A Survey on Traditional and Graph Theoretical Techniques for Image Segmentation

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ABSTRACT
Image segmentation is the process of subdividing a digital image into its systematized regions or objects which is useful in image analysis. In this review paper, we carried out an organized survey of many image segmentation techniques which are flexible, cost effective and computationally more efficient. We classify these segmentation methods into three categories: the traditional methods, graph theoretical methods and combination of both traditional and graph theoretical methods. In the second and third category of image segmentation approaches, the image is modeled as a weighted and undirected graph. Normally a pixel or a group of pixels are connected with nodes. The edge weights represent the dissimilarity between the neighborhood pixels. The graph or the image is then divided according to a benchmark designed to model good clusters. Every partition of the nodes or the pixels as output from these algorithms is measured as an object segment in an image representing a graph. Some of the popular algorithms are thresholding, normalized cuts, iterated graph cut, clustering method, watershed transformation, minimum cut, grey graph cut, and minimum spanning tree-based segmentation.

General Terms
Image processing, graph based segmentation.

Keywords
Image segmentation, histogram, neural network, thresholding, watershed transformation, clustering, quadtree, graph theoretical methods, Euler Graph, minimal spanning tree, grey graph cut, GrabCut.

1. INTRODUCTION
Image segmentation is a matured research topic, which found progress around 1970. But still there is no perfect solution in the direction of it.

In computer vision, image segmentation is the process of dividing a digital image into multiple segments (sets of pixels, also called as super pixels). The objective of segmentation is to simplify or modify the representation of an image into somewhat that is more significant and easier to analyze [3].Image segmentation is normally used to trace objects and boundaries (lines, dots, curves, etc.) that can occur in images. Specifically, image segmentation is the process of allocating a label to each pixel in an image such that pixels with the same label share some pictorial characteristics. The outcome of image segmentation is a set of segments or regions that together represents the entire image. Every pixel in a region is similar with respect to certain characteristic otherwise computed property, such as color, texture, intensity etc. Neighboring regions are meaningfully different with respect to the same characteristics [3]. After applying to a stack of images, typically in medical imaging, the consequent contours after image segmentation can be used to create 3D transformations with the assistance of interpolation algorithms like marching cubes. Numerous practical applications of image segmentation are medical imaging[4], for example, finding tumors and other pathologies trials tissue volumes, Computer-guided surgery, Treatment planning, Optical Character Recognition (OCR), the study of anatomical structure i.e., locating objects in satellite images (roads, rivers, forests, etc.), Face recognition, Iris recognition, Traffic control systems, Fingerprint recognition, Brake light detection, Agricultural imaging – crop disease detection, Machine vision. Some general-purpose algorithms and techniques have been developed for image segmentation. Since there is no common solution to the image segmentation problem, these techniques frequently have to be combined with sphere knowledge towards effective solution of an image segmentation problem for a problem domain.

This review paper delivers many image segmentation methods which we classified into three categories. Traditional methods (1), Graph theoretical methods (2) and combination of both the Traditional and Graph theoretical methods (3). We present motivations and descriptions for each category of methods.

In section 2, a survey of traditional image segmentation is presented, and in section 3, a survey on graph theoretical approach to image segmentation is presented, and in section 4, a survey on combination of traditional and graph based methods of image segmentation is presented. Finally section 5 consists of conclusion about our survey with direction for future work.

2. TRADITIONAL IMAGE SEGMENTATION METHODS
Many traditional segmentation techniques are found in literature. In the following subsections we present few of them.

2.1 Thresholding
It is the simplest technique of all image segmentation methods. This method is constructed on a threshold value, used to transform a gray-scale image into a binary image. The basic objective of this technique is to select the threshold value. Thresholding is one of the broadly used methods for image segmentation. It is useful in discerning foreground from the background. By selecting suitable threshold value T, the gray level image can be transformed to binary image. The binary image should contain every important information about the position and shape of the objects of interest (foreground). The advantage of gaining first a binary image is to reduce the complexity of the data and simplifies the process of recognition and image classification. The best way to convert a gray-level image into a binary image is to select a single threshold value *T*. Then every gray level values below this *T* will be classified as black, and those above the value of

