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A Study on Segmentation of Moving Objects Under Dynamic Conditions

Kala Chandrashekhar L[1*], Manasa B S[2]

[1,2] *Department of Computer Science and Engineering, SJB Institute Of Technology, India*

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Abstract— .One of the challenging factor in computer vision is Moving Object Detection under Dynamic condition, dynamic condition involves changes in the background like illumination changes, shadows, slowly moving background and the object, occlusion, noise in the video or image, motion of the camera. In order to overcome the problems of dynamic back ground, and detect the moving object correctly many algorithms have been proposed in the literature survey. In this paper an attempt has been made to study two algorithms for segmenting the moving objects from a video. Firstly the color and motion cues based segmentation is performed. In this method frames are extracted from the video and the motion information is considered and the color information is extracted using the color histogram method. The color and the motion information is combined using Markov Random Field (MRF) to segment the object from the back ground. The second algorithm is based on Spatio-Temporal method of segmentation. In this method spatial and temporal information of the frames are extracted separately. These features are combined to form Information Saliency Map(ISM) and from ISM the foreground is segmented from the back ground. The comparative study is performed on both the algorithms for segmentation. Analysis is performed on these methods and a little variation is found.

Keywords— ***Image Processing, Segmentation, Histogram, Moving Object Detection, Markov Random Field Information Saliency Map***

I. INTRODUCTION

Image segmentation is a method of dividing a frame into foreground and background. During segmentation various problems affect the quality of the video, noise, scattering of light, reflection of light, refraction etc. Before performing segmentation these unnecessary extra information must be removed. This is done by pre processing. After this the video is subjected to segmentation. An image or video can be captured in static and dynamic conditions. In static condition the background will be static only the object will be in motion and the cameras may also be moving. In dynamic condition the background, object and the cameras all may be in motion or any one may be in motion.

Segmentation Problems in the dynamic conditions are changes in the radiance, shadows, moving tree branches and multiple object occlusion. Object segmentation is a difficult and important issue that needs to be handled. Firstly, the segmentation algorithm must be fast against changes in radiance . Second, it should not detect moving background objects such as leaves, rainfall, snowfall, and shadows cast by objects.

Corresponding Author: Kala Chandrashekhar L, Kalachandru84@gmail.com, Dept. of Computer Science and Engineering, SJB Institute Of Technology, India

Finally, the algorithm should react quickly to changes in environment such as starting and stopping of vehicle.

Any motion detection system must be ready to handle a number of critical situations such as gradual changes in the lighting conditions in the environment(it is cloudy or bright for some time) , small movements of moving objects such as branches of the tree and blowing bushes due to wind, noise in the image due to a poor quality of the image source, permanent changes of the objects in the back ground, such as cars that park (or depart after a long period), multiple objects moving , shadow regions that are formed by foreground objects and are detected as moving objects.

II. RELATED WORKS

There are many approaches available for detection of moving objects. These methods can be used for many applications. Existing methods only give good results in the case of static or small changes in the background, or if both the foreground and the background are not changing.

A new pixel based method [1] for direct detection and segmentation of foreground moving objects has been found. In this method pixels having similar properties like motion, color etc are detected. Then only part of the pixels are taken to make the algorithm robust to noise and to reduce the cost for computation. The mean clustering algorithm is used to validate the optical flow and p-values are introduced and bandwidth is selected for computation. Then segmentation is done based on the group of pixel using MAP/MRF(Markov Random Field) framework. In this method, as they only work on group of pixels, and they do not model the background, this method is not efficient and memory expensive.

An adaptive change detection algorithm [2] for the extraction of multiple moving objects has been proposed. The time related changes are identified by the change detection process and are used to segment the moving objects from the background. However, time related changes can be generated not only by the objects, but also by noise components. The first step is the feature analysis step where the noise components like illumination variations, and camera noise are taken for processing . 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 variation are eliminated in the post-processing stage of the change detector by using a knowledge-based approach organized in a hypothesize-and-test scheme.

