

IMAGE BASED OBJECT RECOGNITION

***Axamol Charly, C.**

PG Scholar, Royal College of Engineering and Technology, Thrissur, India

ARTICLE INFO

Article History:

Received 19th March, 2018
Received in revised form
21st April, 2018
Accepted 03rd May, 2018
Published online 28th June, 2018

Key Words:

Graph matching,
Moving object detection,
Re-gion based matching.

ABSTRACT

Image registration has been long used as a basis for the detection of moving objects. In this method spatial information is often ignored, and different motions from multiple moving objects cannot be efficiently modeled. Moreover, image registration is not well suited to handle occlusion that can result in potential object misses. Here proposes a new approach to address these issues. Video frames are first segmented into uniform regions, followed by the construction of RAGs to represent each frame. The corresponding regions are then matched between consecutive frames by using the multigraph matching algorithm. Occluded regions are also detected in this paper. This method preserves the object boundary for over segmented region. There-fore, integrating the connected regions with the same motions can reveal moving objects.

Copyright © 2018, Axamol Charly, C. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Citation: Axamol Charly, C. 2018. "Image based object recognition", *International Journal of Development Research*, 8, (06), 20735-20737

INTRODUCTION

Automated video analysis is important for many vision applications, such as surveillance, traffic monitoring, augmented reality, vehicle navigation, etc. There are three key steps for automated video analysis: object detection, object tracking, and behavior recognition. As the first step, object detection aims to locate and segment interesting objects in a video. Then, such objects can be tracked from frame to frame, and the tracks can be analyzed to recognize object behavior. Thus, object detection plays a critical role in practical applications. Object detection is usually achieved by object detectors or background subtraction. An object detector is often a classifier that scans the image by a sliding window and labels each subimage defined by the window as either object or background. Generally, the classifier is built by offline learning on separate datasets or by online learning initialized with a manually labeled frame at the start of a video. Alternatively, background subtraction compares images with a background model and detects the changes as objects. It usually assumes that no object appears in images when building the background model. Such requirements of training examples for object or background modeling actually limit the applicability of above-mentioned methods in automated video analysis.

***Corresponding author: Axamol Charly, C**

PG Scholar, Royal College of Engineering and Technology, Thrissur, India

Proposed Framework

In this paper, both appearance similarity and geometrical constraints are imposed on region-based features. If images are seen as a set of connected regions, they can hence be represented by RAGs. Representing images as graphs of regions allows the spatial relationships between pixels to also be incorporated at a higher level, making the model more robust toward local variations such as scaling, translation, rotation, illumination, and intensity changes. In addition, both unary node-to-node and pairwise edge-to-edge relationships can be integrated into the model using graph representation. Therefore, better correspondence matching can be expected. An example is when an object is absent in one frame but then re-enters the scene in a future frame. Furthermore, by imposing structural and geometrical constraints on a frame sequence, which are in turn represented as a sequence of graphs, the model can be more robust toward deformations, missing or incomplete data, and outlier regions.

Region Merging

Initially, all frames go through a segmentation process. Certain segmentation approaches might yield under-segmentation, So we decided to go with an oversegmentation algorithm. In this paper, SLIC superpixel was chosen as it is able to produce small yet uniform regions. Although large numbers of over

segmented regions are generated, at least potential image objects contain many regions. But since our approach processes many frames at a time, the large number of regions can increase computational complexity, specifically during the matching phase.

To solve the problem, we propose to combine homogenous regions through a merging process. Where oversegmented homogenous regions are grouped into individual image objects. Superpixel algorithm used for this. Superpixel algorithms group pixels into perceptually meaningful atomic regions, which can be used to replace the rigid structure of the pixel grid. They capture image redundancy, provide a convenient primitive from which to compute image features, and greatly reduce the complexity of subsequent image processing tasks. They have become key building blocks of many computer vision algorithms, such as top scoring multiclass object segmentation entries to the PASCAL VOC

Challenge depth estimation, segmentation, body model estimation, and object localization.

There are many approaches to generate superpixels, each with its own advantages and drawbacks that may be better suited to a particular application. For example, if adherence to image boundaries is of paramount importance, the graph-based method of may be an ideal choice. However, if superpixels are to be used to build a graph, a method that produces a more regular lattice, such as is probably a better choice. While it is difficult to define what constitutes an ideal approach for all applications, we believe the following properties are generally desirable:

- Superpixels should adhere well to image boundaries.
- When used to reduce computational complexity as a pre-processing step, superpixels should be fast to compute, memory efficient, and simple to use.
- When used for segmentation purposes, superpixels should both increase the speed and improve the quality of the results.

We therefore performed an empirical comparison of five state-of-the-art superpixel methods evaluating their speed, ability to adhere to image boundaries, and impact on segmentation performance. We also provide a qualitative review of these, and other, superpixel methods. Our conclusion is that no existing method is satisfactory in all regards. To address this, we propose a new superpixel algorithm: simple linear iterative clustering (SLIC), which adapts k means clustering to generate superpixels in a manner similar to. While strikingly simple, SLIC is shown to yield state of-the-art adherence to image boundaries on the Berkeley benchmark, and outperforms existing methods when used for segmentation on the PASCAL and MSRC data sets. Furthermore, it is faster and more memory efficient than existing methods. In addition to these quantifiable benefits, SLIC is easy to use, offers flexibility in the compactness and number of the superpixels it generates, is straightforward to extend to higher dimensions, and is freely available. Note that each region is still a part of only one distinct object, while one object may include more than one region. Subsequently, each frame is represented by an RAG that serves as the basis for correspondence matching. The RAGs nodes contain features, which are visual properties of the underlying regions. The edges on the graph correspond to the adjacency relationships between the features. Two benefits

arise from modeling using RAGs: 1) the spatial view of each frame is taken into account and 2) neighborhood relationships between frame regions are also efficiently leveraged into the model.