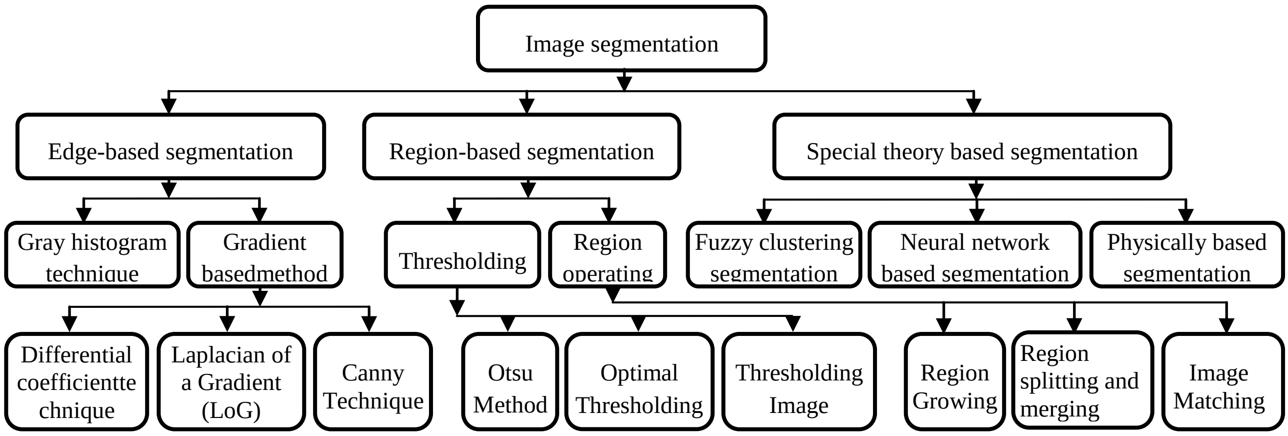


Figure 1: Hierarchy of Image Segmentation Techniques [28]

T will be white. The segmentation problem depends on selecting the proper value for the threshold *T*. A common method used to select *T* is by analyzing the histograms of the type of images that is to be segmented. The perfect case is when the histogram presents only two dominant modes and a clear valley. In this case the value of *T* is selected as the valley point between the two modes. In actual applications histograms are more complex, with various peaks and not clear valleys. One disadvantage of the method is that, it is not always easy to select the value of *T*.

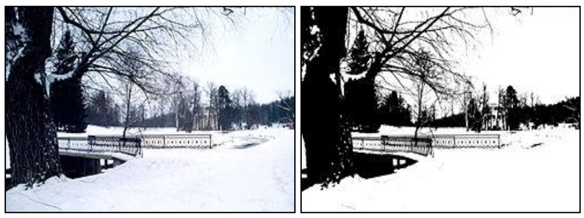
Table 1: Comparison of thresholding methods [28]

Method	Advantage	Disadvantage	Segmentation effect
Minimum Thresholding	Low Complexity	Narrow in application	Normal
Iterative Thresholding	Average Complexity	Image details are fuzzy	Good
Entropy based Thresholding	Very low complexity	Sensitive to noise	Normal
Otsu Thresholding	Very high complexity	Combine with other algorithms to improve its performance	Good

2.2 Clustering methods

In this method, distance between a pixel of an image and a cluster center is used for clustering. The difference is naturally based on certain properties such as color, intensity, texture, and location of a pixel or a weighted grouping of these factors. The parameter *K* is selected randomly, manually or by a heuristic. This method is positive to converge, but it may not yield the optimum solution. The quality of the solution depends on the preliminary set of clusters and also on the value of *K*. The following K-means algorithm is an iterative method which is used to divide an image into *K* clusters or segments. The simple algorithm is:

1. K cluster centers are picked, manually, randomly or grounded on some heuristic.
2. Allocate each pixel of the image to the cluster which minimizes the distance between the pixel and the cluster center.
3. Compute the cluster centers again by averaging all of the pixels in the cluster.
4. Repeat the steps 2 and 3 until convergence is attained (e.g. no pixels change clusters).