One of the segmentation method [3] relies on a division of each frame in 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. The extracted VOP's are converted to a region adjacency graph (RAG), based on movement information. The label field is modeled as a Markov random field (MRF). Then watershed algorithm which is implemented by floating-point based method is used for spatial division of each frame and the object is segmented.. The main disadvantage is VOPs cannot be developed from similar low-level features such as color, texture or motion.

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 method [4]. Firstly a back ground model is estimated and evolved frame by frame from the changing background, moving objects are detected by taking the difference of the current frame and the back ground model, then the back ground is updated by combining the information of detected objects, shadows, and ghosts in the segmentation process. 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 .

A new method [5] for segmentation does not depend upon the intensity of light and background model. This method works by detecting the pixel movement in the x and y co ordinates. This method will detect the moving object from the changing position of the pixels. The movement of the pixel in the x and y co-ordinate in a time period, is used to calculate the velocity and magnitude of the pixel and then the object is detected. On the other way Graph's axis change algorithm does not depend upon intensity of light, it only depends upon single pixel's movement.

III. METHODOLOGY

One of the basic step in the segmentation process is finding out regions that belong to objects that are in motion such as people and vehicle from the video Detecting regions that correspond to moving objects such as people and vehicles in the video. Because of the sudden changes in the environment such as changes in the lightening condition and changes in the weather like sudden rainfall, very hot sun, movement of trees and leaves due to strong breeze. Detection of motion is very difficult in those type of situation. More oftenly used methods for moving object detection are background subtraction, statistical methods, temporal differencing and optical flow.

A. Color and locality cues based object segmentation

In this particular method the sparse and insufficient motion information is collected throughout the video frame by frame. These frames collected contains motion information from these cues moving sub objects are estimated using MRF model, from these sub objects the color information is extracted by using Gaussian Mixture Model(GMM). Then the color and the motion cues are combined to extract the moving object.

1) Motion cues

Motion cues are defined as the difference between the object motion and the universal back ground movement . The motion is considered as the important cue for detecting the moving object. If a pixel/region has important relative motion when compared to the background, then that pixel belongs to the moving object. As the motion between the consecutive frames are very small, it is model using Homography . The Scale Invariant Feature Transform (SIFT) is a feature based method used to develop the Homography, Then the SIFT Features are extracted from each frames to establish the feature correspondence between the consecutive frames and calculate the homography using Random sample Consensus (RANSAC) algorithm An example of motion cues is illustrated in the Fig 1. Motion cues is developed by taking the absolute difference between the consecutive frames.

Fig 1: Motion cues

2) Key frame extraction

The video is taken as input and the input video is converted into frames and the frames are extracted and fed as the input for the algorithm Examples of Key frame extraction is given in the Fig 2.

Fig 2: Key frame extraction

3) Segment moving sub-objects from key frame

As the motion information is sparse, only boundary of the object can be detected ,and is known as aperture problem. Objects may not move through out the video, if it moves only few parts only will move at a time, so we will consider some parts of the moving object to calculate the motion cues.

4) Learning Color and locality Cues

Each One of the moving part appears in one of the frame. The color information of the moving object is calculated by converting frame to gray scale and the image absolute difference is calculated from two consecutive frames. Then the hist features are extracted using color histogram

5) Object Segmentation

The MRF model is extended from the color and locality cues extracted from the previous step. This is applied for each and every frame .The segmented object is shown in the fig 3.

Fig 3: Segmented Object

B. Information saliency based Segmentation

A new method to construct an Information Saliency Map(ISM) using both spatial and temporal information saliencies. The frame details are generated from the Iframe features and Pframe features, and from the frame details generated the Saliency information is calculated. Fig 4 shows the input videos.

Fig 4: Shows the input video

1) Iframe feature extraction

Initially the frames are converted from RGB to YCbCr and the Y, Cb, Cr planes are separated then the Y plane is divided into 8X8 blocks then apply DCT(Discrete Cosine Transform) on each and every block then re- arrange the blocks into frames. This Iframe features are used for frame details generation The Fig 5 shows the static saliency map frame image obtained from the Iframe features.

