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Image Segmentation Methods

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INTRODUCTION

Pictures, when used in a computational environment, are known as digital images, representing the two-dimensional visual information. They are stored in binary files as bitmap or vector images. The former are represented bit-by-bit and the latter by geometric objects such as lines, dot, curves and polygons. Image segmentation is a fundamental step in modern computer vision systems and its goal is to produce a more simple and meaningful representation of the image making it easier to analyze. Image segmentation is a subcategory of image processing of bitmap digital images. Basically, it divides a given image in 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. Recently, other approaches came up such as segmentation by graph partition, using genetic algorithms (GA) and genetic programming (GP). This article presents an overview of this area, starting with a taxonomy of the methods, followed by a discussion of the most relevant ones.

BACKGROUND

Image Segmentation

In bitmap graphics (not in vector graphics) segmentation is a pre-processing step in computer vision where images are partitioned into several distinct regions formed by a set of pixels (picture element). Such regions are further labeled as foreground (objects of interest) or background, based on the common properties the pixels of a region must share (such as color, intensity, texture, etc).

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

Histogram Analysis

A histogram is a graphical representation in which a data set is grouped into uniform classes such that the horizontal axis represents the classes and, the vertical axis, the frequencies in which the values of these classes 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 intra-class variance. This threshold is exhaustively searched and can be defined as a weighted sum of the variances of the two classes, as shown in Equation 1:

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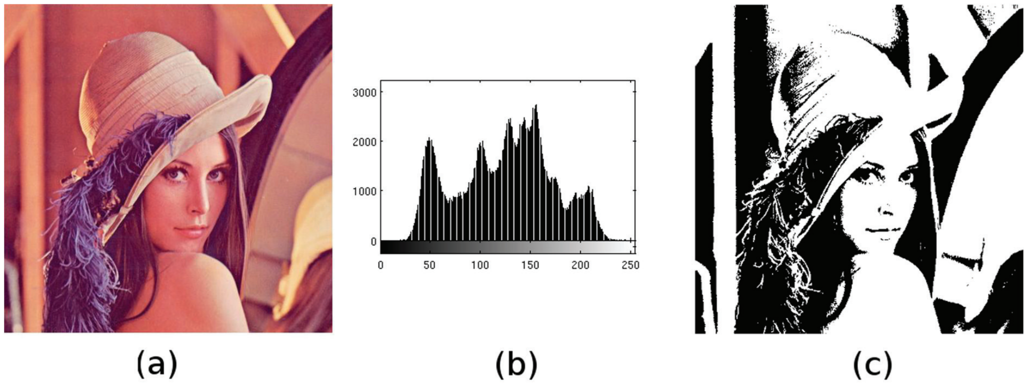


Figure 1. (a) Original color image; (b) Original histogram image; (c) Segmented image using Otsu approach

$$\sigma^2_{intra} = W_a \sigma^2_a + W_b \sigma^2_b \quad (1)$$

where σ represents the variance of these classes and weights W_i represents the occurrence probability of each class being separated by a threshold T. Figure 1 (a) shows the original color image and Figure 1 (c) shows image segmented by Otsu approach.

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 by estimating the gradient intensity. Edges in images can be divided in two distinct categories: intensity edges and texture edges. In the first, the edges arise from abrupt changes in the image pattern and, in the second case, edges are detected by the 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, a convolution mask is a set of weightings applied to pixel values in order to create a new effect. They 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 2 and an example of image segmentation using Roberts edge operator is shown in Figure 2 (a):

$$|G| = |G_x| + |G_y| \quad (2)$$

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

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 a grayscale input 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, and an example is shown in Figure 2 (b).

In the edge detecting process, it is 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.

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 an 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, as shown in Equation 3. The edge direction angle is approximated to one of four angles representing vertical, horizontal and diagonals (0, 45, 90 and 135 degrees).

$$\Theta = \arctan\left(\frac{|\,G_x\,|}{|\,G_y\,)}\right) \tag{3}$$

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, thus giving a thin line edge as result.

Finally, 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, and weak edges that are close to strong edges tend to compose the final result, while the remaining 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 operator.

Segmentation by Regions

There are two approaches for region-based methods: splitting-merging and growth regions.

The splitting-merging 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 critical, and usually requires a set of descriptors based on intensity levels and spatial properties. The most cited region growing images segmentation methods are Watershed Transform and Mumford & Shah Functional (Raut, Raghuwanshi, Dharaskar, & Raut, 2009).