(a) (b)

Fig 2: (a) original image and (b) result using Thresholding technique representing category (1)

22222232221222212222
32222321250132123132
22588897777788888232
12988877707668882122
22888892326669893213
21278221222666665222
22002222220226660225
21221231223266622321
32238852223266821222
21288888342288882232
22328888899888522121
22123988888889223422
23222278888882022122
22232323883212123234
25221212222222222222
22122222320222202102
20222322412212223221
22221212222222342222
21222222221222222142

Fig. 3: An image example

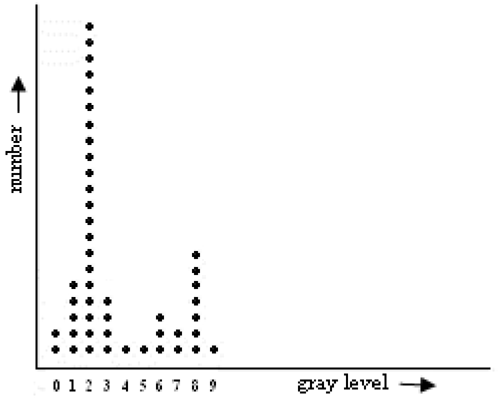


Fig 4: A histogram of the image in Figure 3

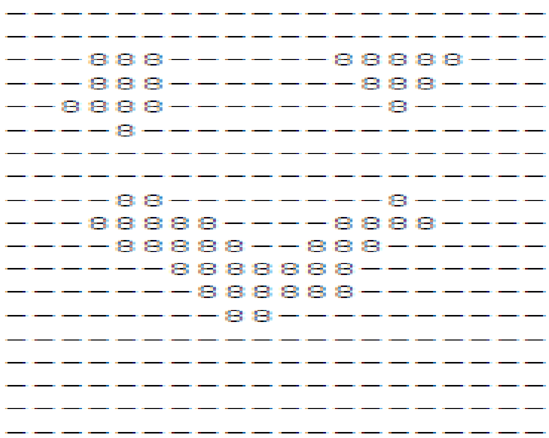


Fig 5: The image in Figure 3 with all the pixels except the 8's blanked out

2.3 Histogram-based methods

These methods are one of the simplest and most commonly used methods. These methods are very skillful when compared to other image segmentation approaches because they normally require only one pass through the pixels. During this method, a histogram is calculated for all the pixels in the image. This histogram is used to select grey levels for grouping the image into regions. For general image there are two attributes: the object and its background. The object of the image is one grey level which is the smaller peak in the histogram. The background of the image is another grey level which represents the large peak in the histogram. The peaks and valleys of the histogram are used to trace the clusters of the image. Color or intensity can be used as a measure. This technique can be improved by applying the histogram-seeking method recursively to clusters in an image with a purpose to divide them into smaller clusters. This procedure is repeated with smaller and still smaller clusters until no further clusters are formed [3, 5]. The disadvantage of the histogram-seeking technique is that it can be difficult to identify significant peaks and valleys in the image. This method segments an image, based on active objects and a still situation, following in a different type of segmentation which is useful in Video tracking.

The histogram in Figure 4 shows us the gray levels of the background and the object. The biggest peak characterizes the background and the next biggest peak describes the object. A threshold point in the valley between the two peaks and threshold of the image is chosen. Thresholding receipts each pixel whose value is on the object side of the point and sets it to one and all others to zero. The histogram peaks and the valley amongst them are the keys for the image segmentation.

2.4 Split-and-merge methods

This segmentation method is based on a quadtree partition of an image. Therefore it is sometimes called quadtree segmentation method. In this method, an image is represented as a tree, which is a connected graph with no cycles. The technique begins at the root of the tree. If it starts with non-uniform (not homogeneous), the split and merge algorithm have two phases; the split and the merge. In the split phase we recursively split regions into four subregions (starting with the whole image as one region) in anticipation of our homogeneity criterion is met in all subregions. Conversely, if four son-squares are identical (homogeneous), then they can be merged as some connected components. This process is called as the merging process. The segmented region is the node of a tree. This process (splitting and merging) is continued recursively so that no further splits or merges are possible [10, 11]. Overall the process can be summarized into two different algorithms i.e., splitting and merging algorithms.

2.41 Algorithm for region splitting

1. Set Process_List = IMAGE
2. Repeat the steps 3 and 4 until (all regions removed from Process_List).
3. Extract the first element of Process_List
4. If the region is not uniform then add it to Region_List Else divide the region into 4 sub-regions and add these to Process_List.

