Enhancement of Image Segmentation Based on Modularity Optimization

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ABSTRACT--Image segmentation is the technique of dividing a digital image into several segments or categories and change the representation of image into something that is more meaningful and easier to analyze. Over segmentation is the major problem in image segmentation. In the problem of over segmenting an image into sizeable homogeneous region various techniques have been followed which seems to be time consuming and produces repetitive pattern. To overcome the over segmentation problem an efficient firefly algorithm is used for segmenting an image. This is proposed by combining image properties and applying modularity optimization to the large range of datasets.

Keywords—over segmentation, firefly algorithm, modularity optimization.

I.INTRODUCTION

Image processing is a technique of converting an image into digital form and performs some effort on it, in order to get an enhanced image or to extract some useful information from it. It takes input as an image, like video frame or photograph and output may be an image or characteristics associated with that image. This technology is used for business, engineering, science and medical field.

A.Image Processing Techniques

Digital processing is a techniques pushed in normal up of the digital images by services computers. As outlying inkling outlandish imaging sensors contains deficiencies in color, shape etc. To get over such flaws and to get originality of information, it has to undergo various phases of processing.

The various image processing techniques are
1. Image Representation

2. Image Preprocessing
3. Image Enhancement
4. Image Restoration
5. Image Analysis
6. Image Reconstruction
7. Image Data Compression

B. Image Segmentation

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as superpixels). Image segmentation is typically used to locate objects and boundaries in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. [12]

Figure 1.1 shows the image segmentation is the process that subdivides an image into its constituent parts or objects. The level to which this subdivision is carried out depends on the problem being solved, i.e., the segmentation should cancel when the objects of interest in an application have been separated e.g., in autonomous air-to-ground target acquisition, suppose our interest lies in identifying vehicles on the path, the first step is to segment the road from the image and then to segment the contents of the road down to potential vehicles. Image thresholding techniques are used for image segmentation.
II. RELATED WORK

In the existing system, many image segmentation algorithms have been proposed. Here we discuss the algorithm that is used in the project.

A. Mean Shift Algorithm

The mean shift algorithm treats image segmentation as a problem of clustering by detecting the modes of the probability density function in the feature space. Every pixel in the image is transformed to the joint spatial-range feature space by joining the pixel color value and its spatial coordinates into a single vector. Then the mean shift procedure is established in this feature space to yield an intersection point for each pixel. All the pixels whose convergence points are nearer than the spatial bandwidth $h_s$ and the range bandwidth $h_r$ are claimed to be in the same segment. Minimum segment size is enforced to gain sizable segmentation. Although this method is usually fast, it is very sensitive to the bandwidth parameter $h_r$ and $h_s$, and often results in over segmentation.

B. Normalized Cut

Normalized cut is a popular graph partition approach incorporates the global information of the image into the segmentation. Given an affinity matrix $W$ with each entry representing the similarity or dissimilarity between two pixels, normalized cut tries to rectify the generalized eigen vector problem.\[ (D - W)y = \lambda Dy \]
where $D$ is the diagonal matrix with its diagonal entry $D_{ii} = \sum_j W_{ij}$. Then the segmentation is achieved by clustering the eigenvectors. A variant is the multiscale normalized cut approach, which allows us to deal with larger images by compressing large images into several scales. However, it has the common problem with normalized cut, specifically, it:

- Often breaks uniform or fine regions where the eigenvectors have smooth gradients
- Has a high time complexity
- Needs a predefined number of segments, which itself is a challenging problem.

More graph-based segmentation can be found. However, they all need human intervention, that is, they need a user to specify the number of regions resulting from image segmentation.

