

# Feature-Based Efficient Moving Object Detection for Low-Altitude Aerial Platforms

K. Berker Logoglu<sup>1</sup>, Hazal Lezki<sup>1</sup>, M. Kerim Yucel<sup>1,2</sup>, Ahu Ozturk<sup>1</sup>, Alper Kucukkomurler<sup>1</sup>, Batuhan Karagoz<sup>1</sup>, Aykut Erdem<sup>2</sup>, and Erkut Erdem<sup>2</sup>

<sup>1</sup>STM Defense Technologies and Trade Inc., Ankara, Turkey.

<sup>2</sup>Computer Vision Lab, Department of Computer Engineering, Hacettepe University, Ankara, Turkey.

<sup>1</sup>{*blogoglu,hlezki,myucel,iaozturk, alper.kucukkomurler, batuhan.karagoz*}@stm.com.tr

<sup>2</sup>{*aykut,erkut*}cs.hacettepe.edu.tr

## Abstract

*Moving Object Detection is one of the integral tasks for aerial reconnaissance and surveillance applications. Despite the problem's rising potential due to increasing availability of unmanned aerial vehicles, moving object detection suffers from a lack of widely-accepted, correctly labelled dataset that would facilitate a robust evaluation of the techniques published by the community. Towards this end, we compile a new dataset by manually annotating several sequences from VIVID and UAV123 datasets for moving object detection. We also propose a feature-based, efficient pipeline that is optimized for near real-time performance on GPU-based embedded SoMs (system on module). We evaluate our pipeline on this extended dataset for low altitude moving object detection. Ground-truth annotations are made publicly available to the community to foster further research in moving object detection field.*

## 1. Introduction

In line with the recent trend of Unmanned Aerial Vehicle (UAV) usage in civilian and military sectors, miniature UAVs became more and more affordable and thus accessible for everyone. In addition to its vast military deployment in various armed forces in the world, civilian applications of UAVs also emerged swiftly; industrial inspection, agriculture, mapping, transport, cinematography and numerous indoor applications are examples for UAV usage in various fields<sup>1</sup>.

The primary issue of UAV-based computer vision (CV)

applications is the platform itself; it is not stable, it tends to have sudden movements, it is exposed to weather conditions, it generates non-homogeneous data (scale, angle, rotation, depth, etc.) and most importantly, it is inherently limited in computational resources. All these difficulties and constraints further the complexity of conventional vision problems, such as object tracking, object detection, object classification and prominently, moving object detection.

Moving object detection is a well-studied problem in controlled environments where ego-motion is not present [31]. Introduction of unconstrained ego-motion, however, transforms moving object detection into a much harder problem. Ego-motion estimation and compensation, which exploits image alignment techniques, is performed to address moving object detection in such scenarios [1]. In Wide Area Motion Imagery (WAMI), these techniques could suffice due to comparably low effect of motion parallax [25]. However, for low-altitude UAV scenarios, motion parallax has a far more detrimental effect [32].

Our contributions are primarily as follows: First, we compile a dataset comprised of sequences from VIVID [6] and UAV123 [18] datasets. We carefully pick sequences with various scenarios; motion parallax, altitude variation, viewpoint variation, presence of multiple objects, varying object sizes and speeds are considered. We hand-annotate the sequences specifically for moving object detection. Second, we present our analysis on this dataset using an efficient, feature-based pipeline which we optimize for near real-time performance on embedded GPU-based SoMs. The annotations are also made publicly available on <https://github.com/LAMODDATASET/LAMOD>.

The remainder of this paper is organized as follows: related work is reviewed in Section 2. The proposed moving

<sup>1</sup><http://www.auvsi.org/auvsiresources/economicreport>

object detection framework is explained in-detail in Section 3. Experimental results as well as details on our extended dataset are given in Section 4. Our conclusions and future works are outlined in Section 5.

## 2. Related Work

Moving object detection task has been an active area of research within the CV community for a couple of decades. Earlier studies suggest simple background subtraction to segment foreground (object) and background in videos [8]. Among other techniques, temporal differencing [19] has been a prominent one. Temporal differencing, however, does not work properly in slow motion, when moving objects are small compared to the overall visual and if the objects have smooth texture. Statistical methods, where background is adaptively learned, successfully addresses these issues. Such techniques include the use of mixture of Gaussians, Eigen backgrounds [13], stereo [9] and motion-layer [4] approaches. For a general overview of the literature, readers are referred to [24] and [13].

The majority of above-mentioned algorithms, however, are not devised to address the presence of ego-motion, therefore fail to successfully operate in such cases. Towards this end, image alignment based algorithms have emerged. The principle idea is to align the images before performing frame differencing; affine or perspective transformation matrix is used to warp the images. Assuming accurate alignment, frame differencing ideally provides the moving regions in the sequence with the help of morphological operations and connected component analysis [12]. Such techniques can be unified as “feature-based” techniques, where various feature keypoints/descriptors can be used to match images for warping. Another way of addressing the pertinent problem is “motion-based” techniques, where motion-layers [4] and optical flow are used to detect moving regions. Stereo vision [26], flow vector segmentation [20] based on orientation have found use in the field as well. Such algorithms can be considered as good fit for WAMI applications where high altitude bird-eye view images are concerned. When planar surface assumption does not hold in the scene (i.e. low altitude UAV footage), false positives due to motion parallax become more severe.