2.42 Algorithm for region merging

1. Put all regions in Process_List
2. Repeat the steps 3 and 4 until (no merges are possible)
3. Extract every region from Process_List
4. Traverse the remaining list to find similar region (homogeneousness criterion). If they are neighbours then merge the regions and recalculate their property values.

Where Process_List contains the elements of image.

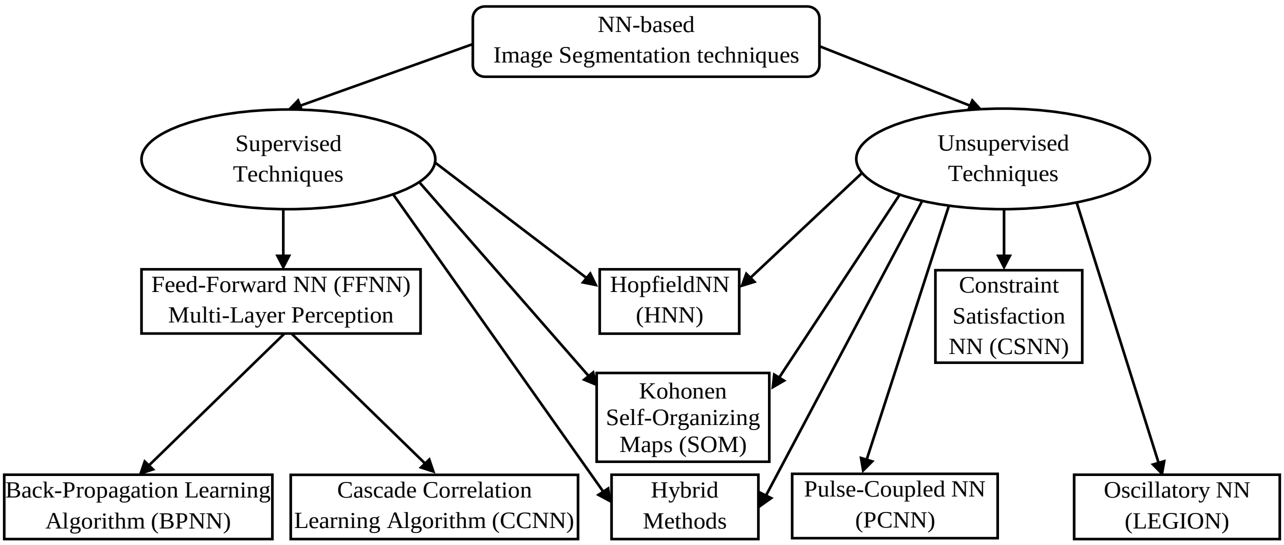


Figure 6: Flowchart of Neural Network-based of image segmentation techniques

A distinctive data structure is involved in the implementation of the algorithm of this method. Its time complexity can reach $O(n \log n)$, an optimal algorithm *of the* method [10, 12].

2.5 Watershed transformation

This is the simple image segmentation technique in which the gradient is treated as the magnitude of an image as a topographic surface. Those pixels which are having the highest gradient magnitude intensities (GMIs) corresponding to watershed lines signify the region boundaries. Water placed on any pixel of an image bordered by a common watershed line, flows downward to a common local intensity minimum (LIM). Pixels draining to a common minimum form a catch basin, which characterizes a segment of an image. Advantage of this technique is that it divides the segmentation process into two separate steps. First detecting the main edges of the image processed, and then computing the watershed of the gradient detected. This method has many advantages, particularly in real life applications.

2.6 Segmentation using Neural Networks

This segmentation method trusts on processing small areas of an image using an artificial neural network or a set of neural networks. Afterwards the decision-making process labels the parts of an image accordingly to the group recognized by the neural network. A type of network is designed especially for this is the Kohonen map. Pulse coupled neural networks (PCNNs) are the neural network models proposed by modeling a cat's visual cortex and developed for high-performance biomimetic image processing (It is a technique which improves quality of image effectively on the basis of brightness adoption and disinhibitory properties of concentric receptive field). Eckhorn introduced a neural model to compete with the mechanism of cat's visual cortex in 1989. The Eckhorn model provided a simple and operative tool for studying small mammal's visual cortex, and was soon acknowledged as having important application potential in image processing. Later Johnson adopted the Eckhorn model to be an image processing algorithm, who termed this algorithm as Pulse-Coupled Neural Network (PCNN) in 1994.Over the past few years PCNNs have been exploited for a diversity of image processing applications, for example image segmentation, feature extraction, face extraction, region growing, noise reduction, and motion detection etc. The flowchart of neural network based image segmentation is shown in figure 6.

