EVALUATION OF DIFFERENT IMAGE SEGMENTATION METHODS WITH RESPECT TO COMPUTATIONAL SYSTEMS

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ABSTRACT

Image segmentation is a fundamental step in the modern computational vision systems and its goal is to produce amore simple and meaningful representation of the image making it easier to analyze. Image segmentation is a subcategory of image processing of digital images and, basically, it divides a given image into two parts: the object(s) of interest and the background. Image segmentation is typically used to locate objects and boundaries in images and its applicability extends to other methods such as classification, feature extraction and pattern recognition. Most methods are based on histogram analysis, edge detection and region-growing. Currently, other approaches are presented such as segmentation by graph partition, using genetic algorithms and genetic programming. This paper presents a review of this area, starting with taxonomy of the methods followed by a discussion of the most relevant ones.

KEYWORDS:

Image segmentation , histogram analysis & Edge detectors.

1. INTRODUCTION

1.1 IMAGE SEGMENTATION

Segmentation is a pre-processing step where images are partitioned into several distinct regions and each is a set of pixels. Mathematically, image segmentation may be represented as P_n representing the regions of pixels R_n with n pixels the region can be described as union of all pixels connected, satisfying equation 1:

$$R_n = \cup_{i=1}^{n} P_i \tag{1}$$

Several image segmentation methods were proposed in the literature. However, a single method may not be efficient for a specific image class. Frequently, it is necessary to combine more than one method to solve interesting real-world problems. The main methods for image segmentation are based on histogram analysis, edge detection and segmentation by regions.

1.2 HISTOGRAM ANALYSIS

The image histogram analysis is a common method for image segmentation. A histogram is a graphical representation in which a data set is grouped into uniform classes such that in the horizontal axis the classes are represented and, in vertical axis, the frequencies in which the values of this class are present in the data set. Based on the central tendency or histogram variation it is possible to determine the cutoff point that will be used as threshold in these segmentation process. In this approach classes with high and low frequency are identified where a class with low frequency between two high frequency classes usually represents the best cutoff point to image threshold. An example of histogram analysis is presented in figure 1 (b) where classes with high and low frequencies can be seen.

An efficient approach for image segmentation based on histogram analysis is the Otsu method(Otsu, 1979).This method performs several iterations analyzing all possible thresholds to look for the best threshold T that presents the highest inter-class variance. This method assumes that the image to be segmented will be classified in two classes, object and background, and threshold point will be determined by the pixel intensity value that represents the minimum variance intra-class. In Otsu's method the threshold that minimizes the intra-class variance is exhaustively search and can be defined as a weighted sum of the variances of the two classes, as shown in equation 2:

$$\sigma^2_{intra} = W_a \sigma^2_a + W_b \sigma^2_b$$

(2)

Where, σ represents the variance of these classes and weights Wire presents the occurrence probability of each class being separated by a threshold T. Figure 1 (a) shows the original image in grayscale and figure 1 (c) shows image segmented by Otsu approach.
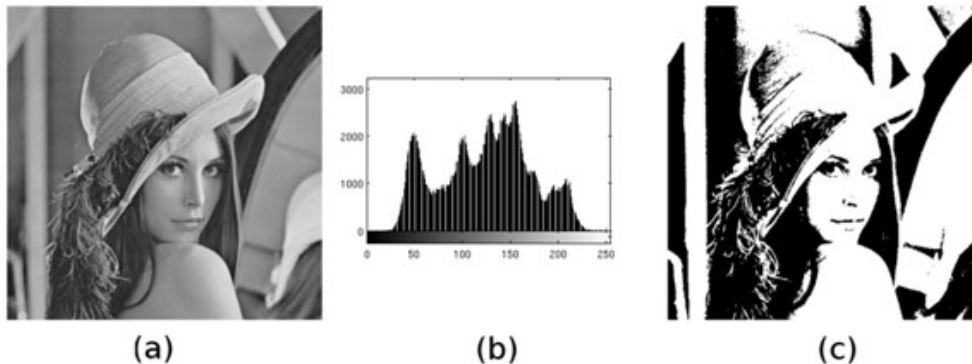

Figure 1. (a) Original gray-level image. (b) Original histogram image. (c). Segmented image using Otsu approach.