Parallax handling is inherently a costly operation; it requires camera calibration and compliance to various constraints. In [14], epipolar constraint along with a “plane-parallax” based structure consistency is implemented to distinguish moving regions from parallax-induced false positives. Another work reported in [21] compare epipolar line directions with optical flow orientation to accurately identify moving objects. Work reported in [15] handles parallax via enforcing epipolar and flow-bound constraints with the help of camera pose estimation via Parallel Tracking and Mapping (PTAM). The authors of [7] handle parallax via

a parametrized epipolar constraint without the need of motion registration. In [29], a “three-view distance constraint” along with epipolar constraint is used to facilitate moving object detection.

Handling parallax does not necessarily require compliance to epipolar constraints, as shown in various studies. [20] and [5] use optical flow and an artificial flow to infer moving regions while handling parallax implicitly. Another study presented in [23] follows an image warping based scheme where moving regions are clustered into moving objects and parallax is handled via object size priors and Kalman-filter based persistency check. There are studies where other priors, such as classifiers for moving object to be detected, are used but this is out of our work’s scope as we do not concentrate on specific classes of objects [22] [28].

Due to operational requirements, moving object detection generally needs to work in real-time. Performing the resource-heavy calculations on a dedicated server is inherently limited by the quality of the data link between the server and the platform. The alternative is to perform the calculations on the UAV itself using a dedicated embedded resource, which is non-trivial from an engineering perspective. There have been several attempts on speeding up moving object detection such as GPU implementations reported in [30] and [3]. For mobility, FPGA has also been used extensively [16], [27]. To the best of our knowledge, however, there has not been an attempt on moving object detection with parallax handling using on-platform embedded resources with near real-time performance.

## 3. Our Approach

The pipeline of our approach is shown in Figure 1. We propose a feature-based, efficient pipeline mostly implemented on GPU. We have divided our approach to four steps for ease of understanding: pre-processing, ego-motion compensation, moving object detection and parallax-filtering.

### 3.1. Pre-processing

In the pre-processing step, the input frames are down-sampled for faster processing. The downsampled frames are pushed to a frame-buffer whose size varies depending on number of frame difference to be used. The number of frame difference depends on height and the minimum desired motion to be detected; as the frame difference increases, smaller motion can be detected. At each acquired frame, keypoints and corresponding descriptors (for our case; SURF [2]) are calculated. Lastly, the descriptors are matched to previous frame to calculate homography and fundamental matrix. An important step is the filtering of the keypoints and the corresponding descriptors based on the (candidate) moving objects found in the previous frame. Without filtering, these unwanted keypoints

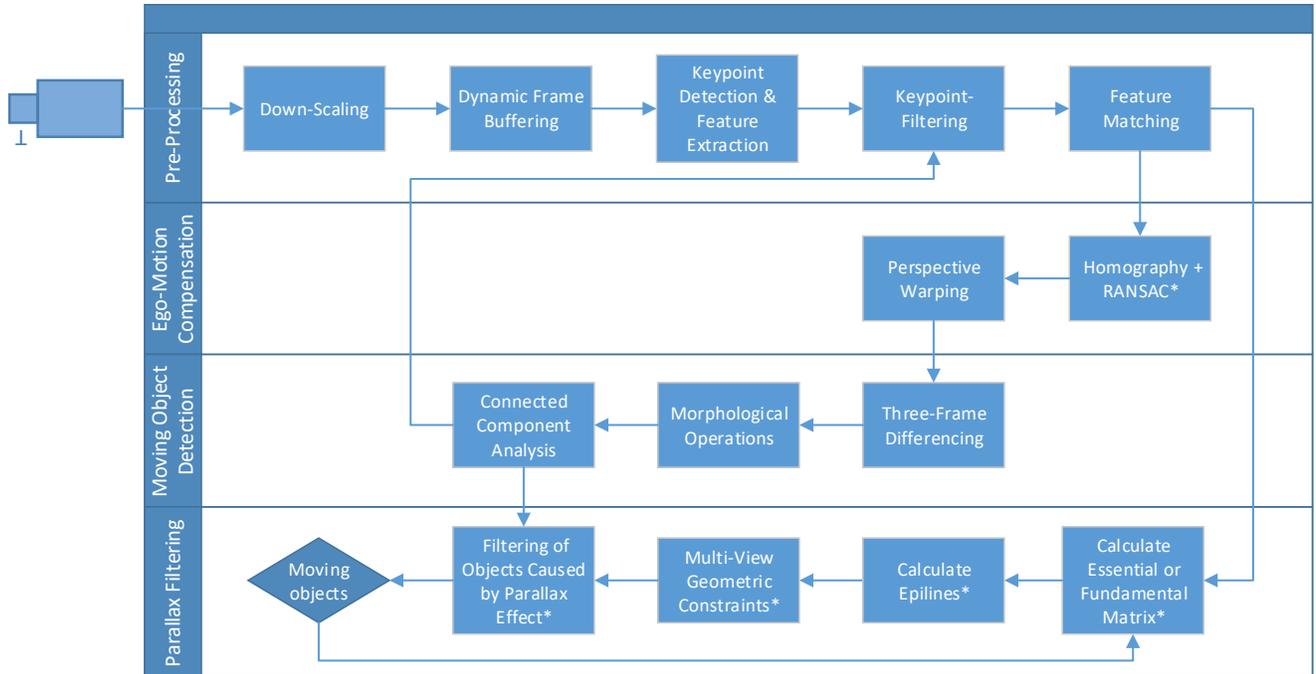


Figure 1. Our proposed moving object detection pipeline. The steps with \* are run on CPU whereas the rest of the pipeline runs on GPU.

have a detrimental effect on homography calculation and results in inferior perspective warping. One such example is shown in Figure 2, where the bottom left image shows the result of inferior perspective warping and the bottom right image shows accurate warping.



