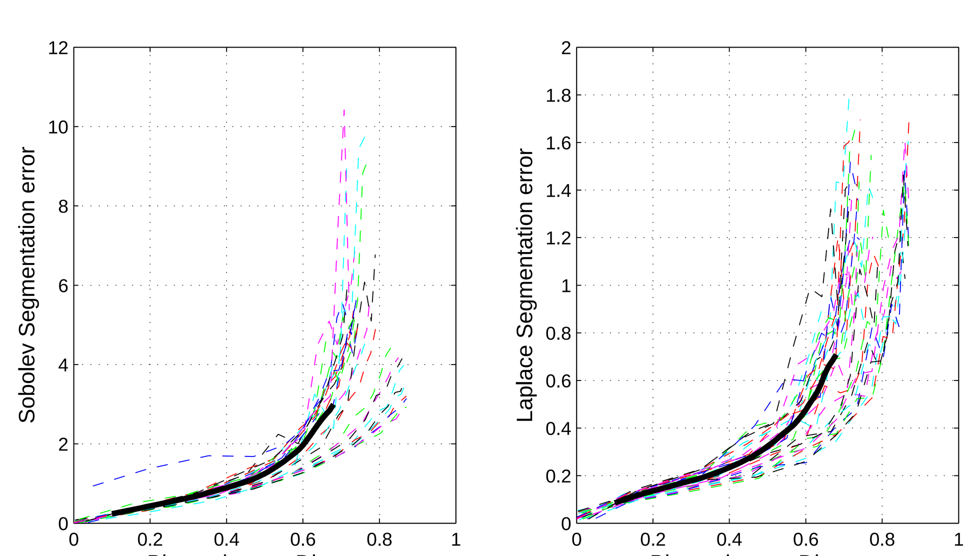
- The Sobolev distance provides a local measure of curve mismatch:

$$S(\Psi_1, \Psi_2) = \alpha \cdot \|\Psi_1, \Psi_2\|^2 + (1-\alpha) \cdot \|\nabla\Psi_1, \nabla\Psi_2\|^2.$$

- The Laplace distance computes the length of non-intersecting trajectories between two curves.

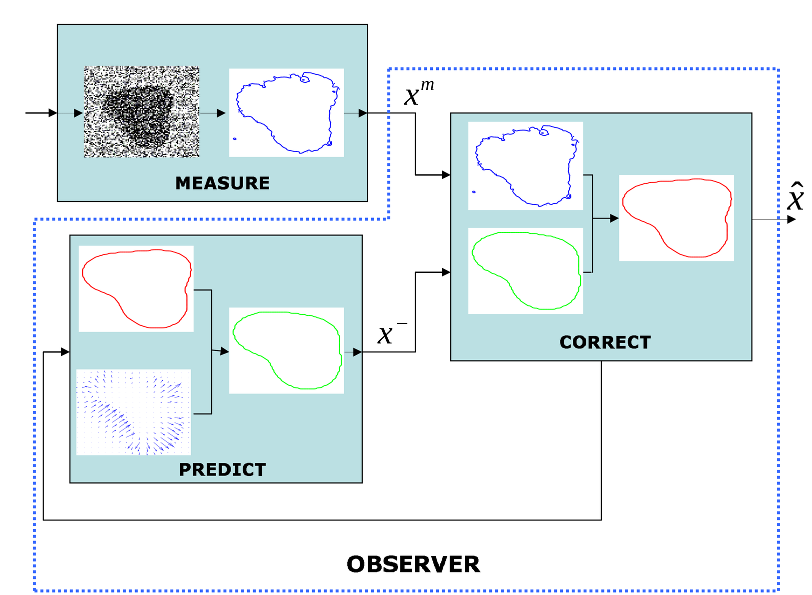
Segmentation error vs contrast parameter

