A Survey on Image Segmentation Techniques for Edge Detection

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Abstract

Images in real world can be categorized based on the mode of capture, information, type i,e nature ,flowers etc. This is of vital importance as the user is interested in retrieving information specific to the category. The images need to be segmented in complex scene for providing the appropriate information. This leads to lot of challenges in real time. This paper presents a complete survey of different image segmentation techniques that are available. The paper offers suggestions for selecting the appropriate technique for segmenting the images based on the different performance parameters. A complete tabulation of the different segmentation techniques analyzed has been presented at the end of the paper. The segmentation techniques has been analyzed considering the edge detection as a vital factor. The paper also provides research directions for using neural approaches for segmentation.

Keywords: Edge, feature vector, neural network, segmentation, training function

1. INTRODUCTION

Image segmentation has been an area of active research for the past two decadesresulting in several image segmentation techniques that have been proposed and described in the image processing research literature. This proliferation is in part due to the fact that there exist several problem domains and applications that need to process and interpret image data in a domain-specific or applicationspecific manner. Moreover, depending on the problem domain or application, there are several types of images that could be processed and analyzed such as, light intensity (grayscale), color, range (depth), thermal (infrared), sonar, X ray (radiographic), nuclear magnetic resonance images (MRI), and so on.

Most existing image segmentation techniques can be broadly classified as based on:

(1) Gray-level thresholding which includes local, global, deterministic, fuzzy, and stochastic thresholding schemes;

(2) Markov random field models;

(3) Neural networks;

(4) Surface fitting, surface classification and region growing/splitting;

(5) Parameter space clustering which includes crisp, probabilistic, and fuzzy clustering;

(6) Edge detection techniques;

(7) Cost function optimization.

2. EXISTING APPROACHES

2.1 Segmentation- General Methods

Image Segmentation is a process by which raw input image is partitioned into different regions such that each region in the image should satisfy the following properties:

(1) Regions of segmented image should be uniform and homogeneous with respect to some characteristic, such as gray level, color, or texture.

(2) Region interiors should be simple and without many small holes.

(3) Adjacent regions of segmentation should have significantly different values with respect to the characteristic on which they are uniform.

(4) Boundaries of each segment should be smooth, not ragged, and should be spatially accurate.

General techniques for Image Segmentation:

(1) Clustering-based approaches

(2) Edge-based approaches

(3) Region-based approaches

(4) Based on Thresholding

2.1.1 Clustering-based approaches

The general problem in clustering is to partition a set of vectors into groups having similar values. In image analysis, the vectors represent pixels or sometimes small neighborhoods around pixels. The components of these vectors i.e. Features can include:

- Intensity values
- RGB values and color properties derived from them
- Calculated properties
- Texture measurements

K-means algorithm

In traditional clustering, there are K clusters C1,C2,...,CK with means m1,m2,..,mK. A least squares error measure can be defined as measures how close the data are to their assigned clusters. Least-squares clustering procedure could consider all possible partitions into K clusters and select the one that minimizes D.

Algorithm:

Form K-means clusters from a set of n-dimensional vectors.

(a) Set ic (iteration count) to 1.

(b) Choose randomly a set of K means m1(1),m2(1),...,mK(1).

(c) For each vector xi compute D{xi,mK(ic)}, for each k = 1,2,..,K and assign xi to the cluster Cj with the nearest mean.

(d) Increment ic by 1 and update the means to get a new set m1(ic),m2(ic),...,K(ic).

(e) Repeat steps c and e until Ck(ic) =Ck(ic + 1) for all k.

The merit is that, it gives good segmented regions than edge-based approach The demerit of K-means is that it is computationally infeasible and we have to mention number of means before clustering.

2.1.2 Edge-based approaches

Edge detection is the most common approach in detecting the discontinuities in intensity value. Such discontinuities are detected by using first- and second order derivatives.

(i) **Edge linking and boundary detection**

The edges getting from Gradient operator are discontinuous. So, we use edge linking methods to combine those edges.

(a) Local Processing: 3x3 masks can be applied to all pixels in order to find the pixels are edge pixels or not. All pixels that are similar according to predefined criteria are linked.

Two principle properties are used to find the similarity between the edge pixels. The merits if this approach is less computation time and good for small images. The limitation is that the edge is discontinuous.

2.1.3 Region-based approaches

Region Growing Approach

In region growing group the pixels that are similar based on predefined criteria. The basic approach is start with set of seed points and from these grows regions by appending to each seed those neighboring pixels that have similar properties

to the seed. The selection of similarity criteria and number of seed points depends upon the type of application.

Algorithm:

(a)Start with an initial seed pixel.

(b)Choose neighboring pixels, based on a connectivity and merge pixels that satisfy the homogeneity condition.

(c)If the region does not grow anymore select another seed and repeat the process Until all pixels are accounted for.

(d)A final tidying operation is often performed to remove very small regions.

The merit of this approach is that it has continuos contour.

2.1.4 Thresholding Techniques

Thresholding: It separates foreground image from background image based on some threshold value. If the pixel gray level intensity value is less than the assumed threshold value then we group that pixel into foreground image and otherwise, it can be grouped into background object.