Figure 2. Effect of filtering keypoints on moving objects (from previous detection) before calculating the current homography matrix. Top to bottom; extracted keypoints, thresholded two frame difference and final results are given. Left and right column images show the results without and with the proposed keypoint filtering loop, respectively.

### 3.2. Ego-motion compensation

Based on the descriptor matching, firstly homography matrix is calculated. RANSAC is used to reject outliers in the process. Secondly, using the calculated homography matrix, previous frame is warped onto the current one using perspective transformation.

### 3.3. Moving object detection

Since the camera motion is compensated in the previous step, basically two-frame differencing gives the moving pixels. In our approach, we are using three-frame differencing method which is an improved version of two-frame differencing in the sense that it removes noise more effectively. We basically apply logical AND operation for two adjacent two-frame difference results. After obtaining the moving pixels, various morphological operations are applied to filter noise and unite points belonging to same object. Finally, connected component analysis is applied to extract individual object bounding boxes.

### 3.4. Parallax removal with geometric constraints

The final step is the removal of objects that are falsely detected as moving due to parallax effect. At this step, instead of pixel wise decisions, we make object wise decisions for efficiency. We use the keypoints already extracted on each frame thus we only make decisions for the candidate objects on which keypoints exists. We basically apply two geometric constraints that is proposed in the literature

[14, 15]; epipolar constraint and flow-vector bound (FVB) constraint.

### 3.4.1 Epipolar Constraint

Let  $I_{t1}$  and  $I_{t2}$  be two images of a scene acquired by the same camera  $c$  at time  $t1$  and  $t2$  respectively from different positions in space. Additionally, let  $P$  denote a point in the scene,  $i$  denote different scene points,  $p_{t1}$  be its projection in  $I_{t1}$ ,  $P'$  denote the new location of  $P$  at  $t2$  and  $p'_{t2}$  be its projection on the image  $I_{t2}$ . There exists a unique fundamental matrix  $F_{t2}^{t1}$  relating the two images where  $I_{t1}$  is the reference, which satisfies

$$p_{t2}^i T F_{t2}^{t1} p_{t1}^i = 0, \quad (1)$$

for all corresponding points  $p_{t1}^i$  and  $p_{t2}^i$ . If  $P$  is a static point, it satisfies  $el_{t2}^{t1} = F_{t2}^{t1} p_{t1}^i$  and  $el_{t1}^{t2} = F_{t1}^{t2} p_{t2}^i$  where  $el_{t1}^{t2}$  and  $el_{t2}^{t1}$  are epipolar lines corresponding to  $p_{t2}$  and  $p_{t1}$  respectively. Thus, we can say that if  $P'$  is a static point, it should lie on the corresponding epilines as shown in Figure 3. On the contrary, if a point is moving, it does not satisfy the aforementioned epipolar constraint as shown in Figure 4 with an exceptional case; when the camera and point/object move along the same direction as shown in Figure 5.

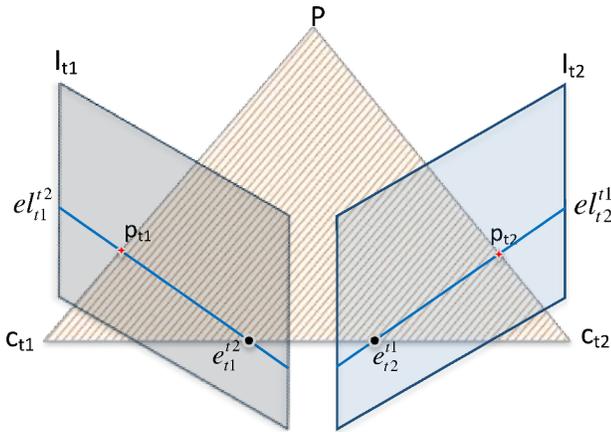


Figure 3. Epipolar constraint in the presence of non-moving objects.

To classify a feature point as static or dynamic we use the perpendicular distance of the feature point to the corresponding epiline as suggested in [15]. Additional to previous works, before applying the epipolar constraint, to calculate fundamental matrix, we use the already extracted keypoints, descriptors and the matches, but with a key difference; instead of using the full set of keypoints or the ones filtered by the candidate moving objects (static + moving) as we did in Section 3.1, this time we filter out the keypoints/descriptors based on the previous final moving object detection result where we expect to detect only the real

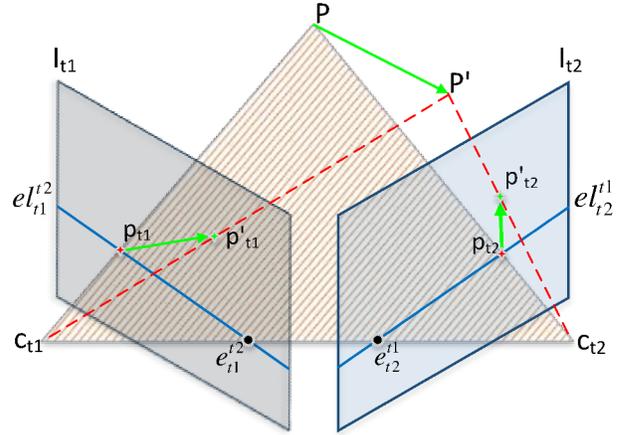


Figure 4. Epipolar constraint in the presence of non-degenerate object motion.