Region Matching

Establishing correspondences between two groups of points is known as point pattern matching. Its objective is to remove outliers in order to estimate the transformations from inliers. This process is complicated in nonparametric and non-rigid models where images are distorted by different types of transformations. In this paper, a set of consecutive frames is considered at a time and their graphical representation (RAG) is exploited. Specifically, correspondence discovery is treated as multigraph matching between RAGs within a set of consecutive frames.

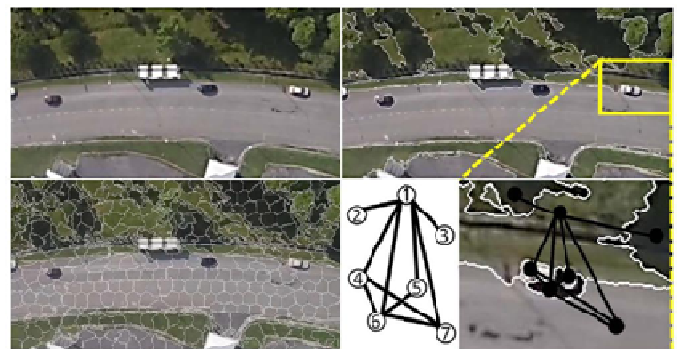


Fig. 1. RAG construction. (Top left) Original image. (Bottom left) Oversegmented image. (Top right) After region merging. (Bottom right) Part of the segmented image where the con-structed RAG shows region connectivity

Region Labeling

Motion similarity between image regions can be induced from the MSG, they cannot simply be labeled as either background or foreground. For instance, two neighboring regions with a similar motion can be constituent parts of one moving object. Alternatively, they can also be two background regions captured by the moving camera. Such discrepancies can be treated as a graph partitioning problem where image regions corresponding to the MSG nodes are assigned to different components present an automatic foreground object detection method for videos captured by freely moving cameras. While we focus on extracting a single foreground object of interest throughout a video sequence, our approach does not require any training data nor the interaction by the users. Based on the SIFT correspondence across video frames, we construct robust SIFT trajectories in terms of the calculated foreground feature point probability. Our foreground feature point probability is able to determine candidate foreground feature points in each frame, without the need of user interaction such as parameter or threshold tuning. Furthermore, we propose a probabilistic consensus foreground object template (CFOT), which is directly applied to the input video for moving object detection via template matching. Our CFOT can be used to detect the foreground object in videos captured by a fast moving camera, even if the contrast between the foreground and background regions is low. Moreover, our proposed method can be generalized to foreground object detection in dynamic backgrounds, and is robust to viewpoint changes across video frames.

In existing feature-based point matching, one main challenge is object shape estimation. This task is important since it defines the bounding boxes around detected moving objects. The proposed method preserves the object boundary for oversegmented region. Therefore, integrating the connected regions with the same motions can reveal moving objects. In other words, the overall bounding box for each moving object is the combination of its constituent regions bounding boxes.

Object Recognition

Object recognition technology in the field of computer vision for finding and identifying objects in an image or video sequence. Humans recognize a multitude of objects in images with little effort, despite the fact that the image of the objects may vary somewhat in different viewpoints, in many different sizes and scales or even when they are translated or rotated. Objects can even be recognized when they are partially obstructed from view. This task is still a challenge for computer vision systems. Many approaches to the task have been implemented over multiple decades. In this section find out the bounding box object and specifically name the object. This feature useful for many real life applications.

Conclusion

In this paper proposes a novel approach for detecting multiple moving objects from challenging videos. Video frames are first segmented into uniform regions, followed by the construction of RAGs to represent each frame. The corresponding regions are then matched between consecutive frames by using the multigraph matching algorithm. Occluded regions are also detected in this paper.

All the matched regions are then processed in groups of frames to form an MSG that keeps motion transformations of the regions in the region trajectories. Hence, multiple moving objects and background regions, which possess different motion patterns, are efficiently detected. Finally labels objects as being background or fore-ground regions. The proposed method seems to benefit from the visual, spatial, and temporal features to effectively capture and represent images for multiple motions estimation. Labeled object can recognize successfully.

REFERENCES

- Bahareh Kalantar, Mohsen Zand, Helmi, Alfian Halin, Shattri "Multiple moving object detection from UAV videos using trajectories of matched regional adjacency graphs", IEEE Transactions on geoscience and re-mote sensing, vol. 4, March 2017
- Yu, H., Chang, Y., Lu, P. Z. Xu, C. Fu, and Y. Wang, "Contour level object detection with top-down information", *Opt.-Int. J. Light Electron Opt.*, vol. 125, no. 11, pp. 27082712, 2014
- Achanta, R., A. Shaji, K. Smith, A. Lucchi, P. Fua, and S. Ssstrunk, "SLIC superpixels compared to state-of-the-art superpixel methods", *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 34, no. 11, pp. 22742282, Nov. 2012
- Hu, W.-C., Chen, C.-H., Chen, T.-Y., Huang, D.-Y. and Z.-C. Wu, "Moving object detection and tracking from video captured by moving camera", *J. Vis. Commun. Image Represent.*, vol. 30, pp. 164180, Jul. 2015.