1.3 EDGE DETECTION

Edge detectors are common methods to find discontinuities in gray level images. An edge is a set of pixels of similar intensity level connected by adjacent points. We can find out edges estimating the intensity gradient. Edges in images can be divided in two distinct categories: edges of

intensity and edges of texture. In the first, the edges arise of abrupt changes in the image pattern and, in the second case, edges are detected by limits of textures in regions invariant to illumination changes(Tan, Gelfand, & Delp, 1989).

The Roberts edges operator(Fu & Mui, 1981) performs a simple 2-D spatial gradient analysis in digital images and emphasizes regions with high spatial gradient that can be edges. This method is a fast and simple convolution-based operator and usually the input of the method is a grayscale. Basically, Convolution masks can be applied to the input image to produce the absolute magnitude of gradient and the orientation. If applied separately it is possible to measure the gradient component in each orientation. The gradient magnitude is given by equation 3 and an example of image segmentation using Roberts edge operator can be seen in figure 2 (a):

$$|G| = |G_x| + |G_y|$$

(3)

In simple terms, the Sobel operator computes an approximation of the gradient of image intensity at each point and finds the contrast by a differentiation process (Duda& Hart, 1973). Thus, regions of high spatial frequency that correspond to edges are detected. The Sobel operator is a discrete differentiation operator and it is used to find the approximate absolute gradient magnitude at each point in an input grayscale image. Technically, the Sobel edge detector uses a simple pair of 3 x 3 convolution mask to create a series of gradient magnitudes like the Roberts edge operator. An example of image segmentation using Sobel edge operator can be seen in figure 2 (b).

In the edge detecting process, itis important consider three criteria: detection, localization and minimal response. Firstly, all edges occurring in image should be detected and there should be no-responses to non-edge. In other words, the signal-to-noise ratio should be minimized. Second, the error between the edge pixels detected and the real image edge should be minimized. A third criterion is to have a unique result to a simple edge, eliminating multiple detections to an edge (one edge should not response in more than one detected edge).

Based on these criteria the Canny edge detection algorithm is known as the optimal edge detector (Canny, 1986). To satisfy these requirements Canny calculated the variations that optimizes a given function and proposed your approach in five stages: noise reduction (smoothing), finding intensity gradients, non-maximum suppression, tracing edges through double threshold, and edge tracking by hysteresis.

Since the Canny method is sensitive to noise, a smoothing is necessary before trying to locate and detect edges. Thus, considering the good results and the facility to compute the Gaussian filter using a simple convolution mask, it is used in the Canny operator. A smoothed and slightly blurred image is produced after this step.

The next step is to find the intensity gradient of the image. So, the Canny operator uses algorithms to detect horizontal, vertical and diagonal edges in smoothed image. In this stage the Roberts or Sobel operators can be used to find the first derivative in the horizontal (Gx) and vertical (Gy) directions. From this edge gradient and direction, the edge direction angle can be determined, by using the arctangent function. The edge direction angle is approximated to one of

four angles representing vertical, horizontal and diagonals (0, 45, 90 and 135 degrees), as shown in equation 4:

$$\Theta = arctan\left(\frac{|G_x|}{|G_y|}\right)$$

(4)

After the directions are known, non-maximum suppression should be applied to trace along the edge in the edge direction and suppress any pixel value that is not considered to be an edge. Basically, this is done to preserve all local maxima in the gradient image ignoring anything else. This procedure will give the inline edge as result.

Tracing edges with double threshold is a way of eliminating streaking. Streaking is the breaking up of an edge contour remaining after non-maximum suppression. The edge pixels after non-maximum suppression step should be analyzed pixel by pixel. Probably many of them are edge pixels, but some may just be noise or color variations because of un even surfaces. To solve this problem it is possible to use double threshold with a high and a low value. Thus, edge pixels below the low threshold are considered non edges, edge pixels between low and high thresholds are considered weak edges, and edge pixels above the high threshold are considered strong edges. Finally, it edge tracing is done by hysteresis. In this process the strong edges are immediately included as edges in the final image and the weak edges are included if and only if they are connected to strong edges. Strong edges represent actual contours in the original image. However, noise and small variations have no influence enough to be characterized as edges. Thus, even in small numbers, the weak edges that are close to strong edges tend to compose the final result. The other weak edges distributed independently by image will be ignored. The final edge tracking process results is a binary image where each pixel is labeled as an edge pixel or non-edge pixel. Figure 2 (c) shows an example of image segmentation using Canny's operator.
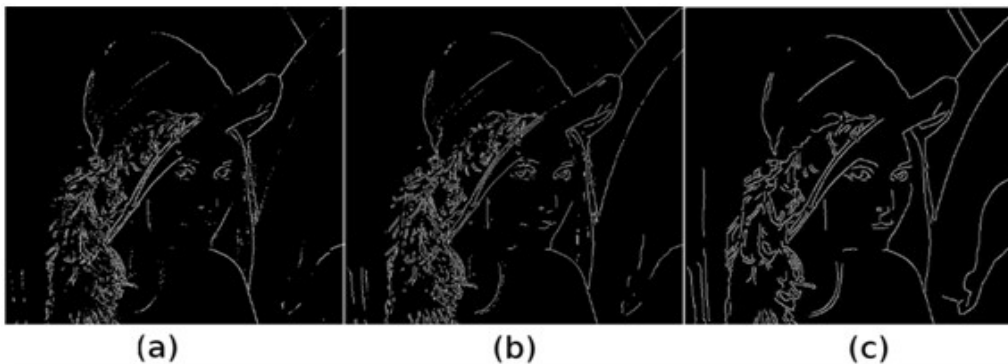