Fig 5 : Shows the static saliency map frame image

2) Pframe feature Extraction

Here initially the frames are converted from RGB to YCbCr color conversion of p frame and Iframe. Find the absolute difference of pframe and iframe and separate Y, Cb, Cr planes apply DCT on each block and rearrange the blocks into frames. Fig 6 shows the motion saliency map frame image obtained from the Pframes.

Fig 6: Shows the motion saliency map frame image

3) Frame Details Generation

Here the saliency measure of all the three frames are taken then the binarisation is applied on the pframe and iframe and mask is calculated from the saliency mat function applied on pframe and iframe and this is applied on each and every frame and the segmentation is performed. The Fig 7 shows the Region enhanced image and Fig 8 shows the segmented object.

Fig 7: Shows the region enhanced image

Fig 8 : Shows the Segmented object

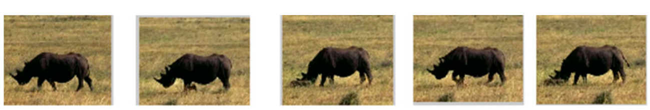
IV. EXPERIMENTAL RESULTS

A. *Experimental setup*

To evaluate the performance of the two methods proposed in the project, a set of 40 frames were drawn from the four videos, from each video 10 frames are extracted each of the algorithm is tested on these frames. The parameter used for comparing these algorithms is the time required to segment each frame from the background. The algorithm color and motion based segmentation (CMBS) segment the object in a less amount of time. The algorithm implemented is compared with respect false positive, false negative, true positive, true negative and precision.

1) Color and motion cues based object segmentation (CMBS)method

The color information is extracted from the video by calculating histogram information . The locality information is calculated from the image absolute difference of the consecutive frames. Then the color and the locality information is combined with the Markov Random Field(MRF). MRF is a tool used for modeling image data as a means of making inference about images. These inferences concern the image and the background structure to solve the problems of image segmentation, reconstruction of image, object labeling etc. Then the frame is segmented. Fig 9(a) and 9(d) shows the input video converted to frames and Fig 9(b) and 9(e)Shows the Difference image and the Fig 9(c) and 9(f) Shows the segmented object.



(a)

(b)

(c)

(d)

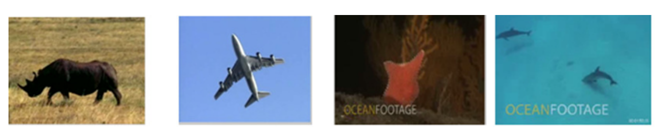
(e)

(f)

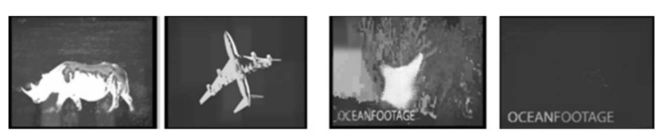
Fig 9 (a),(d) Shows the input frames extracted from video,(b),(e) shows the Difference image between two consecutive frames, (c),(f)Shows the segmented object using CMBS.

2) Spatio-temporal based object segmentation(STBS) method

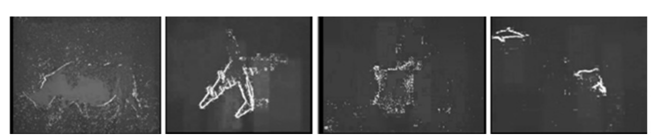
In this method the input video is taken and that video frame is divided into blocks. From that blocks the iframe features and pframe features are extracted. The block is converted from RGB to YCbCr. Then the Y, Cb, Cr planes are extracted separately and the Discrete Cosine Transform (DCT) is applied on that planes then the iframes are generated. The frame that is generated from converting the image to blocks of 8 each and combining to form pframe and iframe is taken and find the absolute difference of these frames separate the Y, Cb, Cr plane apply DCT on these planes separately. From these frame details are extracted and saliency measure is computed and the object is segmented. Fig 10(a) Shows the frames extracted from input video , Fig 10(b) shows the static saliency map frame Image. Fig 10(c) shows the Motion saliency map frame image, Fig 10(d) shows the Region enhanced image and Fig 10(e) shows the segmented object.