- Begin with a collection of shapes that forms the ground truth.
- Select the interior and exterior distributions to be Gaussian, $P_{in,out} = \mathcal{N}(\cdot; \mu_{in,out}; \sigma_{in,out})$.
- For a collection of values $\sigma_{noise} > 0$, add Gaussian noise $\mathcal{N}(\cdot; 0; \sigma_{noise})$ to the images to generate a set of corrupted images.
- Perform segmentation to yield curves partitioning the images
- Determine the contrast coefficient using the Bhattacharyya coefficient in conjunction with the ground truth.
- Compute the curve estimation error using the Sobolev and Laplace metrics.
- Derive the expected segmentation error as a function of the contrast parameter β.

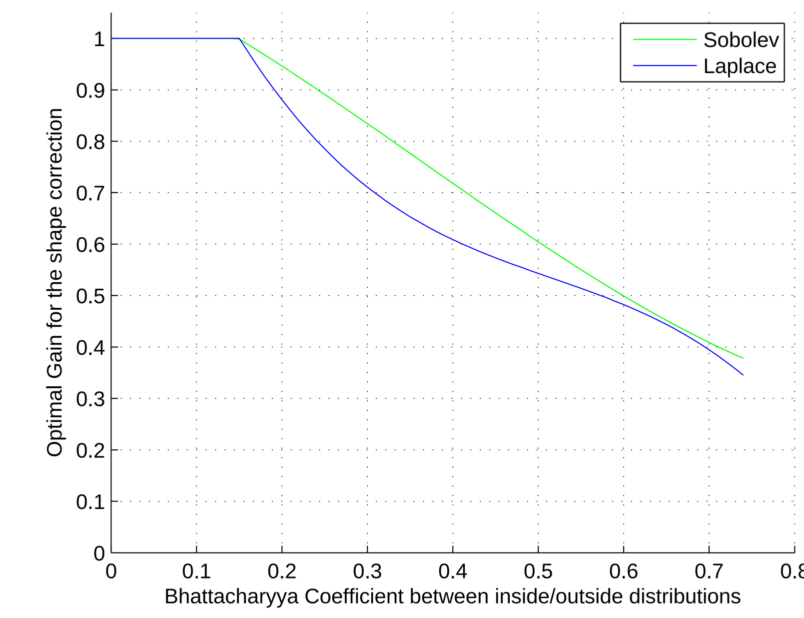


Application to adaptive probabilistic filtering

- Probabilistic shape filter
  1. Prediction: $\begin{cases} \dot{g} = \xi, & \dot{\xi} = 0, \\ \dot{P} = \nabla P \cdot \Theta, & \dot{\Theta} = 0. \end{cases}$
  2. Measurement: by application of a segmentation algorithm.
  3. Correction: $\begin{cases} \widehat{P}^+ = \left(\widehat{P}^-\right)^{1-K_{11}} \cdot (P_m)^{K_{11}} \\ \widehat{\Theta}^+ = \widehat{\Theta}^- + K_{21} \cdot X_{err}(P_m, \widehat{P}^-) + K_{22} \cdot (\Theta_m - \widehat{\Theta}^-). \end{cases}$
- Determination of the optimal gain



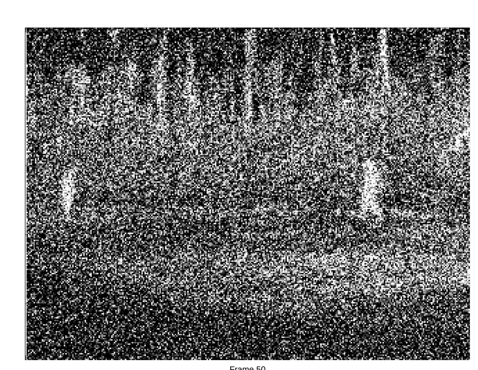
(e) Recursive filter structure



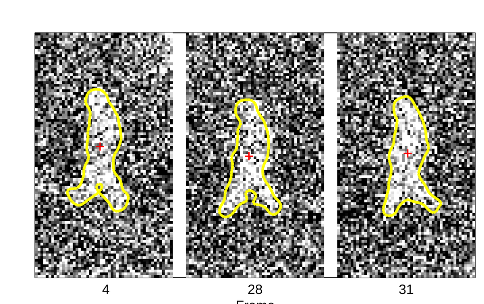
(f) Optimal gain vs. Bhattacharyya coefficient