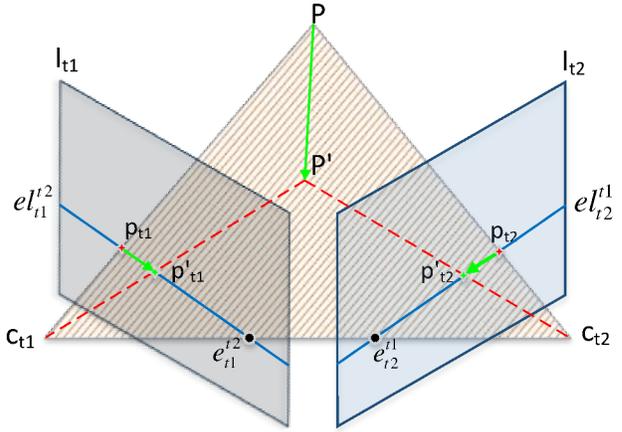


Figure 5. Epipolar constraint in the presence of degenerate object motion.

moving objects. Since the moving objects do not belong to the actual 3D scene, we expect them to hurt the fundamental matrix, thus the epipolar line calculation.

In Figure 6, two different scenes with parallax are shown. It can clearly be seen that the keypoints, which are on static objects falsely detected as moving, move along the corresponding epilines and thus can not be filtered with epipolar constraints. On the other hand, keypoints on real (non-degenerately) moving objects (such as the car in the first row) are not filtered.

### 3.4.2 Flow-Vector Bound Constraint

To handle the degenerate motion cases when the camera and point/object move along the same direction, flow-vector bound (FVB) constraint is used as suggested in [17, 15]. FVB constraint restricts the motion of static points along the epipolar lines.

