IJCSE International Journal of Computer Sciences and Engineering Open Access
Review Paper Volume-1, Issue-3 E-ISSN: 2347-2693

A Review on Segmentation of Moving Object Under Dynamic Condition

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www.ijcaonline.org

Received: 12 Nov 2013 Revised: 18 Nov 2013 Accepted: 22 Nov 2013 Published: 30 Nov 2013

Abstract: Detecting and segmenting moving objects in dynamic scenes is a hard but essential task in a number of applications such as surveillance. Most existing methods only give good results in the case of persistent or slowly changing background, or if both the objects and the background are rigid. It is a difficult task to segment the moving object in the existence of dynamic background. Different kinds of methods exist in this paper to solve the problem of motion detection and motion segmentation. This paper tells us about the various methods used to detect objects under dynamic conditions, where each method is explained in brief along with its merits and demerits.

Keywords: Image Processing, Segmentation, Histogram, Moving Object Detection

I. Introduction

Automatically detecting and segmenting a moving object from a monocular video is useful in many applications like video editing, video summarization, video coding, visual surveillance, human computer interaction, etc. Many methods have been presented. Many of them aim at a robust algorithm for extracting a moving object from a video with rich object and camera motion. However, extracting a moving object from a video with less object and camera motion is also challenging. Most previous automatic methods rely on object and/or camera motion to detect the moving object. Small motion of the object and/or camera does not provide sufficient information for these methods.

Most existing methods use motion to detect moving objects. They assume if a compact region moves differently from the global background motion, it mostly likely belongs to a moving object. Motion-based methods usually take the detected moving pixels as seeds, and cluster pixels into layers with consistent motions (and consistent color and depth). When motion information is sparse and incomplete, they cannot work robustly. Instead of building a moving object model, some other methods build a background model to detect and segment a moving object. These methods work well for videos with static cameras. When videos have complex camera motions, the background model is hard to build.

This paper gives you the brief information about the various methods used to detect moving objects under dynamic conditions along with there merits and demerits.

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II. Related Works

Most existing methods only give good results in the case of persistent or slowly changing background, or if both the objects and the background are rigid.

In the paper [1], we propose a new method for direct detection and segmentation of foreground moving objects in the absence of such constraints. First, groups of pixels having similar motion and photometric features are extracted. For this first step only a sub-grid of image pixels is used to reduce computational cost and improve robustness to noise. We introduce the use of p-value to validate optical flow estimates and of automatic bandwidth selection in the mean shift clustering algorithm. In a second stage, segmentation of the object associated to a given cluster is performed in a MAP/MRF framework

In this method, as we only work on a sub grid of pixels, and because we do not model the background, this method is not computationally and memory expensive. The use of spatial, dynamic and photometric features allows the extraction of moving foreground objects even in presence of illumination changes and fast variations in the background. Distinctive ingredients of our approach include the use of p-value to validate optical flow vectors, the use of automatic multidimensional bandwidth selection in the mean shift clustering algorithm and the use of sparse motion data in a MAP-MRF framework. It is worth emphasizing that the parameters involved in the preliminary motion computations (optical flow and parametric dominant motion) are fixed to the same values in all experiments, while the other parameters (for clustering and segmentation) are automatically selected. We plan in the future to add temporal consistency either on a frame-to-frame basis or within a tracker who's (re)initialization would rely on detection maps.

In the paper [2], an adaptive change detection algorithm for the extraction of multiple moving objects has been presented. The temporal changes identified by the change detection process are used to segment the video objects from the background. However, temporal changes may be generated not only by the objects, but also by noise components. The main sources of noise in the feature analysis step are illumination variations, and camera noise. The algorithm is designed based on a color differentiation between frames, to isolate the error contributions caused by sensor noise and illumination variations. Sensor noise is eliminated in the classification step of the change detector by taking into account its statistics, thus adapting the detection threshold to local information. Local illumination variations are eliminated in the post-processing stage of the change detector by using a knowledge-based approach organized in a hypothesize-and-test scheme.