C. Watershed Segmentation

The Watershed segmentation method is based on the gradient magnitude of an image as a topographic surface. The pixels where a water drop starts from will flow to the local intensity minimum are in one segment, which is called catchment basins. Various improved methods are available, but these methods are generally sensitive to noise and easily produce oversegmentation. [30]

D. Graph Partition Algorithm

In this algorithm the image is regarded as an undirected weighted graph, while each pixel is taken as a node in the graph and the edge weights undertake the similarity or dissimilarity between nodes. Consider each pixel as a single component in the starting stage, and place the edge weights of dissimilarity in a non-decreasing order. For each iteration, the algorithm merges component $C_1$ and $C_2$ connected by the current edge, if the corresponding edge weight is less than $\min(\text{Int}(C_1) + \tau(C_1), \text{Int}(C_2) + \tau(C_2))$ where $\text{Int}(C)$ is the internal difference of component $C$, defined as the largest weight in the minimum spanning tree of component $C$, $\tau(C) = k/|C|$, and $k$ is a constant parameter to control the minimized size of the segment. This algorithm explains nearly linear time complexity, however, it is very difficult to tune the parameter $k$ for optimal segmentation.

III. PROPOSED SYSTEM

A. Overview

The proposed system explains the limitations of modularity based image segmentation. Considering the following:

- Time complexity
- Regularity preservation
- The prevention of over segmentation.
Modularity is a crucial quantity, which is used to calculate the functions of various community detection algorithms. Considering the efficient calculation of modularity in the community detection algorithm, we regard image segmentation problem as a community detection problem, and the optimal segmentation is gained when the modularity of the image is maximized. It still faces similar problems as other aforementioned segmentation algorithms have, owing to the ignorance of the inherent properties of images. Different from the previous algorithms based on modularity, we identify the differences between community detection and image segmentation, starting from superpixels and propose a new texture feature from low-level cues to capture the regularities for the visually coherent object and encode it into the similar matrix, moreover, the similarity among regions of pixels is built in an adaptive manner to generate oversegmentation. Compared with other existing segmentation algorithms, our proposed algorithm can automatically find the number of regions/segments in an image, produces sizable regions with coherent regularities preserved, and achieves good semantic level segmentation to some extent.

- An efficient agglomerative segmentation algorithm incorporating the advantage of community detection and the inherent properties of images is developed.
- A new texture feature, namely, Histogram of States (HoS) is implemented to capture the similarities in the image. The HoS feature, convene with the color feature, encodes better similarity measure of the semantic level, and is more likely to preserve regularities in the object.
- The adaptive similarity matrix is constructed to avoid oversegmentation. In each iteration, the similarity between two areas of pixels is calculated once again to reevaluate the color and texture regularity. It can effectively avoid breaking coherent regions, which share some regularities or have smooth changes in color or texture caused by shadow or perspectives.

B. Efficient Implementation Of Firefly Algorithm

Firefly Algorithm (FA) was first developed by Xin-She Yang in late 2007 and 2008 at Cambridge University which was based on the flashing patterns and behaviour of fireflies. In this paper firefly algorithm is applied in segmentation part in order to increase the efficiency in the steps of precision, sensitivity and accuracy.

FA is infested with intelligence-based, thus it has the similar prudent that other swarm-intelligence-based algorithms have. In fact, a simple analysis of parameters suggests that some PSO variants such as Accelerated PSO are a special debate of firefly algorithm when $\gamma, \delta = 0$.

FA has two major advantages: automatically subdivide and the capability of dealing with multimodality. First, FA is based on attraction and attractiveness that reduces with distance. This leads to the fact that the whole population can automatically subdivide into subgroups. Among all these modes, the perfect solution can be found. Second, this subdivision allows the fireflies to be able to find all optima simultaneously if the population size is inversely proportional to the number of modes. Mathematically, $1/\sqrt{P}$ controls the average path of a group of fireflies that can be seen by adjacent groups. Therefore, a whole population can subdivide into small groups with a given, average distance. In the extreme case when $\gamma = 0$, the whole population will not subdivide. This automatic subdivision ability makes it particularly suitable for highly nonlinear, multimodal optimization problems. In aide, the parameters in FA can be tuned to control the randomness as iterations proceed. This essential advantage makes it flexible to deal with sequence problems, clustering and classifications, and combinatorial optimization as well.

The firefly algorithm (FA) was developed by Yang (2008) and uses three main basic rules

- A firefly will be attracted by other fireflies regardless their sex.
- Attractiveness is proportional to their brightness and decreases as the distance among them increases.
- The landscape of the objective function determines the brightness of a firefly.