3. GRAPH THEORETICAL PPROACHES TO IMAGE SEGMENTATION

Graph based segmentation techniques gaining popularity in recent days. We present the different graph theoretical approached for image segmentation in the following sub sections.

3.1 Normalized Cuts and Image Segmentation

This is a very popular graph based image segmentation method. In this method, the image segmentation is treated as a graph partitioning problem [1] and offers a novel global method, the normalized cut, for segmenting the graph (image) into regions or segments. This technique not only measures both the total dissimilarity between the different regions but also the total similarity within the regions. An effective computational method based on a widespread Eigen value problem can be used to optimize this benchmark. This method is used in many applications such as segmenting immobile images and also motion sequences.

Normalized cut Segmentation Algorithm

1. Begin the problem as a graph $\boldsymbol{G = (V, E)}$ and define affinity matrix $\boldsymbol{A}$ and degree matrix $\boldsymbol{D}$.
2. Solve the equation $\boldsymbol{(D - A)\ x = \lambda D_x}$ for the eigenvectors with the smallest Eigen values.
3. Let $\boldsymbol{x_2}$ = eigen vector with second smallest eigen value $\boldsymbol{\lambda_2}$
4. Threshold $\boldsymbol{x_2}$ to obtain the binary-valued vector $\boldsymbol{x'_2}$ so that $\boldsymbol{ncut(x'_2) = ncut(x^t_2)}$ for all possible thresholds t
5. For every two new regions, if ***ncut < threshold T***, at that time recurse on the region.

The results of this method are found to be very encouraging [18].

3.2 Efficient Graph-Based Image Segmentation

This is a very effective graph based method. This method discourses the problem of segmenting an image into regions or segments. A predicate is defined for measuring the indication for a boundary between two regions of an image, using a graph-based representation. Afterwards, an efficient segmentation algorithm is developed based on this predicate. It shows that although the algorithm makes avaricious decisions it produces image segmentations that fulfill global properties. The algorithm applied for image segmentation is using two unlike kinds of native neighborhoods in creating the graph and determines the results with both actual and artificial images. The algorithm runs in time approximately linear in the number of graph edges and is also quick in practice. The significant quality of the technique is its ability to preserve the low-variability feature of image regions or segments while disregarding detail in high-variability segments or regions.