(a)



(b)



(c)

(d)

(e)

Fig 10(a) Shows the frames extracted from input video , Fig 10(b) shows the static saliency map frame Image. Fig 10(c) shows the Motion saliency map frame image, Fig 10(d) shows the Region enhanced image and Fig 10(e) shows the segmented object

B. Performance analysis

The performance of both the algorithm is studied based on the time required to process a frame. Both the methods are tested on different videos and frames are extracted and the time complexity is calculated and tabulated in the table 1 and table 2.The performance of the CMBS and STBS algorithm is studied by considering the precision rate of the algorithms and then the frame number that is extracted for segmentation The results are tabulated in the table 3 and table 4 respectively.

Table 1:Shows the frames and the time complexity for Performing the CMBS algorithm

Videos	Frame No	Time taken (Seconds)	Average (seconds)
	Frame 5	0.6159	0.6488
	Frame 10	0.6203	
	Frame15	0.6392	
	Frame 20	0.6694	
	Frame 25	0.6415	
	Frame 30	0.5668	
	Frame 35	0.6958	
	Frame 40	0.7005	
	Frame 45	0.6789	
	Frame 50	0.6598	
	Frame 11	0.7076	0.7212
	Frame 21	0.6992	
	Frame 31	0.7214	
	Frame 41	0.6815	
	Frame 51	0.6483	
	Frame 61	0.7368	
	Frame 71	0.7234	
	Frame 81	0.7121	
	Frame 91	0.8269	
	Frame 99	0.7548	

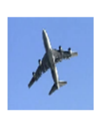
Table 2 :shows the frames and the time complexity for Performing the STBS algorithm

Videos	Frame No	Time taken (Seconds)	Average (seconds)
	Frame 1	18.123	18.123
	Frame 2	16.345	
	Frame 3	17.348	
	Frame 4	19.563	
	Frame 5	20.789	
	Frame 6	21.111	
	Frame 7	20.678	
	Frame 8	19.567	
	Frame 9	19.008	
	Frame 10	16.598	
	Frame 1	16.076	17.773
	Frame 2	18.699	
	Frame 3	15.214	
	Frame 4	16.815	
	Frame 5	17.483	
	Frame 6	16.368	
	Frame 7	19.234	
	Frame 8	18.121	
	Frame 9	20.269	
	Frame 10	15.548	

Table 3 :Shows the frame number and the precision for Performing the CMBS algorithm

Videos	Frame No	Tp	Fp	tn	fn	Precision	Pwc	Prc
	12	16445	6018	75043	391	0.732093	6.54668	93.4533
	22	16185	7470	72840	365	0.684211	8.08899	91.911
	32	16680	7370	73059	470	0.693555	8.03452	91.9655
	42	17400	5884	73412	701	0.747294	6.76099	93.239
	52	16767	8988	71026	631	0.651019	9.87455	90.1254
	16	7357	3287	86100	925	0.691188	4.31252	95.6875
	27	6995	3001	86480	1014	0.69978	4.11837	95.8816
	38	6751	3019	87070	873	0.690993	3.98309	96.0169
	49	5490	3153	88138	1187	0.635196	4.43002	95.57
	60	5050	2559	89391	590	0.663688	3.22677	96.7732

Table 4:shows the frame number and the precision for Performing the STBS algorithm

Videos	Frame No	Tp	fp	tn	fn	Precision	Pwc	Prc
	2	16159	2328	78116	691	0.874074	3.10297	96.897
	4	16693	5477	74398	625	0.752954	6.27823	93.7218
	6	16456	6964	73538	520	0.702647	7.67763	92.3224
	8	15961	5859	74909	475	0.731485	6.51619	93.4838
	10	15928	8447	71804	733	0.653456	9.47251	90.5275
	1	7819	2132	86611	636	0.78575	2.8478	97.1522
	3	7741	4319	84436	588	0.641874	5.05439	94.9456
	5	7818	4319	84547	263	0.644146	4.72629	95.2737
	7	7596	4167	84887	274	0.645754	4.58194	95.4181
	9	7719	4548	84601	186	0.629249	4.8777	95.1223

The table 5 and table 6 shows the precision rate for the all the videos and time taken for all the videos. Then the performance of both the algorithm with respect to precesion and time taken is analysised with the help of a graph in the fig 11 and fig 12.