For any static point, when a camera follows an ob-

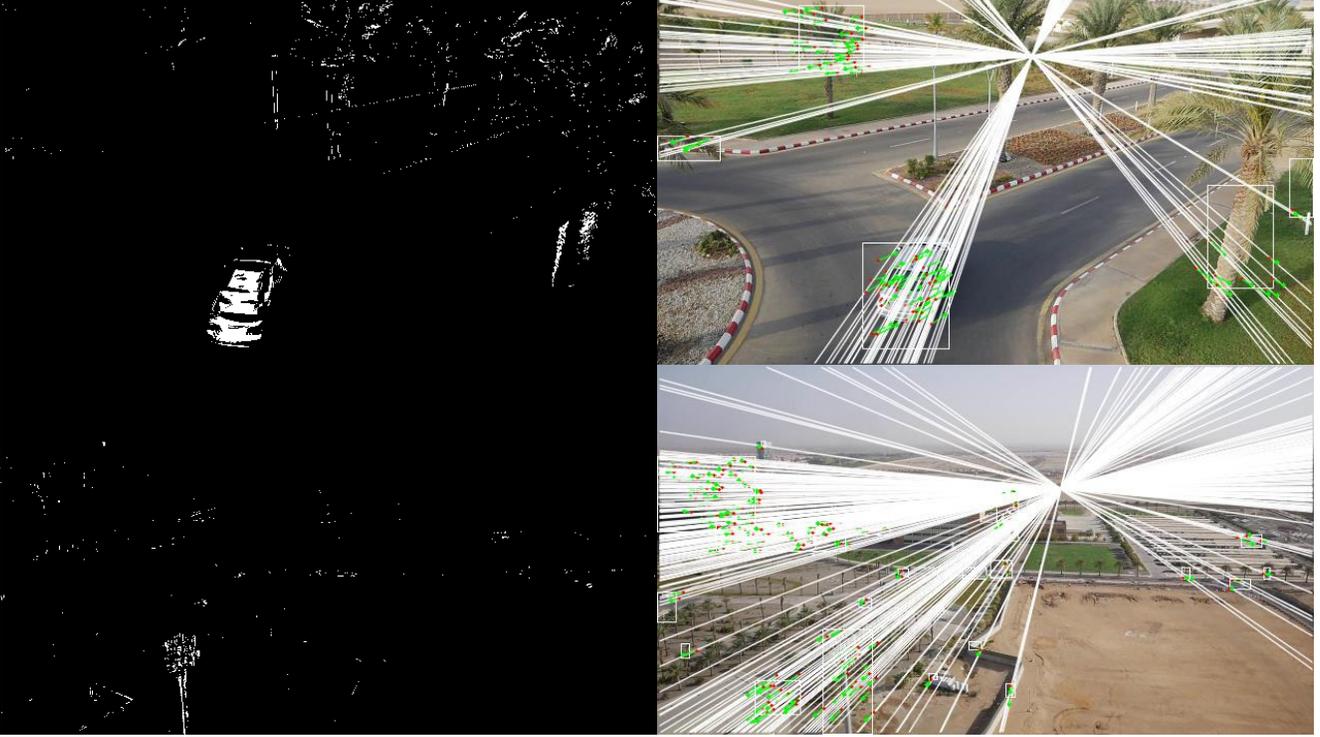


Figure 6. Displacement of keypoints and corresponding epipolar lines in the presence of parallax. Each row belongs to a different scene. Two-frame differences are shown in first column, displacement of keypoints and corresponding epipolar lines are shown in the second. Keypoints on moving object candidates are shown in red, displacement of the keypoints is shown in green and the corresponding epilines are shown in white.

ject/point, assuming the camera translates by  $t$ , the movement of the point is given by [17]

$$p_{t2} = p_{t1} + \frac{Kt}{z}, \quad (2)$$

where  $z$  is the depth of the scene and  $K$  is the intrinsic matrix of the camera. Since we are dealing with already captured videos in this study and we do not have the camera parameters, we can use the following

$$Kt = e_{t2}^{t1}, \quad (3)$$

where  $e_{t2}^{t1}$  is the epipole location on  $I_{t2}$ . Because of the lack of camera matrix and the camera translation amount, we only have the ability to calculate relative depth between matched points ( $z_r^i$ ) as suggested in [10, 14]

$$z_r^i = \frac{(H_{t1}^{t2} p_{t1}^i \times p_{t2}^i)^T (p_{t2}^i \times e_{t2}^{t1})}{\|p_{t2}^i \times e_{t2}^{t1}\|^2}. \quad (4)$$

Using Equations 2, 3 and 4 we can compute the displacement bounds along the epipolar line,  $d_{min}$  and  $d_{max}$ . If a point's displacement is not between  $d_{min}$  and  $d_{max}$ , it is more likely to be a point on a moving object. Since we also have the point pair matches (in our case, keypoint matches),

we also check the deviation between the matched location and result of Equation 2. An example degenerate motion and the result of applying FVB constraint is shown in Figure 7.

## 4. Experiments

### 4.1. Dataset

Even though a handful of moving object detection studies have been published, the field still suffers from the lack of a content-rich and accurately labelled dataset. A general trend in moving object detection literature, especially for low-altitude UAVs, is the use of custom datasets compiled by respective authors. Best to our knowledge, however, neither these datasets nor their ground-truth labels are shared with the community in general.

UAV footage datasets have emerged in recent years due to the increased availability of the platforms, however, they are generally labelled for object tracking purposes [18]. This means only a select number of objects present are labelled. Moreover, tracked objects may or may not be moving, therefore such labels are not reliable for moving object detection evaluation.

**LAMOD Dataset.** In order to address said challenges, we compile our own ground-truths for a combined



Figure 7. Example of degenerate motion and filtering of static points by FVB constraint. From top-left to bottom-right, the detected motion areas, the corresponding keypoint-displacement and epipolar lines on those areas, result without applying FVB constraint and final result with FVB constraint applied are shown in each image.

Table 1. Execution time without parallax filtering.

Video Resolution	TX1	TX2
640x360	110 ms	79 ms
640x480	115 ms	85 ms
1280x720	350 ms	250 ms

Table 2. Execution time with parallax filtering.

Video Resolution	TX1	TX2
640x360	163 ms	135 ms
640x480	175 ms	140 ms
1280x720	450 ms	350 ms

dataset called **LAMOD** (Low Altitude Moving Object Detection) via annotating sequences from VIVID and UAV123 datasets. We hand-label the sequences for moving objects spanning various classes (i.e. bird, pedestrian, car, etc.). We use an internally-developed annotation tool, which uses an optimized version of KCF tracker [11] to aid and automate the labelling process.

As of now, six sequences from VIVID [6] (*egtest01-02-03-04-05*, *redteam*) and eight sequences from UAV123 [18] (*car1-2-3-4-6-8-10* and *person12*) have been labelled. The reasoning behind sequence choices is to make sure a number of scenarios are present; occlusion, motion parallax, out-of-focus, sudden platform motion, altitude and viewpoint variation. We are increasing the number of labelled sequences and also in the process of sequence-wise labelling for various effects (i.e. altitude variation, parallax, occlusion, etc.). New releases will be publicly available for the community. A representative figure for our ground-truth labels is shown in Figure 8.

## 4.2. Results

Following the annotation of the extended dataset, we evaluate our pipeline with and without parallax handling. We tune some hyper-parameters with respect to each video to see the extent of this pipeline with optimal tuning. Parameters that are tuned are the number of frames to be differenced and morphology operations. These parameters could have been adaptively changed if external sensory (i.e. IMU) data were present, but for sequences in LAMOD dataset, they are not available. It must be noted that the pipeline does not make use of split/merge handling or shadow suppression, therefore readers are reminded that these values are produced to be used as benchmarks only. We use NVidia Jetson TX1/TX2 modules in our experiments. Execution times are shown in Table 1 and 2.

For evaluation metrics, we use precision/recall and F-Score, where we take a minimum of 50% overlap to be a correct detection.