In the paper [3] relies on a decomposition of each frame of an image sequence into video object planes (VOPs). Each VOP corresponds to a single moving object in the scene. It is a new method for automatic segmentation of moving objects in image sequences for VOP extraction. We formulate the problem as graph labeling over a region adjacency graph (RAG), based on motion information. The label field is modeled as a Markov random field (MRF). An initial spatial partition of each frame is obtained by a fast, floating-point based implementation of the watershed algorithm. We formulate the segmentation problem as detection of moving objects over a static background. Thus, the first step in the algorithm is to compensate the motion of the camera. The global motion is modeled by an eight-parameter perspective motion model and estimated using a robust gradient-based technique an initial spatial partition of the current frame is obtained by applying the watershed segmentation algorithm. For this purpose, the spatial gradient is first estimated in the color space through the use of Canny's gradient. Then, the optimized Rain falling watershed algorithm is applied

The proposed technique succeeds in locating objects boundaries that are not clearly distinct, where other techniques fail. It also accommodates sequences with rapidly moving objects, without marking uncovered background as foreground. The memory contents are incorporated into a MRF model, along with motion information and spatial information, to obtain a Spatio-temporal segmentation of the scene. Currently automatic segmentation of video sequences remains an unsolved problem, since none of the proposed techniques can accomplish this task for generic video sequences. This is mainly due to the fact that VOPs cannot be characterized by homogeneous low-level features such as color, texture or motion. The key to developing segmentation techniques that achieve the performance of the human visual system is to incorporate higher level information into the segmentation process.

In the absence of any a priori knowledge about target and environment, the most widely adopted approach for moving object detection with fixed camera is based on background subtraction An estimate of the background(often called a background model) is computed and evolved frame by frame: moving objects in the scene are detected by the difference between the current frame and the current background model. The main contribution of the paper [4] is the integration of knowledge of detected objects, shadows, and ghosts in the segmentation process to enhance both object segmentation and background update. The resulting method proves to be accurate and reactive and, at the same time, fast and flexible in the applications. Finally, the method is highly computationally cost-effective since it is not severe in computational time.

In the paper [5] tells about a new method (Graph's axis change method) does not depend upon intensity of light and background model. Graph's axis change method works with the movement of pixel according to x and y axis. This method detects the moving objects according to changeable position of pixels. If pixel changes its position according to x axis and y axis in a time period then we find the velocity and magnitude of positions. So we can detect the objects. When the object is detected an alarm is generated. On the other way Graph's axis change algorithm does not depend upon intensity of light, it only depends upon single pixel's movement.

In the paper [6] proposes to employ the visual saliency for moving object detection via direct analysis from videos. Object saliency is represented by an information saliency map (ISM), which is calculated from Spatio-temporal volumes. Both spatial and temporal saliencies are calculated and a dynamic fusion method developed for combination. We use dimensionality reduction and kernel density estimation to develop efficient information theoretic based procedure for constructing the ISM. The ISM is then used for detecting foreground objects. The proposed method is robust to illumination changes and no prior knowledge of the scene is required. Moreover, ISM not only provides the saliency of each pixel for object detection, but also gives additional higher level object saliency information which can be used as one of the cue for event recognition

In the paper [7] there are five major parts: pixel level motion detection, frame level motion detection, background update, background subtraction and object segmentation. Pixel level motion detection identifies each pixel's changing character over a period of time by frame-to-frame difference and analyzes the dynamic matrix presented in this paper.

Frame level motion detection focuses on the motion pixels ratio in the current frame. Fusing the detection result of both pixel and frame level, the background update model will maintain the suitable background model under different conditions. In background subtraction step, each video frame is compared against the reference background model, pixels the current frame that deviate significantly from the background will be detected. After the real time object segmentation based on connected blob extraction and image down sampling, the moving object positions will be gained and transformed to the original subtraction image to get the accurate final segmentation results . This paper has presented a real-time and accurate algorithm for moving object segmentation in dynamic scene. The algorithm has the unique characteristic of explicitly addressing various difficult situations such as ghosts, automatic background modeling, left object, uncertainty camera shaking, and abrupt illumination changes. Further it avoids problems caused by undesired background modification. This algorithm, which is highly computationally cost effective, the system can perform in real time even on common PC.