Experiments and results

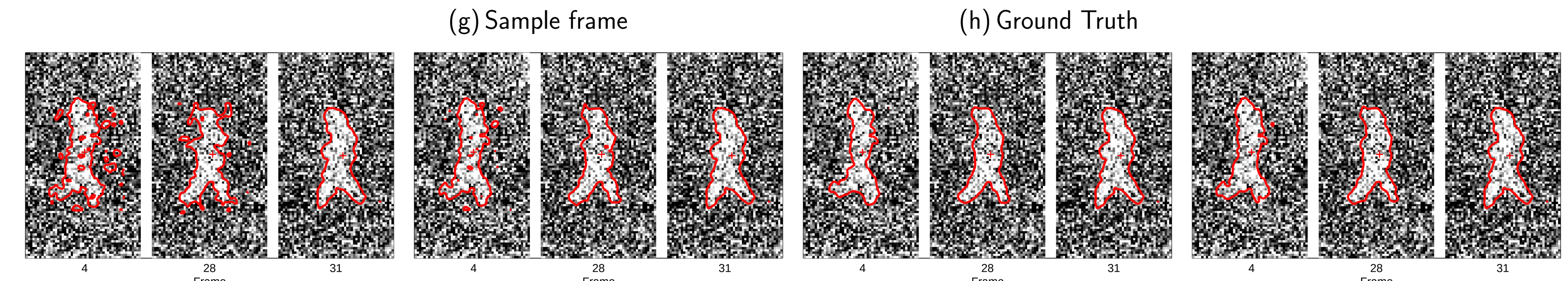
Experiments were conducted to demonstrate the ability of the proposed method to adapt the corrective gain of the probabilistic shape filter. Comparison to the fixed-gain filtering strategy is provided. Performance evaluation used the Laplace metric in conjunction with hand-segmentations (ground truth) of the sequences.