Figure 8. Annotations for (top, left to right) car2, car4, car6 from UAV123 and (bottom, left to right), egtest01, egtest04 and egtest05 from VIVID dataset.

Table 3. Precision-recall and F-Score values without parallax handling.

Sequence	egtest01	egtest02	egtest04	egtest05	redteam	car1	car2	car3	car4	car6	car10
<b>Precision</b>	0.93	0.85	0.72	0.71	0.70	0.68	0.84	0.85	0.77	0.10	0.09
<b>Recall</b>	0.82	0.53	0.72	0.68	0.88	0.58	0.78	0.54	0.39	0.45	0.59
<b>F-Score</b>	0.87	0.65	0.72	0.69	0.77	0.63	0.81	0.65	0.52	0.16	0.15

#### 4.2.1 Without parallax handling

Precision/recall and F-Score values without parallax handling are shown in Table 3. A figure representing the steps of the pipeline is shown in Figure 9.

It is apparent that for *egtest01* results are the best among others. This is expected as this video does not have parallax, viewpoint/altitude variation or any sudden movements. The movement speed is minimal as well. For *egtest02*, a reduction in recall is obvious as severe occlusion exists, as well as sudden movements. *egtest04* shows the detrimental effect of viewpoint variation and out-of-focus effect, which degrades the gradients and thus the feature extraction quality. *Egtest05* has the highest amount of occlusion, although the stability of number of object numbers and altitude helps retain an adequate result. *Redteam* sequence has the lowest resolution, and even though a single object is present, the effect of minor parallax degrades the result quality.

Rest of the videos, *car2-3-4-6*, are harder as altitude variation, parallax and sudden movements are more frequent. With careful tuning, *car2* still manages to keep a good quality, however the others have severely degraded results, especially in recall. *Car4* has parallax, occlusion and various object sizes/movement speeds. *Car6* and *car10* sequences, on the other hand, produce the worst results as severe parallax (degrades precision) coupled with occlusion and vary-

ing object sizes (small objects degrade recall) have apparent detrimental effects.

#### 4.2.2 With parallax handling

As mentioned in the previous section, one of the most severe parallax cases are observed in *car6*, *car10* and *car1* sequences. Therefore, we evaluate only these videos with our proposed parallax handling scheme. A representative figure of the flow is shown in Figure 10. Results are shown in Table 4.

We evaluate our technique using the segments of the videos where parallax is quite severe. As can be seen from the results, we observe solid increase in F-Scores in each video. Parallax primarily degrades precision due to false positives, and accordingly, parallax handling increases the precision the most. As parallax handling eliminates candidate moving objects, it is apparent that some true positives are eliminated as well, thus the slightly lowered recall.

## 5. Conclusions and Future Work

Inspired by the lack of a widely-accepted and carefully annotated dataset for moving object detection from low altitude UAV imagery, we present our hand-annotated dataset

Table 4. Precision-recall and F-Score values with parallax handling. PH stands for parallax handling.

Sequence	car1 (first 1020 frames)		car6 (first 700 frames)		car10 (first 750 frames)	
	without PH	with PH	without PH	with PH	without PH	with PH
Precision	0.55	0.70	0.12	0.78	0.13	0.83
Recall	0.51	0.50	0.71	0.64	0.63	0.41
F-Score	0.52	0.58	0.20	0.70	0.21	0.55

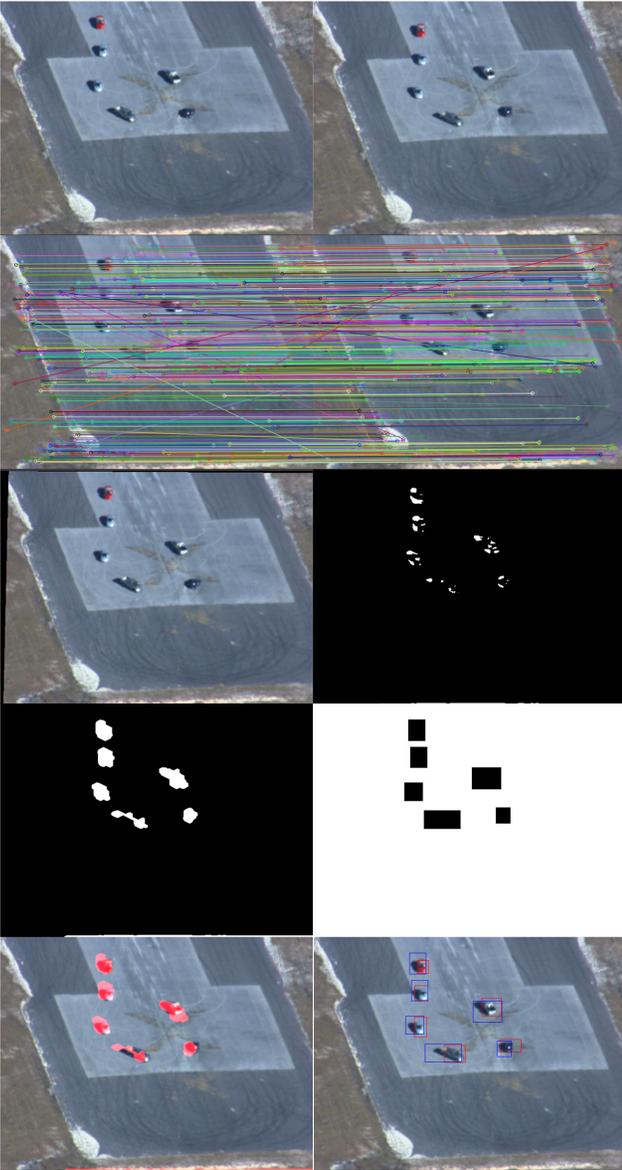


Figure 9. Moving object detection result on VIVID egtest01. Previous frame, current frame, matched features, warped image, three frame difference, morphology result, enclosing rectangles/keypoint mask, blended pixel-wise result and result vs. ground-truth are shown from top left to bottom right respectively.

