Dynamic Object Segmentation Approach For Videos

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Abstract

Video analytics are analyzing video streams in real time and provide timely actionable information to make surveillance systems more predictable, accurate and efficient. Enhancing the quality of video, detecting events related to people, vehicles and enabling easy searching for video of interest. In this video analytics, image segmentation has become an indispensable task in many image and video applications.This work develops an image segmentation method based on, unsupervised dynamic object segmentation of moving and static objects occurring in a video. Objects are spatially cohesive and characterized by locally smooth motion trajectories, so they occupy regions within each frame. And, the shape and location of these regions vary slowly from frame to frame. So the existing methods don't give the fairly good segmentation performance results within a least time. The proposed method is demonstrated to take the least computational time for achieving fairly good segmentation performance results in various image types. Thus, DOS can be formulating as tracking regions across the frames, such that the resulting tracks are locally smooth. Most prior work focuses on simplified formulation of DOS- that of motion segmentation. Typically, these methods require that the number of moving objects or layers is pre-specified.

***Keywords* -** *surveillance, unsupervised, segmentation, cohesive, trajectories, region-growing, filters, stream, predictable, indispensable, frame, DOS.*

I. INTRODUCTION

In many applications involving visual inspection, it is required to separate objects (images) from background in an image taken under conditions of poor and non-uniform illumination. The purpose of this paper to presents a new method is unsupervised dynamic object segmentation approach (DOS) for videos. Not assuming any prior knowledge about location, number or category of objects, we take unlabeled videos as input and estimate motion segmentation. Our goal is to delineate the boundaries of all moving and static objects occurring in an arbitrary video. In general, objects are spatially cohesive and characterized by locally smooth motion trajectories. Therefore, they occupy regions within each video frame. Also, assuming relatively slow camera motions, the shape and location of these regions vary slowly from frame to frame. Thus, DOS can be formulate as tracking regions across the frames, such that the resulting tracks are locally smooth. Most prior work focuses on simplified formulation of DOS- that of motion segmentation typically, these methods require that the number of moving objects or layers is pre-specified.

II. VIDEO SEGMENTATION STRATEGIES

In this paper, we simplify video objects by area morphological operators. This method is different from standard morphology which uses a structuring element and avoids its disadvantages. To use a marker extraction (split and merge), which makes use of both luminance and color information. Then we use a region-growing algorithm to assign the remaining pixels, which follows the principles of [9] with a modification on color distance definition.

Video simplification

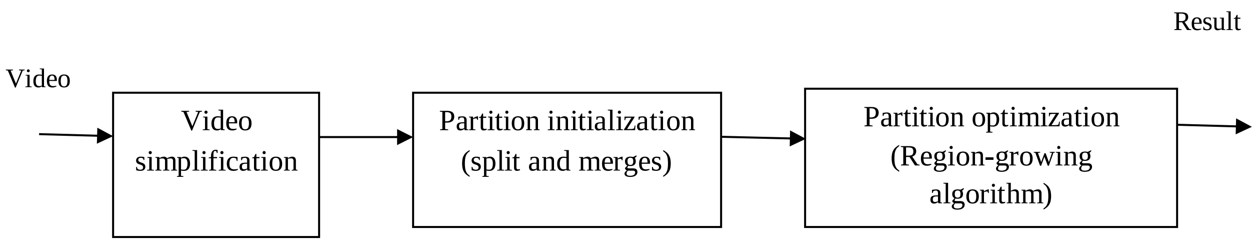

Fig: 1 Video simplification

In video segmentation, videos are first simplified for ease of segmentation. Many standard morphological filters are often designed to smooth noisy gray-level images by a determined composition of opening and closing with a given structuring element. A standard morphological opening (res. closing) simplifies the original image by removing the bright (res. dark) components that do not fit within the structuring element. However, object boundaries may be distorted according to the shape of the structuring element used. Boundary distortion can lead to false segmentation results.

In our work, we use area morphological operators [8], [9].An area open (res. close) operator on an image will remove all bright (res. dark) connected components that do not have a minimum area. Area openings and closings depend only on an area parameter and do not depend on structuring element shape.

