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Moving object detection using Markov Random Field and Distributed Differential Evolution

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ABSTRACT

In this article, we present an algorithm for detecting moving objects from a given video sequence. Here, spatial and temporal segmentations are combined together to detect moving objects. In spatial segmentation, a multi-layer compound Markov Random Field (MRF) is used which models spatial, temporal, and edge attributes of image frames of a given video. Segmentation is viewed as a pixel labeling problem and is solved using the maximum a posteriori (MAP) probability estimation principle; i.e., segmentation is done by searching a labeled configuration that maximizes this probability. We have proposed using a Differential Evolution (DE) algorithm with neighborhood-based mutation (termed as Distributed Differential Evolution (DDE) algorithm) for estimating the MAP of the MRF model. A window is considered over the entire image lattice for mutation of each target vector of the DDE; thereby enhancing the speed of convergence. In case of temporal segmentation, the Change Detection Mask (CDM) is obtained by thresholding the absolute differences of the two consecutive spatially segmented image frames. The intensity/color values of the original pixels of the considered current frame are superimposed in the changed regions of the modified CDM to extract the Video Object Planes (VOPs). To test the effectiveness of the proposed algorithm, five reference and one real life video sequences are considered. Results of the proposed method are compared with four state of the art techniques and provide better spatial segmentation and better identification of the location of moving objects.

1. Introduction

Detection and tracking of moving objects from a given video sequence are challenging tasks in video processing and have been an active research area for the last few decades [1,2]. It has wide applicability in video surveillance, event detection, anomaly detection, dynamic scene analysis, activity recognition, activity based human recognition [1,2] etc. To detect moving objects for a given video sequence, various object regions which are moving with respect to their background are identified [2]. It can be performed using (i) change/motion detection and (ii) motion estimation [2] and the detected objects, in turn, can be tracked. Tracking provides the velocity, acceleration and position of moving objects at different time instants.

Literature on detection of moving objects using different stochastic models is quite rich. Markov Random Field (MRF) model is one such approach which represents spatial continuity among adjacent pixels and is robust to degradation. Since the last few decades, MRF models [3–7] and Hidden MRF models [8] are used for segmenting images and these models are quite popular for segmenting video sequences [9–20]. In [9,21], to detect moving objects, MRF model was considered in the spatial direction only. Whereas, in a video, two image frames are not independent of each other. Hence, temporal coherence can be explored to obtain better segmented output. Considering this temporal coherence, a multi-layer MRF modeling is adhered to in [10–16] (one frame in temporal direction). Kim and Park [11] showed that a combination of spatial segmentation and temporal segmentation provides better results for detecting moving objects. To preserve the boundary of the objects, Sududhi et al. [12] proposed a multi-layer compound MRF model which takes care of the spatial distribution of color, temporal color coherence, and edge map/line-field in the temporal frames (two frames in temporal direction) to obtain a spatial segmentation. Temporal coherence helps in preserving the region information in segmentation. The use of edge map/line-field can preserve the accurate object boundary in segmentation.

To the best of our knowledge, in the literature no method is available which exploits the merits of Differential Evolution (DE) scheme with MRF model. In the present article, the applicability of DE has been explored with MRF model for moving object detection. A preliminary experiment of this work was reported in [17].

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A robust analysis of the results with application in different complex video sequences is reported in the present article. Comparison with recent state-of-the-art techniques along with its quantitative analysis has also been made in the present version.

The present work considers, a spatial segmentation scheme where multi-layer compound MRF model [12] has been used for detecting moving objects in a given video sequence. Spatial segmentation as well as temporal segmentation are combined for detecting moving objects. The assumed MRF model takes care of spatial distribution of color, temporal color coherence, and edge map/line-field in temporal direction (two frames in the temporal direction) of a given video frame. The considered MRF model is found to preserve accurate object boundary. The spatial segmentation using the considered multi-layer compound MRF model is equivalent to a pixel labeling problem and is solved using the MAP estimation principle. A Distributed Differential Evolution (DDE) algorithm is proposed for searching the maximum a posterior probability of MRF modeled frame. In the proposed search technique, a population represents a segmented output of the considered video frame and size of the population is equal to the dimension of the video frame. A population consists of a set of target vectors. Here, each target vector encodes the red (R), green (G), and blue (B) components of the segmented output and a set of such target vectors constitutes each population. The population is initialized randomly. It is to be noted that the segmentation of the MRF modeled frame corresponds to the MAP estimation and the proposed DDE algorithm maximizes this probability. This maximization process has been done iteratively by evolving the target vectors (i.e., possible solutions) of the population using the following three operations: mutation, crossover, and selection. The algorithm continues until some stopping criterion is reached. At the end of the evolutionary process, a stable labeled configuration is obtained. Such a configuration is considered as the required segmented output of the given input video frame.