*LAMOD* which extends the ground-truth annotations of VIVID and UAV123 datasets for moving object detection.

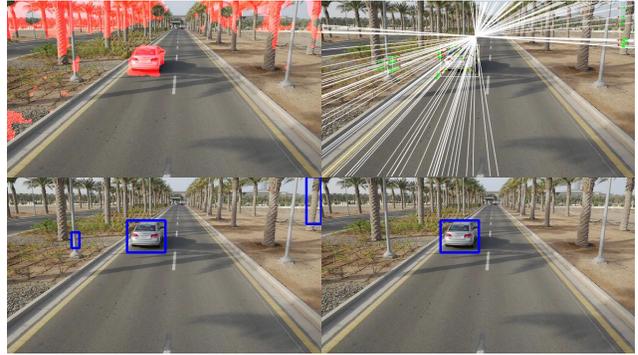


Figure 10. Parallax handling result on car6 sequence. From top left to bottom right; pixel-wise results without parallax handling, epipolar lines for keypoints present on moving object candidates, final results before parallax handling and after parallax handling.

We carefully pick the sequences to facilitate the inclusion of a variety of scenarios and effects, such as motion parallax, occlusion and altitude/viewpoint/object size variation.

We propose a feature-based, lightweight pipeline that draws its strength from object-wise decisions while eliminating parallax-induced false positives. This pipeline makes use of two separate feedback loops to realise accurate homography and fundamental matrix calculation. We evaluate the proposed pipeline for scenarios with and without parallax, and observe favourable quantitative results with near-real time performance on embedded GPU-based SoMs. Our quantitative results will serve as a future benchmark for the community.

As future work, we plan to use three frame geometric constraints instead of two to better handle degenerate motion cases [29]. We plan to use our own camera, allowing us to calibrate and obtain camera parameters, thus using essential matrix instead of fundamental matrix. We believe this will lead to more robust and accurate calculation of epipolar lines. Additionally, we plan to use the IMU measurements to dynamically adapt the system parameters that depend on altitude. Migrating the remaining parts of the pipeline to GPUs is also considered for faster execution. Lastly, our work on *LAMOD* dataset will be updated with new ground-truths and sequence-wise labels (i.e. presence of occlusion, motion parallax, etc.) along with benchmark results of existing techniques.