In the paper [8], the architecture of the segmentation level consists of several steps that must be executed in real time. The initial camera motion correction process uses a calibrated fixed point in the frame and a frame-by-frame correlation for adjusting limited but unavoidable camera movements. The main process of MVO segmentation detects moving points by background subtraction; points are used as a mask in order to select pixels of interest in the frame. Labeling and a simple clustering are then performed, with the final goal to segment individual blobs corresponding to MVOs. Many visual features are computed such as oriented extent, area, inertia moments, textures, average speed, grey levels and color histogram. The average MVO speed is computed as the average optical flow vector. This paper presents a novel approach for moving object segmentation with an improved technique for background computation, called S&KB background update. It exploits both statistical properties of background points and the knowledge of the already segmented moving objects. This S&KB approach allows to

a) Use a limited number of frames for background update, suitable for real-time computation;

b) b) The frame can be sampled with a short time interval, allowing good responsiveness in background adaptation;

c) c)The selectivity together with the knowledge of average motion of detected objects abates the false positive typical of highly responsive background update.

In the paper [9], we have proposed an algorithm for unsupervised moving target detection based on center-surround saliency. The new algorithm is inspired by biological vision, and extends a discriminate formulation of center-surround saliency previously proposed for static imagery. By using dynamic texture models for motion, we derive an information theoretic measure of motion saliency. The discriminate center surround framework, in combination with the modeling power of dynamic textures leads to a robust and versatile algorithm that can be applied to scenes with highly dynamic backgrounds, even when the camera is moving. The algorithm combines spatial and temporal components of saliency in a principled manner. Being completely unsupervised it does not require any training and can thus be automatically deployed to new scenes, with no need for manual supervision or parameter tuning. As the algorithm can work even for moving cameras, it can also be incorporated into hand-held or vehicle mounted sensing devices. Potential applications for the army include automated surveillance with alerts for specific events, detection of events in archived video, crowd monitoring, detection of breaches of borders and other secure areas, path planning for autonomous vehicles and automated target tracking.

In the paper [10] Background modeling and subtraction is a natural technique for object detection in videos captured by a static camera, and also a critical preprocessing step in various high level computer vision applications. However, there have not been many studies concerning useful features and binary segmentation algorithms for this problem. We propose a pixel-wise background modeling and subtraction technique using multiple features, where generative and discriminative techniques are combined for classification. In our algorithm, color, gradient and Haar-like features are integrated to handle spatio-temporal variations for each pixel. A pixel-wise generative background model is obtained for each feature efficiently and effectively by Kernel Density Approximation (KDA). Background subtraction is performed in a discriminative manner using a Support Vector Machine (SVM) over background likelihood vectors for a set of features. The proposed algorithm is robust to shadow, illumination changes, spatial variations of background. We have introduced a multiple feature integration algorithm for background modeling and subtraction, where the background is modeled with a generative method and background and foreground are classified by a discriminative technique. KDA is used to represent a probability density function of the background for RGB, gradient, and Haar like features in each pixel, where 1D independent density functions used for simplicity. Our algorithm demonstrates are better performance than other density-based techniques such as GMM and KDE, and the performance is tested quantitatively and qualitatively using a variety of indoor and outdoor videos.

In the paper [11], we present an unsupervised algorithm to learn object color and locality cues from the sparse motion information. We first detect key frames with reliable motion cues and then estimate moving sub-objects based on these motion cues using a Markov Random Field (MRF) framework. From these sub-objects, we learn an appearance model as a color Gaussian Mixture Model. To avoid the false classification of background pixels with similar color to the moving objects, the locations of these sub-objects are propagated to neighboring frames as locality cues. Finally, robust moving object segmentation is achieved by combining these learned color and locality cues with motion cues in a MRF framework. Currently, our algorithm works off-line because object color and locality cues are learned from the whole video. However, our idea can be extended to online applications. For instance, an object model can be built gradually by incremental learning.

This algorithm provides a robust solution for dealing with camera motion by explicitly estimating the global motion and optical flow. However, explicit motion estimation slows our algorithm down. In fact, 80% of computation is spent on motion estimation. An efficient motion estimation algorithm can speedup our algorithm significantly. Our algorithm only learns the cues of the moving object. Although our experiments prove its initial success, performance may be improved by learning the background model as well. However, it is difficult to build the background model using only the partial object regions because the regions outside these partial object regions are not necessarily the background. Methods from video surveillance have provided rich solutions for learning background models for videos acquired by static cameras. Since we aim to segment moving object from regular videos with possible complex camera motion, it is much harder.