Global Thresholding

This is applied to whole image, and extract foreground from background based on threshold value T. This approach is well suited for images whose background intensity varies with foreground intensity. This approach does not work well for images with high illumination change. The estimation of threshold is also a vital factor.

Basic Adaptive Thresholding

Due to the uneven illumination in the given image the histogram can not be partitioned based on single threshold value like in Global thresholding. So, in order to avoid this sub divide the given image into sub-regions, and then segment or extract foreground image from background image for each sub-region based on local threshold for each sub-region. The approach

i. Works well even the image having different illumination.

ii. Works well for simpler images.

3. SEGMENTATION OF MOVING VEHICLES

Moving vehicles segmentation has been actively investigated in the past decade [3][6] and [8] and has become an important topic in the intelligent transport systems (ITS). In real world scenes, challenges remain in the moving vehicles segmentation, such as unstableness of scenes, vibration of cameras and change of lighting conditions.

Background subtraction [21][3] [8] is an effective technique for foreground objects detection in stationary background. However, there are usually instable objects in the background of scenes, such as waving trees and flags fluttering. It is claimed that frame difference method [3] [6] may be suitable to dynamic scenes, especially for image sequence captured by static cameras. But, its applications in practice are counteracted due to two difficulties: (1) holes may emerge in the segmented objects when the objects move slowly; (2) there are ghosts behind the segmented objects.

Recently, a lot of methods are proposed to describe the dynamic scenes [3][18] [20][12][4][21][19] [17][6][9] . In Stauffer et.al Gaussian mixture model is used to segment the moving objects and can adapt to the changes of the scenes effectively. Some methods are proposed by modifying Gaussian mixture model. A hierarchical Gaussian mixture model [20] is proposed in background modeling to handle the sharp change of the illumination condition. In [16] an on-line EM algorithm is proposed to update the Gaussian mixture model.

Structural information can also be used to segment the moving objects in the dynamic scenes. In [17], the correlation information between the neighboring image blocks is extracted to tackle the waving trees problem. In [19], a set of simple low-level features are incorporated into the background model to capture the structural information.

Statistical models can be used to represent the features of the background to tolerate the unstableness of the scenes. In [9], Bayesian decision rule is used for each pixel with a blurred Gaussian PDF to segment the moving objects. In [14] Bayesian framework is proposed to incorporate spectral, spatial and temporal features within the background model.

The work of Toyama et al. (1999) uses a liner Wiener filter and a self-regression model at each pixel to obtain a prediction of the new intensity value on the basis of the last intensity samples. If the observed value differs significantly from the predicted one, the pixel is classified as foreground. In [6], a homomorphic prefilter is used before the frame difference to reduce the effect of fast illumination changes. In (Pless et al., 2003), several typical background models are discussed and receiver operator characteristic (ROC) curves are used to evaluate the performance of the methods.

Wei Zhang [1]et al(2006) proposed Gaussian motion model for moving vehicles segmentation in the dynamic scenes. By investigating the distinction between the motion vectors of the dynamic background and those of the moving vehicles, it is found that the motion vectors of the moving vehicles cluster in a small region while those of the dynamic background are dispersive. Consequently, Gaussian motion model is proposed to model the motion of the moving pixels in the scene, and Bayesian framework is employed to classify moving pixels into the moving vehicle or the dynamic background. In this methods traditional Exhaustive search method is used for finding the motion vector. Computational cost of the Exhaustive search method is high.

BIRCH[22] stands for Balanced Iterative Reducing and Clustering Using Hierarchies. It is used for clustering very large datasets. The algorithm preclusters data points using a clustering feature tree (CF-tree). A CF-tree is height-balanced, storing the clustering features (CF) (summarized or condensed representations) for the application of a hierarchical clustering. The clustering feature is defined as CF = (N,LS,SS), where LS is the linear sum and SS is the square sum of N data points in a cluster or leaf.

The basic steps of the algorithm are as follows:

For each point

1. The CF-tree is traversed to find the closest cluster

2. If the cluster is within a threshold then the point is absorbed into the cluster. The corresponding CF representation is updated

3. Otherwise, the point starts a new cluster with its own CF representation (involving insertion and/or node split)

BIRCH requires only a single scan of the data, with the computational complexity being O(N). The rebuilding process of the CF-tree is similar to insertion and node split of B+ trees. The algorithm is linearly scalable for large data and is capable of handling noise. The cluster summaries stored in the CF-tree are given to the hierarchical clustering algorithm for further processing. It works for spherical clusters of uniform size and considers only limited available memory. The weakness of the algorithm is that it handles only numeric data and is sensitive to the order of the pattern point insertions. The non-leaf nodes store sums of the CFs of their children. The parameters involved are the branching factor (maximum number of children per non-leaf node) and the threshold (maximum diameter of cluster stored at leaf node.

4. CONCLUSION

This paper has presented a complete survey of segmentation approaches for images. The information in video domain also can be completed with this approaches considering the fact that the video frames are handled as images. A broad idea of connecting the information in the images using clustering approaches has been presented. This could be taken to a selected domain of images and the approach can be evaluated.

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