## References

- [1] S. Baker and I. Matthews. Equivalence and efficiency of image alignment algorithms. In *Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on*, volume 1, pages I–I. IEEE, 2001.
- [2] H. Bay, T. Tuytelaars, and L. Van Gool. Surf: Speeded up robust features. In *European Conference on Computer Vision*, pages 404–417. Springer, 2006.
- [3] D. Berjon, C. Cuevas, F. Moran, and N. Garcia. Gpu-based implementation of an optimized nonparametric background modeling for real-time moving object detection. *IEEE Transactions on Consumer Electronics*, 59(2):361–369, 2013.
- [4] X. Cao, J. Lan, P. Yan, X. Li, et al. Vehicle detection and tracking in airborne videos by multi-motion layer analysis. *Mach. Vis. Appl.*, 23(5):921–935, 2012.
- [5] T. Castelli, A. Trémeau, H. Konik, and E. Dinet. Moving object detection for unconstrained low-altitude aerial videos, a pose-independent detector based on artificial flow. In *Image and Signal Processing and Analysis (ISPA), 2015 9th International Symposium on*, pages 42–47. IEEE, 2015.
- [6] R. Collins, X. Zhou, and S. K. Teh. An open source tracking testbed and evaluation web site. In *IEEE International Workshop on Performance Evaluation of Tracking and Surveillance (PETS 2005)*, volume 2, page 35, 2005.
- [7] S. Dey, V. Reilly, I. Saleemi, and M. Shah. Detection of independently moving objects in non-planar scenes via multi-frame monocular epipolar constraint. In *European Conference on Computer Vision*, pages 860–873. Springer, 2012.
- [8] A. Elgammal, R. Duraiswami, D. Harwood, and L. S. Davis. Background and foreground modeling using nonparametric kernel density estimation for visual surveillance. *Proceedings of the IEEE*, 90(7):1151–1163, 2002.
- [9] C. Eveland, K. Konolige, and R. C. Bolles. Background modeling for segmentation of video-rate stereo sequences. In *Computer Vision and Pattern Recognition, 1998. Proceedings. 1998 IEEE Computer Society Conference on*, pages 266–271. IEEE, 1998.
- [10] A. Fusiello, S. Calderer, S. Ceglie, N. Mattern, and V. Murino. View synthesis from uncalibrated images using parallax. In *Image Analysis and Processing, 2003. Proceedings. 12th International Conference on*, pages 146–151. IEEE, 2003.
- [11] J. F. Henriques, R. Caseiro, P. Martins, and J. Batista. High-speed tracking with kernelized correlation filters. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 37(3):583–596, 2015.
- [12] M. Irani and P. Anandan. A unified approach to moving object detection in 2d and 3d scenes. *IEEE transactions on pattern analysis and machine intelligence*, 20(6):577–589, 1998.
- [13] K. A. Joshi and D. G. Thakore. A survey on moving object detection and tracking in video surveillance system. *International Journal of Soft Computing and Engineering*, 2(3):44–48, 2012.
- [14] J. Kang, I. Cohen, G. Medioni, and C. Yuan. Detection and tracking of moving objects from a moving platform in presence of strong parallax. In *Computer Vision, 2005. ICCV 2005. Tenth IEEE International Conference on*, volume 1, pages 10–17. IEEE, 2005.
- [15] M. Kimura, R. Shibasaki, X. Shao, and M. Nagai. Automatic extraction of moving objects from uav-borne monocular images using multi-view geometric constraints. In *IMAV 2014: International Micro Air Vehicle Conference and Competition 2014, Delft, The Netherlands, August 12-15, 2014*. Delft University of Technology, 2014.
- [16] T. Kryjak, M. Komorkiewicz, and M. Gorgon. Real-time moving object detection for video surveillance system in fpga. In *Design and Architectures for Signal and Image Processing (DASIP), 2011 Conference on*, pages 1–8. IEEE, 2011.
- [17] A. Kundu, K. M. Krishna, and J. Sivaswamy. Moving object detection by multi-view geometric techniques from a single camera mounted robot. In *Intelligent Robots and Systems, 2009. IROS 2009. IEEE/RSJ International Conference on*, pages 4306–4312. IEEE, 2009.
- [18] M. Mueller, N. Smith, and B. Ghanem. A benchmark and simulator for uav tracking. In *European Conference on Computer Vision*, pages 445–461. Springer, 2016.
- [19] N. Paragios and R. Deriche. Geodesic active contours and level sets for the detection and tracking of moving objects. *IEEE Transactions on pattern analysis and machine intelligence*, 22(3):266–280, 2000.
- [20] G. R. Rodríguez-Canosa, S. Thomas, J. del Cerro, A. Barrientos, and B. MacDonald. A real-time method to detect and track moving objects (datmo) from unmanned aerial vehicles (uavs) using a single camera. *Remote Sensing*, 4(4):1090–1111, 2012.
- [21] G. Salgian, J. Bergen, S. Samarasekera, and R. Kumar. Moving target indication from a moving camera in the presence of strong parallax. Technical report, DTIC Document, 2006.
- [22] X. Shi, H. Ling, E. Blasch, and W. Hu. Context-driven moving vehicle detection in wide area motion imagery. In *Pattern Recognition (ICPR), 2012 21st International Conference on*, pages 2512–2515. IEEE, 2012.
- [23] M. Siam and M. ElHelw. Robust autonomous visual detection and tracking of moving targets in uav imagery. In *Signal Processing (ICSP), 2012 IEEE 11th International Conference on*, volume 2, pages 1060–1066. IEEE, 2012.
- [24] A. Sobral and A. Vacavant. A comprehensive review of background subtraction algorithms evaluated with synthetic and real videos. *Computer Vision and Image Understanding*, 122:4–21, 2014.
- [25] L. W. Sommer, M. Teutsch, T. Schuchert, and J. Beyerer. A survey on moving object detection for wide area motion imagery. In *Applications of Computer Vision (WACV), 2016 IEEE Winter Conference on*, pages 1–9. IEEE, 2016.
- [26] N. Sukanuma and T. Kubo. Fast dynamic object extraction using stereovision based on occupancy grid maps and optical flow. In *Advanced Intelligent Mechatronics (AIM), 2011 IEEE/ASME International Conference on*, pages 978–983. IEEE, 2011.
- [27] J. W. Tang, N. Shaikh-Husin, U. U. Sheikh, and M. N. Marsono. Fpga-based real-time moving target detection system for unmanned aerial vehicle application. *International Journal of Reconfigurable Computing*, 2016, 2016.

- [28] M. Teutsch and M. Grinberg. Robust detection of moving vehicles in wide area motion imagery. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, pages 27–35, 2016.
- [29] W. Yang, G. Gu, and W. Wang. A new geometric constraint method of moving object detection using moving camera. In *SPIE Optical Engineering+ Applications*, pages 95960J–95960J. International Society for Optics and Photonics, 2015.
- [30] Q. Yu and G. Medioni. A gpu-based implementation of motion detection from a moving platform. In *Computer Vision and Pattern Recognition Workshops, 2008. CVPRW'08. IEEE Computer Society Conference on*, pages 1–6. IEEE, 2008.
- [31] X. Zhou, C. Yang, and W. Yu. Moving object detection by detecting contiguous outliers in the low-rank representation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 35(3):597–610, 2013.
- [32] S. Zokai and G. Wolberg. Image registration using log-polar mappings for recovery of large-scale similarity and projective transformations. *IEEE Transactions on Image Processing*, 14(10):1422–1434, 2005.