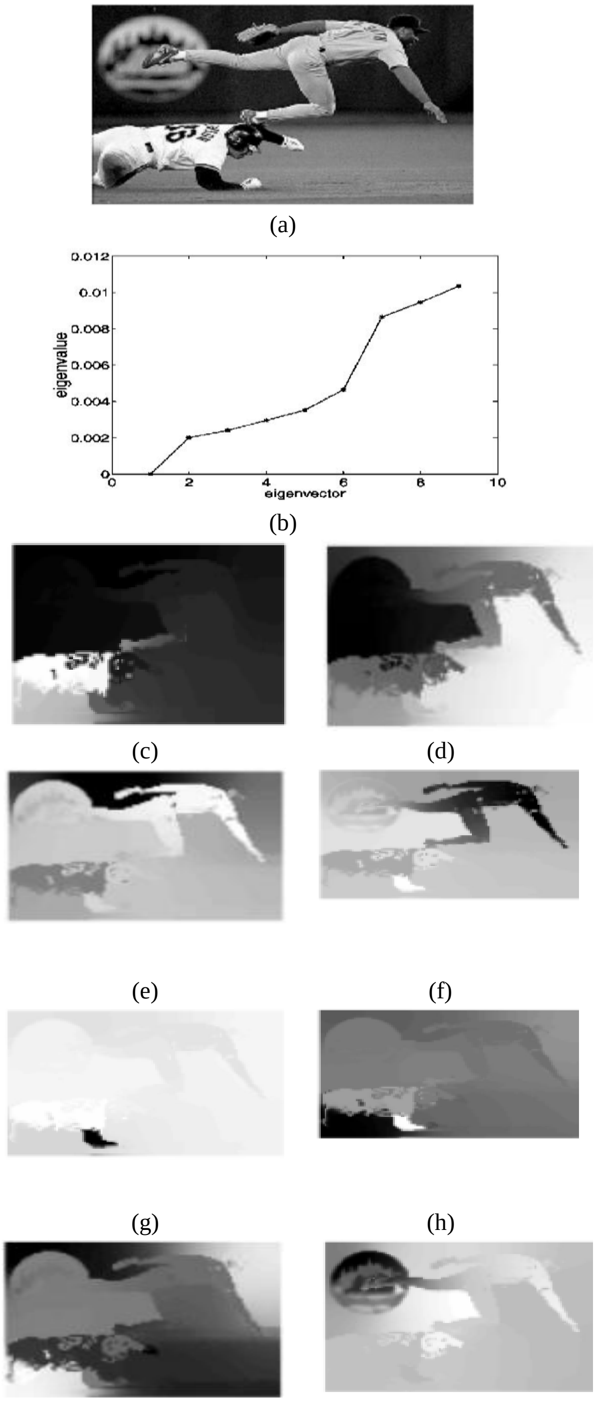


Fig 7: (a) Original image. (b) Plots the smallest eigenvectors of the generalized eigenvalue system. Subplots (c)-(j) show the eigenvectors corresponding the second smallest to the ninth smallest eigenvalues of the system. The eigenvectors are reshaped to be the size of the image.

The technique runs in O (m log m) time for m graph edges and is also quick in practice, commonly running in fractions of a second [16].

3.3 Iterated Graph Cuts for Image Segmentation

In this technique, an iterated graph cuts algorithm is very briefly explained, which begins from the sub-graph of graph which represents an image. This includes the user labeled foreground or background regions. This technique works iteratively to label the neighboring un-segmented regions or image segments. During the process of each iteration the local neighboring regions or segments to the labeled regions only are tangled in the optimization so that considerable interference from the unknown regions which are very far can be ominously reduced. In order to get better efficiency and robustness of image segmentation, the mean shift method to divide the image into homogenous regions is used, and then the iterated graph cuts algorithm is implemented by compelling each region, rather than every pixel, as the graph node for image segmentation. Widespread experiments on benchmark datasets revealed that this technique contributes much improved image segmentation results than the typical graph cuts and the GrabCut approaches in both quality and quantity aspect of calculations. Another important advantage is that it is impervious to the parameter in optimization [14].

3.4 Segmentation using minimal spanning trees

A minimum spanning tree (MST) is subgraph of a tree with minimum-weight, containing no cycles such that all nodes are connected. Felzenszwalb presented a segmentation method [16] which is based on Kruskal's MST algorithm method in the year 2004. According to this algorithm, edges are quantified in increasing order of their weight. The endpoint pixels of edges are combined into a region. Pixel similarity is adjudicated by a heuristic, which compares the weight of an each segment threshold. The algorithm outputs a forest which is a multiple disjunction Minimal Spanning Trees (MSTs), where each tree represents a segment. Wassenberg et al. developed an algorithm [17] in 2009, which computes multiple autonomous Minimum Spanning Forests and then stitches them collectively. This allows parallel processing without dividing objects on tile borders. As an alternative, a constant weight threshold i.e., an initial connected component labeling is used to estimate a lower bound on the threshold, which further can cause the reduction of both over segmentation and under segmentation. Calculations show that the implementation outclasses Felzenszwalb's sequential algorithm method by the directive of magnitude. Segmentation results are satisfactory and are not sensitive to noise.

3.5 Segmentation using Euler Graphs

This technique explains an algorithm for image segmentation problem using the concepts of Euler graphs in graph theory. Here the image is treated as an undirected weighted non-planar finite graph (G), and then image segmentation is treated as graph partitioning problem. This method locates region boundaries or clusters and runs in polynomial time. Subjective comparison and objective estimation shows the efficiency of the method in different image domains. The algorithm begins by randomly choosing an edge and tries to form closed regions. During the process, open paths are formed. The color look up table is used for the edges to trace their transition. A white color indicates unvisited edge, a gray color indicates visited edge and may go for the refinement and black color indicates visited and marked permanently for no refinement as it is already a part of a region boundary. This method runs in polynomial time [9].