Figure 2. (a) Segmented image using Roberts's method. (b) Segmented Image using Sobel's method.
(c) Segmented image using Canny'soperator.

1.4 SEGMENTATION BY REGIONS

This section presents region-based methods for image segmentation using growth regions and splitting-merging approach.

In the splitting-merging approach, images are subdivided arbitrarily disconnecting regions and then these regions are again connected, or disconnected, to satisfy predefined constraints. The algorithm is iterative and first divides the image into four disconnected quadrants and then joins any adjacent region that satisfies the constraints. This process will be performed while one can split and join regions considering the constraints conditions(Trémeau & Borel, 1997).

In image segmentation by growing region, pixels are grouped based on predefined criteria that are started from a set of initial seeds. Starting from seed points, new regions are created by grouping neighboring pixels with similar properties. The selection of seed points in color images is a critical procedure. In this case, a set of descriptors based on intensity levels and spatial properties are required. The region growing images segmentation methods more cited in the literature are Watershed Transform and Mumford & Shah Functional(Raut, Raghuwanshi, Dharaskar, &Raut, 2009).

In Watershed Transform it is considered the gradient magnitude of image and surface topography. Pixels with gradient magnitude intensity (GMIs) represent the limits of the largest area and correspond to watershed threshold. This method has some variants and calculates the gradient magnitude intensity for all pixels in the image. With variance values of gradient it is possible to perform a topographic surface with valleys and mountains. The lower regions will correspond to low gradient while the highest regions correspond to the high gradient. The growth region procedure would be equivalent to flood performed at same speed in each local minimum, starting from the lowest one and then flooding the region until the maximum altitude reaches the global maximum.

In Watershed Transform the segmentation is perform with watershed regions that are formed flooding from local minimum. Flooding is controlled by dams that separate different local minima. The dams that emerge to the water surface are watershed lines. These dams are formed by closed contours around each regional minimum and correspond to ridges performing the segmentation by division line(Bleau& Leon, 2000). Figure 3 (b) shows an example of region growing image segmentation using watershed approach applied to figure shows in figure 3 (a).

Figure 3. (a) Original gray-level image. (b) Segmented image using watershed approach.

The Mumford and Shah functional algorithm assumes that each region is a group of pixels that behaves like an elastic material (like rubber). Regions can grow as long as possible to stretch this rubber. The basic principle is that the higher the variance between pixels in an area, the lower the elasticity of the material. Mathematically, the Mumford and Shah functional algorithm is very

simple and produces best results for general use when compared with other region growing algorithms. However, depending on the image, its time computational complexity can become a problem. In most cases it is necessary high investments to perform complex computational computation to obtain results(Jiang, Zhang, &Nie, 2009).

The image segmentation method is based on am a the metical model described by the energy equation of Mumford and Shah functional. This functional energy equation uses image grayscale variance considering that the higher gray level variance, the larger the difficulty to join these regions. This energy will determine if one can group with other regions, thereby delimiting the regions endings(Mumford &Shah, 1989). The simplified form of the Mumford and Shah functional expresses the segmentation problem as a minimization, as shown in equation 5:

$$E(u, K) = \int_{\Omega/k} \|u - g\|^2 \mathrm{dxdy} + \lambda l(K)$$

(5)