Morphological operations

The core operations of video segmentation are mapped to morphological operations. First of all, the gradient operation can be shown as the following equation:

$G=I\oplus P-I\Theta P$ where G is a gradient image.

Where $\oplus$ is dilation, Θ is erosion, I is input image, and P is structuring element. It is a combination of morphological operations.

Post-Processing

The post-processing of our algorithm includes region size filtering and close-open operations. The region size filtering can be replaced with dilation and conditional erosion operations.

$$\underbrace{(((I\oplus P_n)\ \Theta P_n;I)\ldots\ \Theta P_n;I)}_{k}$$

Where k > (n−1)/2, n is proportion to the smallest allowed region size.

Moreover, the closing and opening operations are originally morphological operations. This can be shown as the following equations:

$I\circ P=(I\Theta P)\oplus P$ and $I\bullet P=(I\oplus P)\ \Theta P$

Where $\circ$ is opening and $\bullet$ is closing. These operations can also be employed for other change detection based algorithms.

A. Split and Merge Technique

In this technique first the image is split depending on some criterion and then it is merged. The whole image is initially taken as a single region then some measure of internal similarity is computed using standard deviation. If too much variety occurs then the image is split into regions. This is repeated until no more splits are further possible. Then comes the merging phase, where two regions are merged if they are adjacent and similar. Merging is repeated until no more further merging is possible. The major advantage of this technique is guaranteed connected regions.

In this improved method they have used three steps first splitting the image, second initializing neighbors list and the third step is merging splitted regions. They have divided the third step into two phases, in-house and final merge and have shown that this decomposition reduces problems involved in handling lengthy neighbour list during merging phase. The drawbacks of the split and merge technique are, the results depend on the position and orientation of the image, leads to blocky final segmentation and regular division leads to over segmentation (more regions) by splitting. This drawback can be overcome by reducing number of regions by using “minimum intra region variance and maximum inter region distance”.

Based on this principle we determine the optimal region number. Below we establish a compactness region based on this principle to find compact clustering so as to determine the optimal number of regions.

First, we want to find compact clustering with "minimum intra region variance." An intra-region distance measure is defined as the average distance between the data items and their cluster centers within clusters, and we want it to be as small as possible. It can be defined as

$$\text{Intra} = \frac{1}{N} \sum_{i=1}^{k} \sum_{x \varepsilon C_i} \|x - \mu_i\|^2$$

where |.| denotes the Euclidean norm, is the number of clusters, is the number of pixels in the image, and is the cluster centre of cluster . We obviously want to minimize this measure.

B. The Split-and-Merge (SM) Algorithm

The **split-and-merge** (SM) algorithm being developed by Pavilidis [6] in 1974 is still one of the most popular classical image segmentation algorithms and is widely used directly or indirectly in image processing. Let R represent the entire image having different objects. Segmentation may be viewed as a process that partitions R into n sub-regions, R_1, R_2, …, R_n, such that:

(a) $\bigcup_{i=1}^{n} R_i = R$,

(b) R_i is a connected region, $\forall i$,

(c) $R_i \cap R_j = \varphi \ \forall i, j, i \neq j$,

(d) $P(R_i) = \text{TRUE} \ \forall i$,

(e) $P(R_i \cup R_j) = FALSE \ \forall i, j, i \neq j$

Where $P(R_i)$ is a logical predicate over the set of pixels in the set of pixels in R_i and φ is the empty set.

Proposition (a) indicates that segmentation must be complete, that is, every pixel must be in a region while the second one indicates the pixels belonging to a region must be connected. The proposition of (c) represents that the regions must be disjoined and (d) deals with the properties that must be satisfied by the pixels in every segmented region R_i in such a way $P(R_i) = TRUE$ if all the pixels in R_i are equivalent with respect to predicate P. Finally, the proposition (e) indicates the regions R_i and R_j are different in the sense of predicate P. Now, the SM algorithm may be summarized by the following steps:

(a) Split any region R_i into four almost equal regions where $P(R_i) = FALSE$.

(b) Merge any adjacent regions R_i and R_j for which $P(R_i \cup R_j) = TRUE$.

(c) Stop when no further merging or splitting is possible. Otherwise repeat steps (a) and (b).