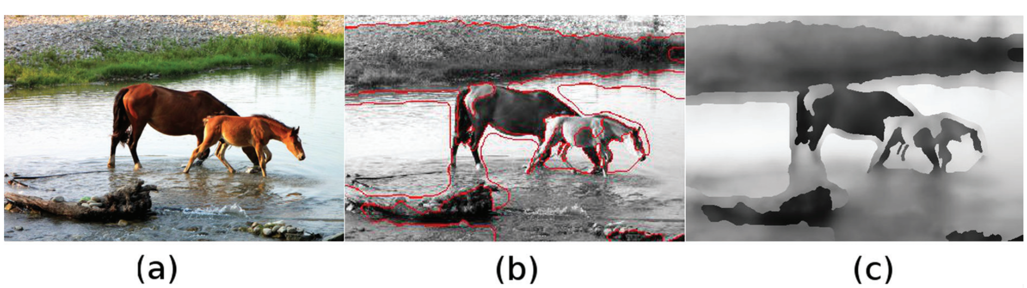
In Watershed Transform it is considered the gradient magnitude of image and surface topography. Pixels with gradient magnitude intensity (GMIs) represent the limits of the largest area and correspond to watershed threshold. This method has some variants and calculates the gradient magnitude intensity 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. Flooding is controlled by dams that separate different local minima. The dams that emerge to the water surface are watershed lines, and 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 the figure shown in Figure 3 (a).

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 (Jiang, Zhang, & Nie, 2009).

The method is based on a mathematical 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, by delimiting the regions endings (Mumford & Shah, 1989). The simplified form of the Mumford and Shah functional expresses the segmentation problem as a minimization. Figure 4 (c) shows an example of region growing image segmentation using this model and the algorithm proposed by (Grady & Alvino, 2009) applied to Figure 4 (a). Figure 4 (b) shows the corresponding contours of the segmentation.

Figure 3. (a) Original color image; (b) Segmented image using watershed approach

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



Graph Partitioning

Using graph partitioning, the initial image is partitioned as a weighted undirected graph. Each pixel is considered a vertex (V) in an undirected graph G = (V, E) and edges (E) are formed between each pair of pixels. Edge weights are measured by similarity between pixels. For each pair of edges it is assigned a correspondent non-negative weight that indicates the dissimilarity measure between neighbor elements (Felzenszwalb & Huttenlocher, 2004). Therefore the image is partitioned into disjoint sets aiming at removing edges that connect segments (Raut et al., 2009). The optimal graph partitioning is performed by minimizing edge weights (energy function) that will be removed. Shi and Malik (2000) proposed an algorithm to minimize normalized cut using a ratio that will can be standard for all the edges set.

EVOLUTIONARY COMPUTING APPROACHES

A number of important segmentation image approaches based on evolutionary computing have been proposed in the literature, including mainly GA and GP, although other approached also can be found. GA and GP are a stochastic search optimization methods based on the Darwin natural selection principles. This principle states that individuals better adapted to the environment have more probability of surviving and to generate descendants. In the computational world, individuals are candidate solutions to problems, adaptability is the quality of solutions and the environment is the problem instances where the solutions will be validated.

Genetic Algorithms

In GA 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 GA 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.

The use of GA 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 GA 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 where in regions with different characteristics, according to the segmentation criterion, are as many as ecological niches. In this approach GA 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 GA-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).

Genetic Programming

GP is a method for automatic programs and it was derived from GA. In GP 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, GP 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 GP: 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).

Vojodi, Fakhari, and Moghadam (2013) proposed an approach describing a combined evaluation measure based on GP. One of the main challenges for image segmentation algorithms is a comprehensive measure to evaluate their accuracy. The proposed approach can search linear and nonlinear combinations of single evaluation measures and basic operators to find a good measure.

Another interesting approach for image segmentation based on GP was presented by (Perlin & Lopes, 2013) that used GP to solve an image segmentation problem. In this work, the image segmentation problem is seen as classification problem where pixels are labeled either as foreground or background. A set of terminals and non-terminals composed by algebraic operations and convolution filters are provided to the GP. The fitness function is defined as the difference between the desired segmented image and that obtained by the application of the mask evolved by GP. An example of image segmentation using this approach is shown in Figure 5 (a) and (b), respectively, the original image and the segmented one.

