ABSTRACT— In this paper, we discuss about the importance of Image Segmentation for use in Target Detection. There are many ways to segment an image into Regions. Depending on the Application, an Image segmentation technique is chosen. We compare available segmentation.

Keywords— Object detection, Image Segmentation, Region-based Merging

I. INTRODUCTION

The common problem encountered in Target detection is choosing a suitable approach for isolating different objects from each other with respect to the background. To make the object different and isolate it from rest of the object we simplify and/or changing the representation of the image by enhancing the visual representation of boundaries. This process is called Image Segmentation [1]. Image segmentation is the primary step towards image analysis for object detection, thus image segmentation is an important process in Image detection and recognition, there are various segmentation techniques like edge detection method[1,3], histogram based method[4,5], region growing method[1,2], region splitting method[1,2], clustering method, etc. The segmentation techniques is a technique which is being developed for ages, if we look back in time the segmentation technique like Edge Detection are based on abrupt changes in image intensity or colour, thus salient edges can be detected. However, due to often discontinued and over-detected resulting edges they can only provide candidates for the object boundaries.

II. REGION-BASED SEGMENTATION

The segmentation technique of region-based segmentation consists of region merging and region splitting [2], and split and merge [2]. The region-based segmentation algorithm is based on the similarities among the pixels with a region, the similarity can be any property of the region or the pixel. For clustering the collection of pixels of image into meaningful groups of region or objects, the region homogeneity is used as an important segmentation criterion. The widely used cut criteria includes normalized cut [6], minimum cut [8], ratio cut [7] and so on.

The basic approaches to region segmentation:

- Region merging – Recursively merge regions that are similar.

- Region Splitting – recursively divide regions that are heterogeneous.

- Split and merge – iteratively split and merge regions.

Image Regions and Partitions:

- Let \( R_m \subseteq S \) denote a region of the image \( m \in M \).
- We say that \( \{ R_m | m \in M \} \) partitions the image if
  \[
  \bigcup_{m \in M} R_m = S
  \]
  \( R_m \cap R_k = \emptyset \)
- Each region \( R_m \) has features that characterize it.
The advantages of region-based segmentation method: region carries more information in describing the nature of the object rather than each pixel. The number of regions in an image is much fewer than that of the pixels in an image thusly speeding up the process of region merging process. There are two fundamental issues in a region-based merging algorithm: order of merging and the stopping criterion.

After focusing on the issues related to region-based merging we can set a predicate, which is defined by sequential probability ratio test (SPRT)[9]. The predicate becomes the merging factor and decides whether to merge the regions obtained by over segmenting of an image.

Fig. 3 Flow of the Region Merging Algorithm

The following steps are involved in the region merging:

A. Image Pre-Processing

Image pre-processing can significantly increase the reliability of an optical inspection. Several filter operations which intensify or reduce certain image details enable an easier or faster evaluation. Before the image is used for over segmentation it is pre-processed as followed:

1) Convert to Grey scale
2) Calculate gradient magnitude
3) Removing noise

B. Image Over Segmentation

After pre-processing the image it is segmented using watershed algorithm [10]. The major drawback of watershed algorithm is that the result is over segmented (i.e. large number of regions are created). To overcome this problem we have a solution “flooding” from the selected marker [16+] such that only the most important regional minima are saved for segmentation.

C. Labelling

Labelling is to label the similar regions after using the image over segmentation by watershed algorithm. With these labels, an image is partitioned into a meaningful collection of regions and objects. Now for to make a region meaningful we need to combine the regions with the help of RAG [13]. The RAG (region adjacency graph) is an algorithm which computes the graph of adjacent regions in a labelled image. Each vertex in the graph represents a region and is associated to some attribute of that region.

Let $G = (V, E)$ be an undirected graph, Where $\forall v \in V$ is a set of nodes corresponding to image elements, The region is represented by a component $R \subseteq V$ The dissimilarity between two neighbouring regions $R_1, R_2 \subseteq V$ as the minimum weight edge connecting them.

$$S(R_1, R_2) = \min_{v_i, v_j \in R_1 \cup R_2} w((v_i, v_j)) \quad (1)$$

The RAG basically helps us to initialise the merging of the image; the advantage of RAG is that it can provide a “spatial view” of the image.
After we find the RAG, we will find the region merging predicate which will then decide the merging between the pair of regions.

### D. Region Merging Predicate

The merging of the two regions depends upon the two similarity between the two region, after finding out the similarity between the edges of the two regions the data is however not sufficient to merge the two region thus a predicate $P$, will decide to merging of the regions.