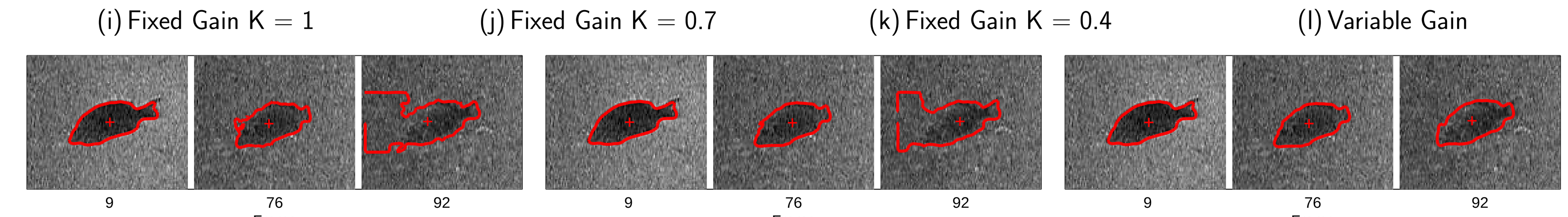
(g) Sample frame



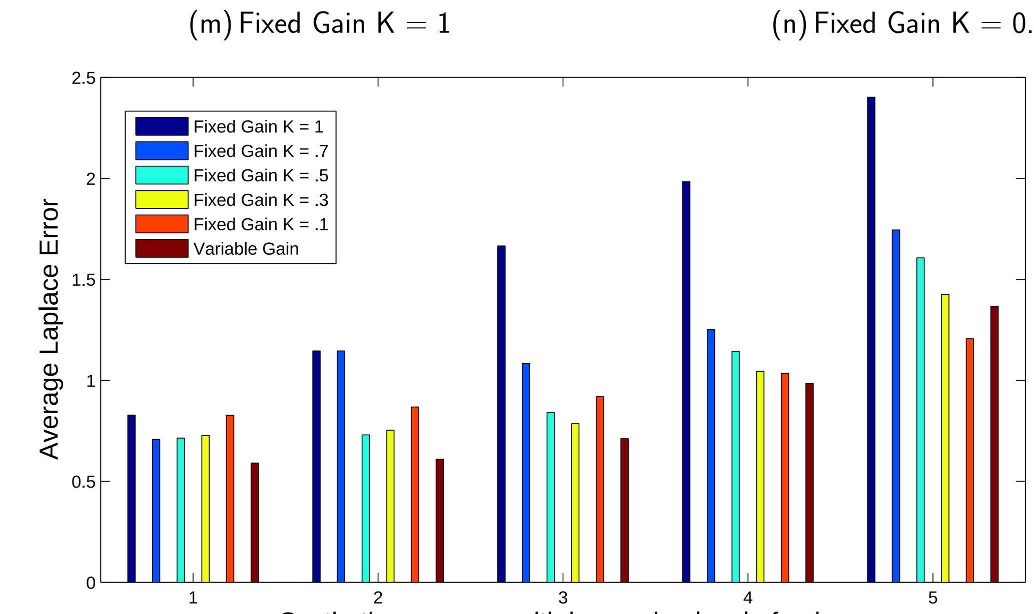
(h) Ground Truth



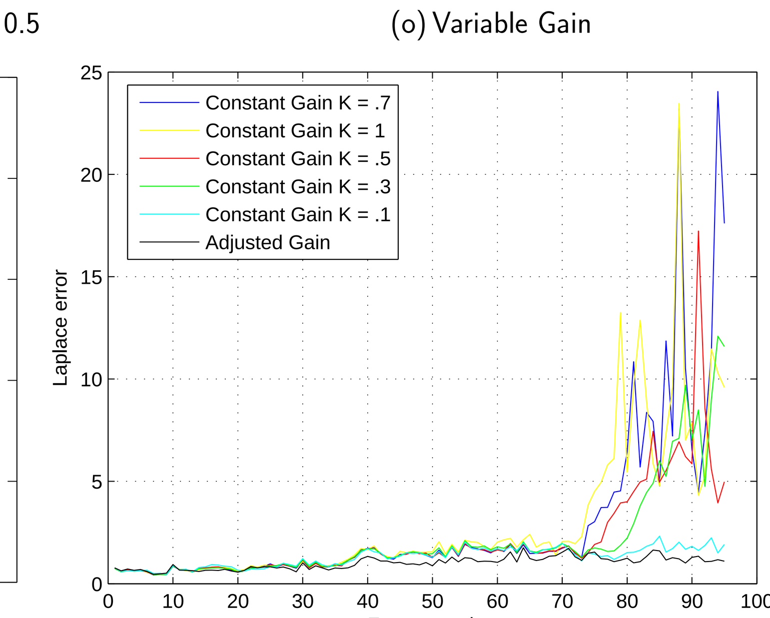
(i) Fixed Gain K = 1 (j) Fixed Gain K = 0.7 (k) Fixed Gain K = 0.4 (l) Variable Gain



(m) Fixed Gain K = 1 (n) Fixed Gain K = 0.5 (o) Variable Gain



(p) Average Laplace error (IR sequence)



(q) Laplace error vs. time (aquarium sequence)

Conclusion

This paper presented a procedure to characterize the behavior of segmentation algorithms in the presence of noise. The Bhattacharyya coefficient between target and background distributions proves to be an adequate contrast parameter for assessing segmentation errors. Future work seeks to extend the analysis to color images.