4. COMBINATION OF TRADITIONAL AND GRAPH BASED METHODS

Some approaches are found which combine the traditional segmentation methods with the graph based techniques to improve the performance of segmentation. Few such approaches are presented in the following subsections.

4.1 Segmentation Method Based On Grey Graph Cut

To improve the performance and efficiency of image segmentation, this method presents a new image segmentation technique constructed on grey graph cut, which combines grey theory and graph cut theory. In this method, the image is taken as a weighted undirected graph first. Later, after the relationships of grey-levels and positions in local regions are conferred via grey relational analysis, a grey weight matrix is constructed, based on which a grey partition function is constructed. Afterwards the image is binarized with the gray-level corresponding to the minimum value of the grey divider function. Experimental outcomes on visible light image and Synthetic Aperture Radar (SAR) image shows that this method is being far better than to some of the existing methods like watershed, histogram, clustering, Normalized Cut etc. This method not only can segment the images with obvious difference between targets and backgrounds, but also reduces image noise very effectively [7, 14].

4.2 Medical Image Segmentation Based on the combination of Watershed and Graph Theory

Some of the common characteristics of medical images are tough noise, reduced gray-scale contrast, and blurred margins of tissue. The challenging task is to extract the object of interest in medical images. A segmentation method that syndicates watershed algorithm with graph theoretical technique is presented as a new method. This algorithm reconstructs gradient before the watershed segmentation method. Based on this reconstruction, a floating-point active-image is introduced as the orientation image of watershed transform technique. Finally, a graph theory based algorithm (combination of graph theory and statistics) Grab Cut is used for sufficient segmentation. Incorrect contours which are caused by over-segmentation are efficiently omitted and total segmentation quality significantly improved which is essential for medical image segmentation [6].

4.3 Segmentation by the combination of Iterated Region Merging and Localized Graph Cuts

This method results in an algorithm which is a novel extension of the typical graph cuts algorithm. Graph cuts discourses image segmentation in an optimization agenda and finds a solution which is globally optimal to a widespread class of energy functions effectively. However, the extraction of objects in a composite background frequently requires huge amount of user interaction. This algorithm begins from the user labeled sub-graph and then works with iteration, to label the neighboring un-segmented regions of an image. In each iteration only the local neighboring regions to the labeled regions are tangled in the optimization. As a result a lot of interference from unknown regions, which are very farer, can be expressively reduced. In the meantime, the data models of the object and background are simplified iteratively based on high confident labeled regions. The sub-graph requires less user supervision for segmentation and thus improved results

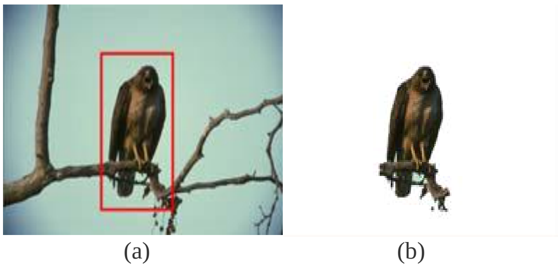


Fig 10: (a) original image and (b) result of GrabCut algorithm

can be obtained with the same amount of user interaction. Experimentations on standard datasets validated that this method produces much improved segmentation results than the standard graph cuts and the GrabCut methods in either qualitative or quantitative estimation [15].

4.4 Segmentation by the combination of Fuzzy and Graph-Theoretical Clustering

Image segmentation using the traditional graph-theoretical clustering method is sensitive to noise and fuzzy edges, which will produce incorrect image segmentation. Also, the higher computational complexity affects its application. Targeting at these deficits, the traditional approach is improved in this