The typical region features are given below:

1. **Colour**
   - Mean RGB value
   - 1-D colour histograms in R, G, and B
   - 3-D colour histogram in (R,G,B)
2. **Texture**
   - Spatial autocorrelation
   - Joint probability distribution for neighbouring pixels
   - Wavelet transform coefficients
3. **Shape**
   - Number of pixels
   - Width and height attributes
   - Boundary smoothness attributes
   - Adjacent region labels

The recursive region merging

Define a distance function between regions. In general, this function has the form

$$d_{k,l} = D(R_k, R_l) \geq 0$$

Ideally, $D(R_k, R_l)$ is only a function of the feature vectors $f_k$ and $f_l$.

$$d_{k,l} = D(f_k, f_l) \geq 0$$

Then merge region with minimum distance.

Example of Merging Criteria by predicate:

Distance formed by a weighted combination of the two

$$d_{k,l} = \alpha \left( \frac{N_k}{N_{new}} \sqrt{(k - new)^2 + \frac{N_l}{N_{new}} \sqrt{(l - new)^2}} \right) + \beta \left( \frac{N_k}{N_{new}} \sqrt{c_k - c_{new}}^2 + \frac{N_l}{N_{new}} \sqrt{c_l - c_{new}}^2 \right)$$

Where $N_k = |R_k|$

$$k = \frac{\sum_{s \in R_k} x_s}{N_k}$$

$$c_k = \frac{\sum_{s \in R_k} s}{N_k}$$

$$R_{new} = R_k \cup R_l, N_{new} = N_k + N_l$$

$$c_{new} = \frac{N_k c_k + N_l c_l}{N_{new}}$$

There exists another way to find the consistency by the consistency test of cues [14].

The algorithm for consistency test of cues is:

$P_d(x | \theta_0)$ and $P_f(x | \theta_1)$ are the distributions of visual cues, $I_a$ and $I_b$ are the average colour of sampled data in a and b regions respectively. $I_{a+b}$ is the average values of the sample, $S_i$ is the covariance matrix of the regions, $\lambda_1$ and $\lambda_2$ are scalar parameters, $A$ and $B$ are the upper limit and lower limit of the likelihood ratio[12], $\alpha$ and $\beta$ are the probability of the decision error.

Present $\lambda$;

Let $\lambda_2 = 1, \alpha = 0.05, \beta = 0.05$;

Compute parameters:

$N_0$: be a constant greater than $\max\{|E(\delta | \theta_0), E(\delta | \theta_1)|\}$

$A=\log (1-\beta)/\alpha, B=\log \beta (1-\alpha)$;

$P_d(x | \theta_0), P_f(x | \theta_1)$ are computed using:

$$P_d(x | \theta_0) = \lambda_1 \exp(-((I_b - I_{a+b})^T S_i^{-1} (I_b - I_{a+b})))$$

$$P_d(x | \theta_1) = 1 - \lambda_2 \exp(-((I_b - I_a)^T S_i^{-1} (I_b - I_a)))$$

Input: a pair of neighbouring regions.
Output: the decision D that the two regions are “consistent” (D=1) or “inconsistent” (D=0).

1) Set evidence accumulator δ and the trials counter n to be 0.
2) Randomly choose m pixels in each of the pair of regions, where m equals the half size of the region.
3) Calculate the distributions of visual cues x using Eq. (5) based on these pixels.
4) Update the evidence accumulator
\[ \delta = \delta + \log \frac{P_0(x_i | \theta_0)}{P_1(x_i | \theta_1)} \] (6)
5) If n ≤ N0
   - If δ ≥ A, return D=1 (consistent)
   - If δ < B, return D=0 (inconsistent)
6) Go back to step 2.

After we find the region merging predicate we merge the regions together, there are different ways to merge the regions like Recursive merging algorithm [15], statistical merging algorithm [11], dynamic region merging algorithm [14], etc.

1) Recursive merging algorithm
   - Define a distance function between regions
   \[ d_{k,l} = D(f(R_k), f(R_l)) > 0 \]
   Repeat until |M| = 1 {
   Determine the minimum distance regions
   \[ (k*, l*) = \arg\min_{k_i \in M} \{d_{k,l}\} \]
   Merge the minimum distance regions
   \[ R_{k*} \leftarrow R_{k*} \cup R_{l*} \]
   Remove unused region
   \[ M \leftarrow M \setminus \{l*\} \]
   • This recursion generates a binary tree.

2) Dynamic region merging segmentation:

Input: the initially over segmented image S0.
Output: region merging result.

1) Set i=0.
2) For each region in segmentation Si, use Algorithm 1 to check the value of predicate P with respect to its neighbouring regions.
3) Then merge the pairs of neighbouring regions whose predicate P is true, such that segmentation S_{i+1} is constructed.
4) Go back to step 2 until S_{i+1} = S_i.
5) Return S_i.

III. RESULTS

Fig. 4 Example (1) Image of a defence plane.

Fig. 5 Result after segmenting the Example (1) Image by dynamic region merging
IV. CONCLUSIONS

Thus we conclude this paper by describing briefly about the different techniques of region merging and its implementation. We also discussed about the various ways of finding the predicate for the region merging like the consistency test of cue used in dynamic region merging and distance between color means, region center, etc.

REFERENCES