FA algorithm is used for segmenting the mammogram images. The FA has been designed based on the flashing lights of a swarm of fireflies. The glowing light is important for a firefly. Using the flashing light, a firefly can detect the tumour part. To inspire an algorithm from the behaviours of fireflies it seems that the flashing light intensity should be used.

A firefly contract its movement by considering the flashing side stress of targets. A swarm of fireflies attracts to the brighter and more interesting locations by the flashing element intensity that associated with that Discourse. In the prosecution of the FA, it is stilted that the brighter locations represent better solutions. Significance, the algorithm tries to help the fireflies to find such
locations in the search space. In middling, the blast of the flashing light is considered as the plan function. The attraction of a firefly depends on the flashing brightness of the target location. The brightness decreases as the distance between a firefly and the target location increases.

In the simplest case for maximum optimization problems, the brightness $I$ of a firefly at a fixed location $x$ can be chosen as $I(x) \propto f(x)$. The attractiveness $b$ is relative, it should be found in the eyes of the beholder or judged by the other fireflies. Thus, it will vary with the distance $r_{ij}$ between firefly $i$ and firefly $j$. In addition, light intensity decreases with the distance from its source, and light is also seen in the media, so we should permit the attractiveness to vary with the degree of absorption. In the simplest form, the light intensity $I(r)$ varies according to the inverse square law $I(r) = I_s r^{-2}$ where $I_s$ is the intensity at the source. For a given medium with a fixed light absorption coefficient $g$, the light intensity $I$ varies with the distance $r$. That is $I = I_0 r^{-1}$ where $I_0$ is the original light intensity.

As a firefly’s attractiveness is proportional to the light intensity seen by adjacent fireflies, we can now define the attractiveness $b$ of a firefly by $b = b_0 r^{-2}$ where $b_0$ is the attractiveness at $r = 0$.

The firefly algorithm can be presented in the following pseudo-code form:

1. Initialize algorithm’s parameters
   - number of fireflies ($n$),
   - maximum number of generations (iterations, Max-Gen),
   - Define the objective function $f(x)$, $x = (x_1, \ldots, x_d)^T$.
   - Generate initial population of fireflies $x_i$ ($i = 1, 2, \ldots, n$) //generate $n$ initial solutions
   - Light intensity of firefly $I_i$ at $x_i$ is determined by value of objective function $f(x_i)$

2. While $k < \text{MaxGen}$//($k = 1 : \text{MaxGen}$)
   - For $i = 1:n$//all $n$ fireflies
     - For $j = 1:n$
       - If ($I_j > I_i$) move firefly $i$ towards firefly $j$ in $d$-dimension according to Equation;
       - End if
     - Obtain attractiveness, which varies with distance $r$ to find new solutions and update light intensity.
   - End for $j$
   - End for $i$
   - Rank the fireflies and find the current best
   - End while

3. Find the firefly with the highest light intensity, visualization.

The figures 3.1,3.2,3.3 represents the function of fireflies and also explains the initial locations and their iteration during the process.

Fig. 3.1 - example function

Fig. 3.2 - The Initial Location of 50 Fireflies

Fig. 3.3 - The Location of Fireflies after 50 Iterations

IV. CONCLUSION AND FUTURE ENHANCEMENT

Thus an efficient algorithm for segmenting an image is proposed by combining image properties and applying modularity optimization to the vast range of datasets. The count of image segments can be detected automatically and similarity matrix among different regions is constructed using color
and HoS texture features, thereby optimizing the modularity and recursively aggregating the neighborhood regions. When there is no modularity increase, the segmentation is set to be optimized. Experimental results have been qualitatively tested using popular performance metrics using VOl. SSDS and Precision on BSDS500. The algorithm is faster than CTM and TBES and since it avoids over segmentation, lower recall values are achieved.

Agglomerative algorithm has been widely studied. This algorithm mainly focused on the computational efficiency by using the data structure of region adjacency graph and nearest neighbor graph.

REFERENCES


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