In the paper [12] an iterative algorithm for segmenting independently moving objects and refining and updating a coarse depth map of the scene under unconstrained camera motion (translation and rotation with the assumption that the independently moving objects undergoes pure translation is presented. Given a coarse depth map acquired by a range-finder or extracted from a Digital Elevation Map (DEM), the ego-motion is estimated by combining a global ego-motion constraint and a local brightness constancy constraint using least median of squares (LMedS) which treats independently moving objects as outliers. Using the estimated camera motion and the available depth estimate, motion of the 3D points is compensated. We utilize the fact that the resulting surface parallax field is an epipolar field and use a corresponding parametric model to estimate the parallax vectors for all pixels. We use the previous motion estimate to get the epipolar direction and hence pixels where the parallax direction is not aligned towards the epipolar direction are segmented out as moving points. The depth map for static pixels is refined using the estimated parallax vectors. All segmented regions are removed for robustly estimating the ego-motion in subsequent iterations. A parametric flow model is fitted to the segmented regions and their 3D motion is estimated using subspace analysis. The algorithm works well for unconstrained translational motion of moving objects.

In the paper [13] we propose a simple yet effective background subtraction method that learns and maintains dynamic texture models within spatio-temporal video patches (i.e. video bricks). In our method, the scene background is decomposed into a number of regular cells, within which we extract a series of video bricks. The background modeling is solved by pursuing manifolds (i.e. learning subspaces) with video bricks at each background location (cell). By treating the series of video bricks as consecutive signals, we adopt the ARMA (Auto Regressive Moving Average) Model to characterize spatio-temporal statistics in the subspace. In the initial learning stage, each manifold can be analytically learned, given sequences of video bricks. In the real-time detection stage, we segment foreground objects by estimating the appearance and state residuals of the new video bricks within the corresponding manifolds. Afterwards, the structure of each manifold is automatically updated by the Incremental Robust PCA (IRPCA) algorithm and its state variation by estimating the state of the new brick and re-solving linear problems.

In the paper [14], A method for detecting and segmenting periodic motion is presented. We exploit periodicity as a cue and detect periodic motion in complex scenes where common methods for motion segmentation are likely to fail. We note that periodic motion detection can be seen as an approximate case of sequence alignment where an image sequence is matched to itself over one or more periods of time. To use this observation, we first consider alignment of two video sequences obtained by independently moving cameras. Under assumption of constant translation, the fundamental matrices and the homo graphics are shown to be time-linear matrix functions. These dynamic quantities can be estimated by matching corresponding space-time points with similar local motion and shape. For periodic motion, we match corresponding points across periods and develop a RANSAC procedure to simultaneously estimate the period and the dynamic geometric transformations between periodic views. Using this method, we demonstrate detection and segmentation of human periodic motion in complex scenes with non-rigid backgrounds, moving camera and motion parallax. We presented a method for detecting and segmenting periodic motion in video sequences. The particular advantage of the proposed method is that it can be applied to complex scenes, but does not rely on camera stabilization, on segmentation nor on tracking. Our solution is formulated in the framework of sequence alignment. In this respect we

(i) Investigated a general case of sequence-to-sequence alignment for independently translating cameras and

(ii) Showed how this approach applies to the detection and segmentation of periodic motion in complex video sequences with motion parallax and non-rigid motion of the background. One limitation of our approach is the assumption of constant translation. To address the general class of motion while preserving linear estimation of F(t) and H(t), one could consider piecewise linear or polynomial approximations of F(t),H(t). Another direction for future investigation concerns alignment of non-periodic motion in different video sequences using the framework of point-wise sequence alignment developed here.

In order to extract the moving object robustly in complex background, the paper [15], presents a novel background subtraction method for detecting foreground objects in dynamic scenes. The difference image of color distance between current image and the reference background image in YUV color space is first obtained. According to the mono-modal feature of histogram of the difference image, an adaptive clustering method based on histogram is given. With morphological filtering, the flecks of noise existed in the segmented binary image can be removed. Finally, an updating scheme for background image is introduced to follow the variation of illumination and environmental conditions. The information extracted by algorithm in this paper was used for segmenting moving targets. In particular, the background subtraction was applied to detect image motion, and the algorithm correctly distinguished the changed areas in the scene from the background. the proposed algorithm is simple and effective in segmenting moving objects.

Since the background update was performed only in the changed areas where the moving objects occurred too frequently, the computational load is reduced significantly. Moreover, the proposed methods are based on general scenes, so it is suitable for other surveillance sequence.