Where Ω is the domain of the image, K is a set of boundaries with total length l(K), g is a scalar or vector-valued function of the channels of the image on the domain Ω, u is a piecewise constant approximating scalar and λ is the regularization parameter for the boundaries. If λ is small, then a lot of boundaries are allowed and a good segmentation may result(Redding, Crisp, Tang, & Newsam, 1999). Figure 4 (c) shows an example of region growing image segmentation using Mumford and Sha mathematical model using the algorithm proposed by (Grady &Alvino, 2009) applied to figure shows in figure 4 (a). Figure 4 (b) shows the contours of the segmentation shown in figure 4 (c).
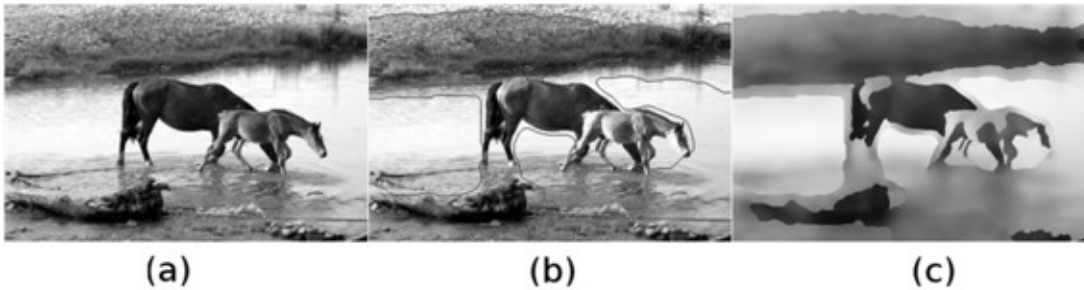

Figure 4. (a) Original gray-level image. (b) Original gray-level image with contours of the segmentation. (c) Segmented image using Mumford and Sha mathematical model and the algorithm proposed by (Grady & Alvino, 2009).

1.5 GRAPH PARTITIONING

In image segmentation by graph partitioning the initial image is partitioned as a weighted undirected graph. Each pixel is considered a node in the graph and edges are formed between each pair of pixels. Each edge weights is measured by similarity between pixels. The image is partitioned into disjointed sets aiming at removing edges that connect segments(Raut, Raghuwanshi, Dharaskar, &Raut, 2009). The optimal graph partitioning is performed by minimizing edge weights (energy function) that will be removed. Shi and Malik (Shi & Malik, 2000) proposed an algorithm to minimize normalized cut using a ratio that will can be standard for all the edges set.

In graph partitioning, G = (V, E)is an undirected graph with vertices Vi∈ V, where V is a segmented elements set and (Vi, Vj)∈ E are edges that corresponds to pair of neighboring vertices. For each (Vi, Vj) ∈ Eit is assigned a correspondent non-negative weight w(Vi, Vj) that indicates the dissimilarity measure between neighbor elements Viand Vj. In the case of image segmentation, the elements in V are pixels and the edge weights have the same dissimilarity measure between two pixels connected by same edge(Felzenszwalb & Huttenlocher, 2004).

Image segmentation by graph partitioning can be considered labeling problem. The object label (s-node) is set to1 and background (t-node) is set to 0. This process will be used in an energy minimization function by graph partitioning. For a reasonable segmentation, the graph partitioning should occur at the boundary between object and background. More specifically, object boundary energy should be minimized. The representation for this labeling can be L = {l1, l2, l3, … , li …, lp}, where p is the number of pixels of an image and li∈{0,1}. Thus, the L set is divided into two parts and pixels labeled to1 are part of theobject and theother are grouped as background(Yi & Moon, 2012). The energy function is defined by equation 6and can be minimized by approach presented in (Boykov & Funka-Lea, 2006):

$$E(\text{L}) = \alpha \, \text{R}\,(\text{L}) + \text{B}\,(\text{L}) \qquad (6)$$

2. EVOLUTIONARY COMPUTING APPROACHES

A number of important segmentation image approaches based on evolutionary computing have been proposed in the literature, including genetic algorithms and genetic programming. Genetic algorithms and genetic programming are a stochastic search or optimization method based on the Darwin natural selection principles. This principle says that individuals better adapted to the environment have more probability of surviving and to generate descendants. Computing analyzing, individuals are candidate solutions to problems, adaptability is a quality of solutions and the environment is the problem instances where the solutions will be validated.