The basic idea of region splitting is to break the image into a set of disjoint regions which are coherent within themselves. If only a splitting schedule is used then the final segmentation would probably contain many neighboring regions that have identical or similar properties.

To illustrate the basic principle of these methods let us consider an imaginary image.

i) Let **I** denote the whole image shown in Fig 1(a).

ii) Not all the pixels in **I** are similar so the region is split as in Fig 1(b).

iii) Assume that all pixels within regions $\mathbf{I_1}$, $\mathbf{I_2}$ and $\mathbf{I_3}$ respectively are similar but those in $\mathbf{I_4}$ are not.

iv) Therefore $\mathbf{I_4}$ is split next as in Fig 1(c).

v) Now assume that all pixels within each region are similar with respect to that region, and that after comparing the split regions, regions $\mathbf{I_{43}}$ and $\mathbf{I_{44}}$ are found to be identical.

vi) These are thus merged together as in Fig 2 (d).

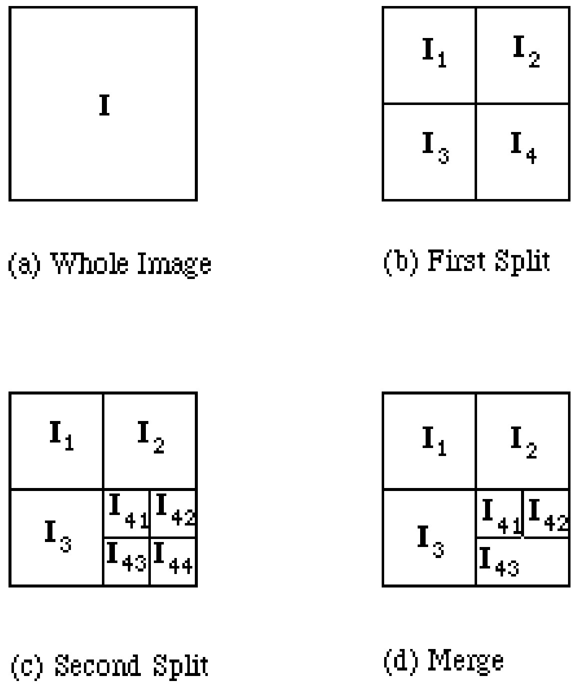

Fig: 2 Example of region splitting and merging

C. Region growing

Region growing [4] is a technique for extracting a region of the image that is connected based on some predefined criteria. This criteria based on intensity information. Region growing is an approach to image segmentation in which neighbouring pixels are examined and apply the validation process. In validation process first scans the segmented image and labeling the objects. Labeling should be done separately for black connected components and white. After labeling, the process scans the boundaries of labeled objects and looks up corresponding edge values in the region segmented in earlier. An object the average of its edge values in the region is not exceeded. This process is iterated for each boundary pixel in the region. If adjacent regions are found, a region-merging algorithm is used in which weak edges are dissolved and strong edges are left intact. A modified region growing algorithm is used in this paper based on the vector angle color similarity measure.

Let S = The set of pixels inside the region.

(x_0, y_0) = A pixel inside the region.

Q = Queue of pixels to be checked.

The region growing algorithm as-

Initialize S = Ø

Q = { (x_0,y_0) }

1. Select seed pixels within the image
2. From each seed pixel grow a region:

2.1 Extract pixel P from Q.

2.2 Add P to S.

2.3 For each region P′ of P:

If P’ is similar to P and P′ ∉ S then

Add P to Q.

2.4 If Q = Ø then end, else return to step 2.

2.5 Go to the next region to be examined.

This algorithm presents several advantages over the existing image segmentation algorithms. Region growing approach is simple. The border of regions found by region growing is perfectly thin and connected. The algorithm is also very stable with respect to noise.

***Region growing examples*:** Region growing methods often give very good segmentations that correspond well to the observed edges. Starting with a particular seed pixel and letting this region grow completely before trying other seeds biases the segmentation in favour of the regions which are segmented first.