Table 5: Shows the comparison study of the algorithms on the No of frames segmented

Video no	Precision for CMBS	Precision for STBS
1	92.1352	93.3874
2	95.9861	95.5863
3	88.1342	81.2041
4	89.9856	92.6063

Table 6: Shows the comparison study of the algorithms on time taken to segment the object

Video no	Time taken for CMBS	Time taken for STBS
1	0.6488	18.123
2	0.7212	17.773
3	0.639	13.776
4	0.6852	14.859

The graph in the fig 11 shows that the algorithm CMBS and STBS are segmenting the moving objects with the same precision rate for different videos. The graph in the Fig 12 shows that the CMBS algorithm take less amount of time for segmentation when compared to the STBS algorithm.

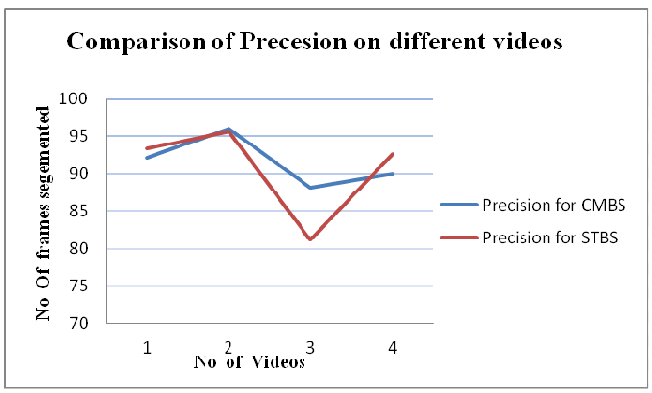


Fig 11: Shows the comparison of segmentation algorithm on Precision

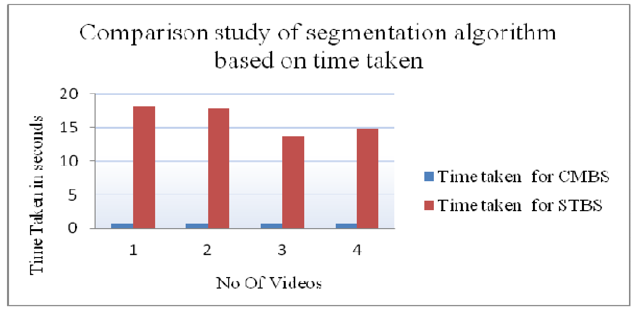


Fig 12: Shows the comparison of segmentation algorithm on Time taken

V. CONCLUSION

Video surveillance systems are becoming more popular in monitoring security sensitive areas such as banks, highways, borders, forests etc. In general, the video outputs of these more sensitive areas are processed in online by human operators and the remaining video outputs are recorded and kept for future use in case of a forensic event. However, as the number of surveillance systems increase, human operators and storage devices are becoming insufficient for operating of these systems. Sensors for detecting the moving objects in almost all video surveillance applications. Several techniques for moving object detection have been proposed

The existing methods presented in the literature survey fail to perform well, in the presence of limitations like illumination changes, changes in the back ground like sudden sunlight or cloudy weather, movement of trees and leaves due to wind and water movement in case of underwater condition that exists in moving object segmentation, which makes moving object segmentation a challenging and a difficult task.

In this paper an attempt has been made to segment the object using two algorithms, both the algorithms have segmented the object almost with the same precision rate of 93.56 frames and the time required to segment the object and the precision rate for both the algorithms are calculated and tabulated the CMBS algorithm on an average takes 0.65 seconds and STBS method takes on average 16.5 seconds.

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AUTHORS PROFILE

Ms.Kala Chandrashekhar L, working as Assistant professor in Department of Computer Science and Engineering, SJB Institute of Technology, Bangalore, Karnataka, India.

Ms. Manasa B S, working as Assistant professor in Department of Computer Science, SJB Institute of Technology, Bangalore, Karnataka, India.