

Covariance Tracker

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I. DESCRIPTION

This video presents several object tracking results of a simple and elegant algorithm that can detect the non-rigid objects using a covariance based object description and an update mechanism based on means on Riemannian manifolds.

We represent an object window as the covariance matrix of features as illustrated in Fig. 1, therefore we manage to capture the spatial and statistical properties as well as their correlation within the same representation. The covariance matrix enables efficient fusion of different types of features and modalities, and its dimensionality is small. We incorporated a model update algorithm using the elements of Riemannian geometry. The update mechanism effectively adapts to the undergoing object deformations and appearance changes. The covariance tracking method does not make any assumption on the measurement noise and the motion of the tracked objects, and provides the global optimal solution. We show in our technical paper [1] that it is capable of accurately detecting the non-rigid, moving objects in non-stationary camera sequences while achieving a promising detection rate of 97.4 percent.

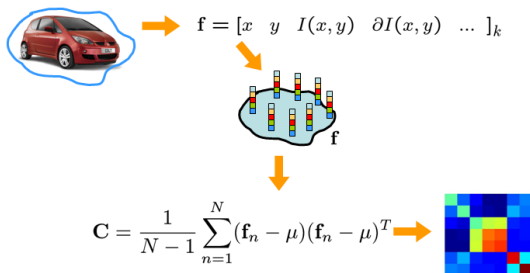


Fig. 1

COVARIANCE DESCRIPTOR

Fig. 2 shows a flow diagram of the covariance tracker. At each frame, we construct a feature image. For a given object region, we compute the covariance matrix of the features as the model of the object. In the current frame, we find the region that has the minimum covariance distance from the model and assign it as the estimated location. To adapt to variations, we keep a set of previous covariance matrices and extract a mean on the manifold.

The provided video shows several real-life tracking results for moving camera scenarios. This examples include such cases as the motion of the object is very fast, the size of the object is very small, the object shaoe undergoes severe deformations, and the image noise is extremely high. In addition to the side by side comparison with a mean-shift

based tracker, we assessed the performance using 15 sequences totaling more than 3000 frames. These include moving and stationary camera recordings, infrared sequences, etc., and some of the results are listed in Table I.

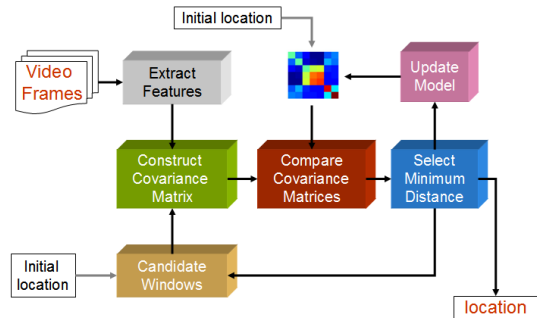


Fig. 2

FLOW DIAGRAM OF THE COVARIANCE TRACKER

The algorithm runs at ~ 150 msec/frame when we apply a sampling based hierarchical search.

TABLE I
TRACKING PERFORMANCE SCORES

| | miss/total | detection [†] | trials [‡] |
|------------------------------|------------|------------------------|---------------------|
| Pool Player ¹ | 8/92 | 91.4 | 0.0356 |
| Running Dog ¹ | 9/125 | 92.8 | 0.0284 |
| Subway ¹ | 4/173 | 97.6 | 0.0091 |
| Jogging ¹ | 20/824 | 97.7 | 0.0096 |
| Street-color ¹ | 16/180 | 91.1 | 0.0351 |
| Street-infrared ¹ | 61/180 | 66.2 | 1.6376 |
| Street-joint ¹ | 8/180 | 95.6 | 0.0175 |
| Race ² | 2/692 | 99.7 | 0.0015 |
| Crowd ³ | 7/522 | 99.1 | 0.0034 |

Percentages of correct estimation rates[†], ratio of the number of trials to get a correct estimate to the total number of total locations[‡]. Video size 352×288^1 , 352×240^2 , 440×360^3 .

II. ACKNOWLEDGEMENTS

We thank the following people for their valuable comments and acquisition of the input data sequences:

- Peter Meer, Rutgers University, USA
- Kent Wittenburg, MERL, USA
- Jay Thornton, MERL, USA
- Keisuke Kojima, MERL, USA
- Ryo Kodama, MERL, USA

REFERENCES

- [1] F. Porikli, O. Tuzel and P. Meer, "Covariance Tracking using Model Update Based on Means on Riemannian Manifolds," *Computer Vision and Pattern Recognition, New York City*, 2006.