Moving Object Detection in UAV-Video Using Flux Tensors

Kannappan Palaniappan & Ilker Ersoy
Dept of Comp. Science
University of Missouri
Columbia, MO 65211, USA

Adel Hafiane
ENSI de Bourges
10 boulevard Lahitolle
18020 Bourges Cedex, France

Guna Seetharaman
Dept. of Electrical & Computer Engineering
Syracuse University
Syracuse, NY, USA

Persistent moving object detection and tracking for surveillance applications using UAV platforms are challenging processes due to platform motion and jitter, platform motion induced parallax arising from structures in the scene including buildings, variations in illumination (such as moving cast shadows or cloud movements), clutter, noise, and occlusions. Particularly in outdoor settings, these variations can cause false detections, missed objects, shape deformations, false merges, etc. In this paper we describe a system to analyze global platform motion, and detect moving objects. The approach to video registration using feature matching has been described in earlier work.

In order to reliably detect only the moving structures in UAV-video, we propose using the recently developed *flux tensor* operator, which captures the temporal variations of the optical flow field within the local 3D spatiotemporal volume. Unlike the traditional 3D structure tensor, the flux tensor detects only the moving structures, and is less sensitive to illumination related problems compared to classical background subtraction methods such as mixture of Gaussians and results in more spatially coherent motion segmentation. It is also more efficient in comparison to the 3D grayscale structure tensor since motion information is more directly incorporated in the flux calculation which is less expensive than computing the eigenvalue decompositions at each pixel as with the 3D grayscale structure tensor.

The flux tensor is defined as:

$$J_F = \begin{bmatrix} \int_\Omega \left\{\frac{\partial^2 I}{\partial x \partial t}\right\}^2 dy & \int_\Omega \frac{\partial^2 I}{\partial x \partial t}\frac{\partial^2 I}{\partial y \partial t} dy & \int_\Omega \frac{\partial^2 I}{\partial x \partial t}\frac{\partial^2 I}{\partial t^2} dy \\ \int_\Omega \frac{\partial^2 I}{\partial y \partial t}\frac{\partial^2 I}{\partial x \partial t} dy & \int_\Omega \left\{\frac{\partial^2 I}{\partial y \partial t}\right\}^2 dy & \int_\Omega \frac{\partial^2 I}{\partial y \partial t}\frac{\partial^2 I}{\partial t^2} dy \\ \int_\Omega \frac{\partial^2 I}{\partial t^2}\frac{\partial^2 I}{\partial x \partial t} dy & \int_\Omega \frac{\partial^2 I}{\partial t^2}\frac{\partial^2 I}{\partial y \partial t} dy & \int_\Omega \left\{\frac{\partial^2 I}{\partial t^2}\right\}^2 dy \end{bmatrix}$$

Where I(x,y,t) represents the frames of video and partial derivates are with respect to spatial and temporal components of the field. The trace of the flux tensor matrix is used to determine the likelihood of moving objects in the scene. A sample results is shown below:

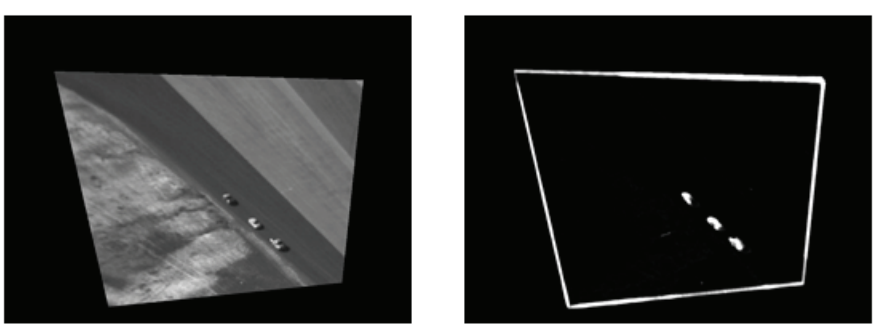

Figure 1: A sample frame and its flux tensor response for (5,5,5,5) filter set.

Figure 2 – Some of the sequences used to test our system: Hollywood, Motorcycle, Model City, Egtest01, Egtest02, Egtest03, Egtest04, Egtest05, Red Team, MU1, MU2, and MU-UAV.

Sequence Title	**Start Frame**	**End Frame**	**#of Frames**	**Successes**	**Failures**	**%**
Hollywood	150	450	301	264	37	87.7
Motorcycle	701	1200	500	360	140	72
Model City	600	800	201	197	4	98
Red Team	0	270	271	245	26	90.4

Table 1 – Success rate in tracking moving objects per video sequence.

References

A. Hafiane, K. Palaniappan, G. Seetharaman, "UAV-Video registration using block-based features", *IEEE Int. Geoscience and Remote Sensing Symposium*, Boston, MA, July 6-11, 2008, Online.

F. Bunyak, K. Palaniappan, S. K. Nath, G. Seetharaman, "Flux tensor constrained geodesic active contours with sensor fusion for persistent object tracking", *Journal of Multimedia,* Vol. 2, No. 4, Aug, 2007, pp. 20-33.