Other Approaches

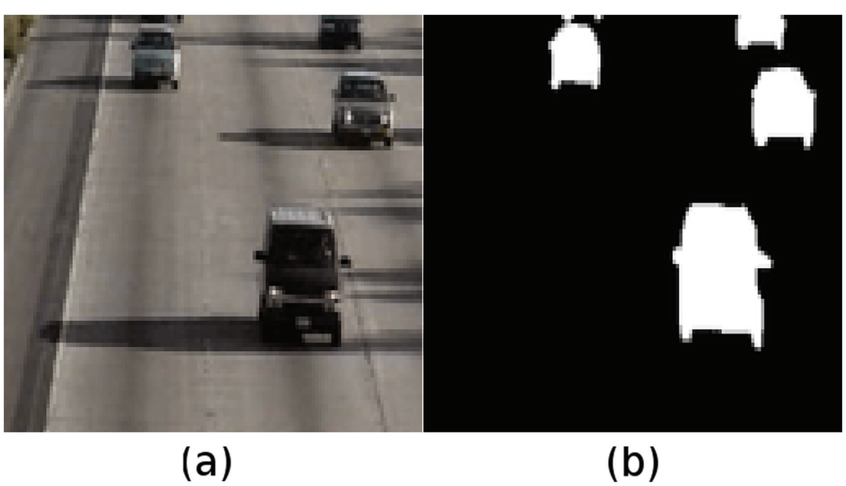
Particle Swarm Optimization (PSO) is a bio-inspired method for general-purpose optimization. This method simulates the collective behavior of a swarm of particles (possible solutions) that fly over the possible space of solutions. In (Fornarelli & Giaquinto, 2013) a multi-swarm PSO method was used to automatically segment gray level images. This is an unsupervised approach, such that the PSO the first swarm moves in the search space according to a minimal distance criterion, and a second swarm is used to refine the previous solution.

Differential Evolution (DE) is another evolutionary computation paradigm usually reputed as faster, easy tunable and more efficient than GA for a number of real-world problems. In (Saraswat, Arya, & Sharma, 2013) an interesting approach for multilevel segmentation of images is presented. They have used DE for segmenting leukocytes from images of mice skin sections. This is a difficult problem due to the large variability of image characteristics, such as illumination color and noise.

FUTURE RESEARCH DIRECTIONS

Despite the numerous approaches for image segmentation with solid mathematical background, no method is

Figure 5. (a) Original color image; (b) Segmented image using GP method proposed by (Perlin & Lopes, 2013)



general enough to be efficient for any kind of images. Certainly, more research on this direction is necessary so as to create more robust methods, applicable to a wide range of images.

The use of evolutionary computation in the context of image segmentation has attracted the interest of the scientific community due to its robustness and the ability to handle large and complex search space. Notwithstanding, the computational efficiency of the methods is still an issue to be improved in the future, so as to allow real-time segmentation of digital images.

CONCLUSION

In this article we presented a review concerning methods for image segmentation that is a key procedure in image processing and computer vision. We presented traditional methods based on histogram analysis, edge detection, region-growing and graph partition, as well as some recent approaches based on GA, GP and PSO.

Image segmentation is still an open problem in image processing. Many different approaches have been proposed along time, including evolutionary computing methods. However, to date, there is still no gold standard method for image segmentation, mainly due to the large of visual nature of the problem. Anyway, evolutionary computing methods are very promising in this scenario, decreasing the burden for complex mathematical approaches, although dealing heuristically with the problem as an optimization problem.

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KEY TERMS AND DEFINITIONS

Computer Vision: A discipline of Computer Science that includes methods for acquiring, processing, analyzing, and understanding.

Convolution Masks: In image processing convolution mask is a small matrix with a set of weightings which is applied to pixel values in order to create a new effect such as blurring, sharpening, embossing, edge-detection, and more.

Edge Detector: It is mathematical methods which aim at identifying points where the image brightness changes sharply, or discontinuities, in a digital image.

Evolutionary Computation: Subfield of computational intelligence that involves continuous optimization and combinatorial optimization problems and can be considered global optimization methods.

Genetic Algorithm: Belongs to the larger class of evolutionary algorithms and is a search heuristic inspired on process of natural selection and is routinely used to generate useful solutions to optimization and search problems.

Genetic Programming: It is a specialization of genetic algorithms where each individual is a computer program and consists in is an evolutionary algorithm-based methodology to find computer programs.

Gradient: A gradual transition between one or more colors. In mathematics, the gradient is a generalization of the usual concept of derivative to functions of several variables.

Image Segmentation: Process of partitioning a digital image into object(s) and background. The goal of segmentation is to simplify the representation of an image into something that is more meaningful and easier to analyze.

Pixel: Short for picture element, it is physical point in a bitmap image, or a smaller addressable element in an all points of an addressable display device.

Region Growing: Simple region-based image segmentation method. It is also classified as a pixel-based image segmentation method since it involves the selection of initial seed points.