In the proposed DDE, to mutate each target vector, instead of considering the whole population, a small window centered at the target vector is considered thereby reducing computational time as compared to the conventional Differential Evolution algorithm. It also provides a better spatial segmentation as the considered window maintains the spatial regularity of the lattice in MRF.

In temporal segmentation, the difference images of each of the R, G, and B channels are obtained by taking absolute difference of the respective R, G, and B components of the two consecutive spatially segmented image frames. Thereafter, Change Detection Masks (CDMs) of each of the R, G, and B channels are obtained by thresholding the corresponding difference images. The changed and the unchanged regions in the current frame are obtained by considering the union of CDMs of these three channels. To obtain the exact location of the moving objects in the current frame, we modify the obtained CDM by considering the information of pixels belonging to the moving objects in the previous frame and result of the corresponding current spatial segmentation. Video Object Plane (VOP) is extracted by superimposing the intensity/color values of original pixels of the current frame on the changed regions of the modified CDM.

To test the effectiveness of the proposed algorithm investigation was carried out on five reference and one real life video sequences. Results obtained by the proposed method are compared with those of MRF with DGA scheme [10,11], MRF with DGA scheme with multi-layer compound MRF model as used in the proposed method (henceforth, called as modified MRF with DGA scheme), MRF with Graph Cut scheme [7,22], and MRF with SA and ICM scheme [12].

Organization of the article is as follows. Section 2 describes the related work. In Section 3, the proposed methodology for moving object detection where spatial segmentation (spatio-temporal MRF based image modeling, MAP estimation framework for MRF modeling), DE algorithm, DE algorithm with neighborhood-based mutation, the proposed DDE algorithm for MAP estimation, segmentation of subsequent frames based on change information, and temporal segmentation are described. Experimental results and discussion are given in Section 4 and conclusive remarks are put in Section 5.

2. Related work

For change/motion detection initially a reference frame is considered where no objects are present [2]. Detection of moving objects becomes very difficult using temporal segmentation if the reference frame is absent or movement of objects is either very slow, or very fast, or they halt for some time and then move again [1,2].

In order to solve these problems a region based robust video frame segmentation algorithm is needed [1,2]. Salember and Marques [23] had proposed a computationally efficient watershed based spatial segmentation scheme. To detect the object's boundary, they have used both spatial and temporal segmentations. But this scheme sometimes produces over-segmented results.

Image segmentation using MRF model can be achieved by estimating maximum a posteriori (MAP) probability of the concerned model [3,10,11,24]. For a given observed image or a video frame Y, segmentation is obtained by searching a configuration X which maximizes this probability. This maximization process is quite complex owing to the large search space. Hence, efficient and effective optimization algorithms are required to maximize the posterior probability.

The MAP of the MRF model has been estimated using various optimization algorithms such as Simulated Annealing (SA) [4,24,25], Iterated Conditional Mode (ICM) [3,24], and Genetic Algorithm (GA) [5,24]. Though the convergence speed of SA is less but it has the capability of finding better solutions [5,24]. On the other hand, ICM consumes less time as compared to other optimization techniques; but sometimes it may get stuck to local optima [5,24]. In [12], Subudhi et al. has proposed an MRF model based spatial segmentation scheme by combining both SA and ICM to estimate the MAP of the corresponding model. It has the ability to provide comparable results quickly. In [12], the SA was initially executed for a few iterations to get a suboptimal solution and thereafter ICM (with suboptimal solution as initialization) was used to obtain the optimal solution. As SA is executed for a few iterations, the suboptimal solutions obtained using SA sometimes correspond to the local optima or nearer to the local optima and thereafter ICM may get stuck to the same and may not reach the global optimum or near to the global optimum. Hence, segmentation using the same algorithm may not be a good choice. Moreover, the setting of the number of iterations in SA, is not easier.

GA was used as an alternative optimizer to SA and ICM in [5] due to suitable values of the parameter, its ability to explore and exploit the search space quickly using the concept of natural evolution and selection [26]. It is robust for identifying solutions to combinatorial optimization problems. In [5,26,27], it is mentioned that the GA sometimes converges to a premature solution and has low searching speed. To overcome these problems, GA has been modified in [28,29]. In [28], a deterministic hill-climbing procedure was embedded into GA. Although the computational cost was low, it still landed up to a suboptimal solution. Zhang et al. developed evolutionary algorithm based on a combination of GA and SA [30,31]. These algorithms produce better segmentation than those obtained using GA alone, but had a lower convergence speed. A combination of ICM and GA was proposed by Lai and co-worker [5]. For quick convergence and to obtain better segmentation, a new version of GA called, Distributed Genetic Algorithm (DGA) has been proposed