III METHODOLOGY

In this paper we perform a study on 4 detection algorithms under Dynamic conditions and perform a comparison on these algorithms. The detection methods are like this:

- Background Subtraction method
  In this method a novel background subtraction method for detecting foreground objects in dynamic scenes is studied. The difference image of color distance between current image and the reference background image in YUV color space is first obtained. According to the mono-modal feature of histogram of the difference image, an adaptive clustering method based on histogram is given.

- Graph Based Method
  The Graph's axis change method does not depend upon intensity of light and background model. Graph's axis change method works with the movement of pixel according to x and y axis.

- Spatio-temporal Method
  This method proposes to employ the visual saliency for moving object detection via direct analysis from videos. Object saliency is represented by an information saliency map (ISM), which is calculated from Spatio-temporal volumes. Both spatial and temporal saliencies are calculated and a dynamic fusion method developed for combination. We use dimensionality reduction and kernel density estimation to develop efficient information theoretic based procedure for constructing the ISM. The ISM is then used for detecting foreground objects.

- Colour and motion based method
  In this method, we present an algorithm to learn object color and locality cues from the sparse motion information. We first detect key frames with reliable motion cues and then estimate moving sub-objects based on these motion cues using a Markov Random Field (MRF) framework. From these sub-objects, we learn an appearance model as a color Gaussian Mixture Model. To avoid the false classification of background pixels with similar color to the moving objects, the locations of these sub-objects are propagated to neighboring frames as locality cues. Finally, robust moving object segmentation is achieved by combining these learned color and locality cues with motion cues in a MRF framework

IV CONCLUSION

This paper gives a brief review of various methods used for object detection under different back ground condition. The above four methods of object detection will be implemented and a comparative study on all these algorithms will be done based on various parameters under dynamic conditions.

REFERENCES

[1] Aurelie Bugeau Patrick Perez, "Detection and segmentation of moving objects in highly dynamic scenes", Proc. Int. Conf. Computer Vision.

[2] Andrea Cavallaro and Touradj Ebrahimi , "Accurate Video Object Segmentation Through Change Detection", Proc. Int. Conf .Signal Processing Institute.

[3] Yaakov Tsaig and Amir Averbuch,"Automatic Segmentation of Moving Objects in Video Sequences: A Region Labeling Approach" IEEE Transactions On Circuits And Systems For Video Technology, Vol. 12, No. 7, July 2002.

[4] Rita Cucchiara, Costantino Grana, Massimo Piccardi, and Andrea Prati,"Detecting Moving Objects, Ghosts, and Shadows in Video Streams"IEEE Transactions On Pattern Analysis And Machine Intelligence,Vol. 25, No. 10, October 2003.

[5] Gagandeep Kaur"Detection of Moving Objects in Colour based and Graph's axis Change method" International Journal of Computing & Business Research.

[6] Chang Liua, PongC.Yuena,GuopingQiu, “Object motion detection using information theoretic spatio-temporal saliency ”, published in Elsevier journal 2009.
[7] Tao Yang , Stan Z.Li , Quan Pan, Jing Li “Real-Time and Accurate Segmentation of Moving Objects in Dynamic Scene”, published in ACM transactions.
[8] R.Cucchiara, C.Grana, M.Piccardi, A.Prati, “Statistic and Knowledge-based Moving Object Detection in Traffic Scenes”.
[9] Vijay Mahadevan and Nuno Vasconcelos “Unsupervised Moving Target Detection In Dynamic Scenes”.
[10] Bohyung Han, *Larry S. Davis, Fellow*, “Density-Based Multi-Feature Background Subtraction with Support Vector Machine” IEEE Transactions On Pattern Analysis And Machine Intelligence.
[11] Feng Liu and Michael Gleicher, “Learning color and locality cues for moving object detection and segmentation”.
[12] Amit K Agrawal and Rama Chellappa “Moving object segmentation and dynamic scene reconstruction using two frames”.
[13] Yuanlu Xu, Liang Lin “Moving object segmentation by pursuing local spatio-temporal manifolds” April 17, 2013
[14] Ivan Laptev, Serge J. Belongie, Patrick P´erez and Josh Wills, “Periodic Motion Detection and Segmentation via Approximate Sequence Alignment”.
[15] Jinglan Li,“Moving Objects Segmentation Based on Histogram for Video Surveillance”, published in Modern Applied Science Vol. 3, No. 11, November, 2009.

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