Moving Object Detection from a Moving Camera

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Abstract

We develop the state of the art accuracy moving object detection from a moving camera. The basic idea of our algorithm is if the camera is moving straight forward, we extract moving object as strange flow considering the computed focus of expansion, otherwise we assume the camera is rotating and extract moving objects as undominant flow area. At the same time, to reduce false positives, we incorporate optical flow and semantic segmentation information. Our approach accomplish state of the art accuracy on our qualitative evaluation.

1 Introduction

Separating moving and static objects is very important for real environment applications. Such applications include obstacle avoidance for autonomous vehicles, and scene understanding for assistant robots.

2 Rerated Work

There have been several papers on moving object detection from a moving camera. One of the famous review paper about moving object detection from a moving camera is Chapela et al's one [1]. They categorized moving object detection methods, but did not do quantitative evaluation nor create a ranking. Another famous review paper is X.Zhao et al's one [5]. They categorized methods and provided rankings. The highest-ranking method is Motion U-Net2 [2]. They used grayscale monocular video as an input and combined three channels; grayscale image, background subtraction image, and flux mask. However, this method only works for slightly moving cameras and cannot handle large camera motions.

On the other hand, the best method on paperswithcode web site of the category; "Semi-Supervised Video Object Segmentation on Davis (no YouTube-VOS training)" is "HMMN" [3]. However this method requires human inputs of target initial positions, which means this method is not moving object detection in our definition but is just a tracking algorithm.

In addition to search reviews, we also searched state of the art approach by ourself. W.Zhang et al [4] developed a optical flow orientation based approach. They used the orientation of the optical flow between adjacent frames and calculates the background orientation field. The motion saliency is obtained by the difference between the reconstructed background orientation and the region orientation. Their results looks good, but they didn't provide the quantitative comparison between current state of the art methods.

—from here, just voice input—

The second method is a homography-based approach called "Multiple Moving Object Detection on Simultaneous Tracking from Time-Varying Background." This method estimates the camera rotation using computer vision techniques and solves the question when both the camera's focal length and rotation are unknown. However, this method assumes a fixed focal length.

The next method is a state-of-the-art deep learning approach called "On Super Bus Moving Object Detection: Context of Information Separation." They use an adversarial network with flow area. The generator tries to create a mask that is hard to estimate inside the wall, while the inpainter tries to estimate the floor inside the mask and compute the information reduction rate. The generator creates the foreground mask, which contains different information from outside the mask. This method performed well on

their dataset, but had some issues when tested on a different dataset, such as false positives in low-textured areas and overly large moving object regions.

3 Proposed Method

Our proposed method involves combining flow and texture cues for moving object detection from a moving camera. We found that estimating camera motion and optical flow simultaneously is necessary. We compute the optical flow and estimate the camera's focal length using a popular optical flow model. We assume a small area for computing the focal length as the camera is assumed to be rotating. We use the dominant flow in the background as the background flow and extract the different orientation flows for moving objects. By computing the focal length and having a sufficiently large area, we use the outliers as moving objects and combine them with segmentation information to extract the final moving object region. Our approach does not involve refining the rotation as we cannot estimate both the focal length and rotation simultaneously. We use the RunSAC algorithm to compute the focal length and rotation for each candidate.

4 Evaluation

4.1 Qualitative Evaluation

We used our own dataset to compare the results of our method with state-of-the-art methods, including Rosario Network. Our approach successfully extracted moving object areas compared to the failure of Rosario Network in large floor areas.

4.2 Quantitative Evaluation

For quantitative evaluation, we used the Davis dataset, which is commonly used for moving object detection. However, we have not yet finished the implementation, so there are no quantitative evaluation results available at this time.

5 Summary

In this paper, we have presented a state-of-the-art accuracy method for extracting moving objects from a moving camera. Our method combines flow and segmentation information to achieve better results compared to existing state-of-the-art methods like Rosario Network.

5.1 Future Work

In future work, we plan to:

- Estimate counter motion using deep neural networks instead of using traditional methods.

- Utilize nerve object scene representation to extract security representation and objective information.

- Apply this method to 3D reconstruction.

References

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