In genetic algorithms a possible solution is represented as individual composed by chromosomes, which are formed by genes. Several encoding schemes are used to represent chromosomes such as natural binary(the most usual), integer, gray code and real values. During the evolutionary process of genetic algorithms genetic operators, like crossover and mutation are applied. These operators change the individuals of a population to create new generations of solutions. The natural selection principle is performed by a selection procedure where individuals with good fitness evaluation have a higher probability to be selected for reproduction. The quality of a solution is evaluated by a fitness function that is calculated over an objective function. Both, fitness function and objective functions, evaluate how the solution is near the optimal value of the problem.

A. GENETIC ALGORITHMS

The use of genetic algorithms is motivated in the context of image segmentation by ability of to deal with a large and complex search space in situations where only a minimum knowledge is available about the objective function. An example of application is to adjust parameters in segmentation image algorithms as proposed in(Bhanu, Lee, & Ming, 1995). Usually, image segmentation algorithms have many parameters to be adjusted where the corresponding search

space is quite large and there are complex interactions among parameters. This approach allows determining the parameters set that optimize the output of segmentation. Other approach is proposed in(Bhandarkar, Zhang, & Potter, 1994)where genetic algorithms are used for edge detection that is cast as the problem of minimization of an objective cost function over the space of all possible edge configurations. A population of edge images was evolved using specialized operators. Finally, in another approach, the image to be segmented is considered as an artificial environment wherein regions with different characteristics, according to the segmentation criterion, are as many as ecological niches. In this approach genetic algorithms are used to evolve a population of chromosomes that are distributed all over this environment and each chromosome belongs to one out of a number of distinct species. The genetic algorithm-driven evolution leads to distinct species to spread over different niches. The distribution of the various species at the end of the evolution unravels the location of the homogeneous regions in the original image(Andrey, 1999).

B. GENETIC PROGRAMMING

Genetic programming is a method for automatic programs and it was derived from genetic algorithms. In Genetic programming the possible solutions for a problem are represented as programs in the form of trees. The functions are represented as internal nodes of trees and the inputs to the functions are represented as terminals (leaves) of the tree. The function set and terminals can be provided by the user and oriented to the specific problem to be solved. Recently, genetic programming has received interest as a methodology for solving computer vision problems because of its ability to select specific filters for detecting image features or to construct new features. It is possible to detect three approaches based on genetic programming: to detect low-level features, which have been predefined by human experts, such as corners, edges and vegetation indices using remote sensing; to construct new low-level features to specific problem domain and that is not necessary to be interpreted by human experts; and approaches to solve a high-level recognition problem such as object detection, image classification and texture segmentation(Olague& Trujillo, 2011).

An example of image segmentation based in genetic programming is presented in (Perlin& Lopes, 2013) that use genetic programming to solve a segmentation image problem. In this work the image segmentation problem is seen as classification problem where some regions of an image are labeled as foreground (object of interest) or background. A set of terminals and non-terminals composed by algebraic operations and convolution filters are provided for the genetic programming. The fitness function is defined as the difference between the desired segmented image and that obtained by the application of the mask evolved by genetic programming. Another approach describes a combined evaluation measure based on genetic programming. One of the greatest challenges while working on image segmentation algorithms is a comprehensive measure to evaluate their accuracy. Thus, the proposed approach allows nonlinear and linear combination of single evaluation measures and can search within many and different combination of basic operators of single measures to find a good set(Vojodi, Fakhari, & Moghadam, 2013). An example of image segmentation using genetic programming can be seen in figure 5 (a). This image was performed by (Perlin & Lopes, 2013) approach and was applied to image shows in figure 5 (b).

Figure 5. (a) Original color image. (b) Segmented image using Genetic
Programming and algorithm proposed by (Perlin & Lopes, 2013).

3. CONCLUSION

In this paper a comprehensive analysis of concerning methods for image segmentation is discussed, that is a very important procedure in image processing and computer vision. We presented methods based on histogram analysis, edge detection, region-growing and graph partition. Finally, we pointed out some recent approaches based on genetic algorithms and genetic programming.

Image segmentation based on the analysis of the histogram is the most commonly used method, specially the method proposed by Otsu. Methods of edge detection and region growing have been widely used in image segmentation since they have pretty good results. The main methods of edge detection and region growing most frequent in the literature were Canny, Mumford & Sha and Watershed. We also present a more recent image segmentation using graph partitioning. This approach has attracted the interest of researchers who work in this area.

Finally, we presented an approach for image segmentation using evolutionary computation, particularly genetic algorithms and genetic programming. The use of evolutionary computation in the context of image segmentation has attracted the interest of the scientific community by the robustness that this methodology has the ability to handle large and complex search space.

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