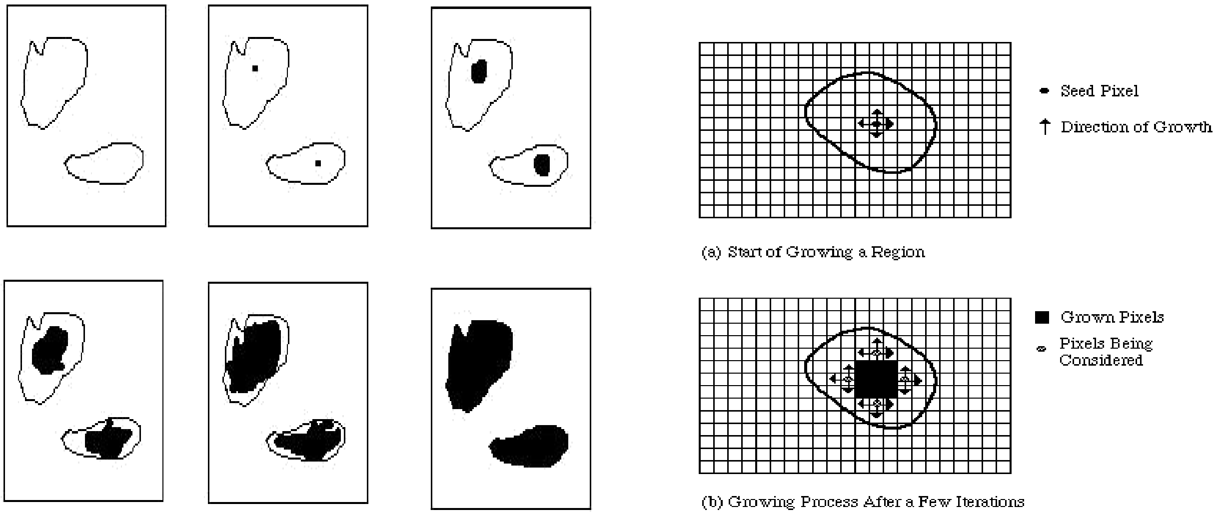

Fig: 3 Example of region growing

Experimental Results

***Opening*:** Opening is the compound operation of erosion followed by dilation (with the same structuring element), can show that the opening of I by B is the union of all translations of B that fit entirely within I

$I \circ B = (I \ominus B) \oplus B$

Example: I =

1	0	0	0	0
0	1	0	0	0
0	0	1	0	0
0	0	0	1	0
0	0	0	0	1

B=

1	$\underline{1}$	1

Erosion =

1	0	0	0	0
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0
0	0	0	0	1

Dilation=

1	1	0	0	0
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0
0	0	0	1	1

Therefore I o B=

1	1	0	0	0
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0
0	0	0	1	1

Closing: Closing is the compound operation of dilation followed by erosion (with the same structuring element), can show that the closing of A by B is the complement of union of all translations of B that do not overlap A.

I●B=(I⨁B) ϴB

Dilation=

1	1	0	0	0
0	1	1	0	0
0	1	1	1	0
0	0	1	1	0
0	0	0	1	1

Erosion=

1	0	0	0	0
0	0	0	0	0
0	0	1	0	0
0	0	0	0	0
0	0	0	0	1

Therefore I ● B =

1	0	0	0	0
0	0	0	0	0
0	0	1	0	0
0	0	0	0	0
0	0	0	0	1

Where I is a binary image, B is a structure element and 1s and 0s are pixels.

Erosion: Erosion shrinks the connected sets of 1s of a binary image. It perform OR operation.

It can be used for: •Shrinking features

•Removing bridges, branches, protrusions.

Dilation: Dilation expands the connected sets of 1s of a binary image. It perform AND operation.

It can be used for: •Growing features

•Filling holes and gaps

III. CONCLUSION

In this paper presents, an unsupervised dynamic object segmentation of moving and static objects based on area morphological tools has been presented. It involves three steps: simplification, split and merge (Marker-extraction) and region-growing.

Simplification removes disturbing component 0f the image while retaining the contours of the remaining elements. Marker extraction takes advantage of simplification, which identifies flat regions. Marker-extraction (split and merge) output is an image indicating the presence of homogeneous regions whose contours are not precisely defined. The last step decides accurate object boundaries by region-growing algorithm. As demonstrated, this unsupervised segmentation technique is robust. Our experimental work also shows that we can obtain very good spatial segmentation results from this technique.

IV. REFERENCES

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