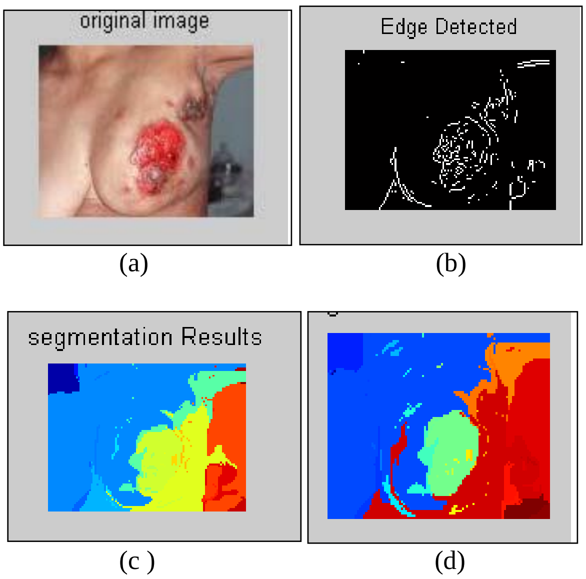


Fig 11: (a) original image and (b) result edge detection, (c - d) segmentation results representing category (3) [27]

method. First to reduce the computational complexity, the pixels of image of same grey level are divided into one class while initialization. Later, in the customary algorithm, the statistics of pixel's gray and the distance between pixel and clusters' center is calculated. But the longitudinal character distribution between pixel and region is neglected. This will cause data to become independent of each other. Image segmentation is not only the objective of gray statistics but also pixel gap between the neighbour relationships to maintain the integrity of the target but also plays a vital role. The neighbours relationship is defined between pixels and region in calculating weight coefficient, via increasing the constraint of spatial relationship to alter the value deviation affected by only allowing for the pixels' gray and two-dimensional locality relations. Furthermore, the fuzzy method and graph-theoretical clustering method are combined. By using certain parameters such as weight coefficient, fuzzy similarity, a relationship between each pixel is constructed. Later the image may be mapped from space arena to fuzzy arena. At the end, cluster is analyzed by using the leading fuzzy subsidiary tree on the new fuzzy graph. Therefore some problems which come across in image processing using the old-fashioned graph-theoretical clustering technique may be solved using this combination of methods [8].

4.5 GrabCut segmentation technique

Graph Cut is an algorithm that has gained popularity in recent times for use in image segmentation tasks. This technique is the resultant of the combination of both graph method and statistical method. GraphCut technique is used as a part of refining process in an initial user image segmentation between foreground and background. GrabCut technique was originally developed at Microsoft Research Cambridge, UK. The effort for the user is as follows: The user selects an image which should be used to perform the image segmentation on and draws a rectangle around the object of interest that should be segmented. Later the user can do a last touch up of the image if needed or use the image again input by selecting a new rectangle. GrabCut Technique helps for image segmentation quite interactively. The user needs to input the very rough segmentation only between foreground and background. Normally this is done by drawing a rectangle around the body of interest [22].

The steps for the GrabCut algorithm are as follows.

1. The user need to input three things: foreground, background, and the unknown part of the image which can be either foreground or background. This is generally done by selecting the rectangle around the body of interest. Mark the region inside that rectangle as unknown. Pixel outside the rectangle will be marked as known background later.
2. The algorithm generates initial image segmentation, such that, the unknown pixels are classified as foreground and all known background pixels are classified as background.
3. Both the foreground and backgrounds are modeled as Gaussian Mixture Models (GMMs) using the Orchard-Bouman clustering algorithm.
4. Each pixel in the foreground is assigned as most feasible Gaussian component in the foreground GMMs. The same process is done with the pixels in the background but with components of the background GMMs.
5. The new GMMs are learned from the pixel sets that were created in the previous step.
6. A graph is built and Graph Cut is used for a new classification of foreground and background pixels.
7. Repeat step 4-6 until the classification converges.

5. CONCLUSIONS

In this review paper, we thoroughly discussed the survey on useful methods of traditional, graph based and combination of both methods of image segmentation. These Image segmentation methods are highly efficient particularly, graph based image segmentation methods. Medical imaging is one of the most active research topics in image processing. Latest research in image segmentation has highlighted the prospective of graph based approaches for medical applications. In order to use graph theory in image segmentation efficiently especially in medical image processing we need to establish functioning between mathematical exceptional junior scientists and biological scientists, and define the plan to develop the new tools of this field. The inspiration should be on the study of possessions of minimal spanning trees, Euler graphs, shortest paths trees Fuzzy graphs, Normalized cuts and minimal cuts and we revisit these ideas for image segmentation purposes. This systematic survey is helpful for those researchers who wish to carryout research in the field of image segmentation. From this survey we conclude that there is no general segmentation technique that can be implemented for all types of images, but some techniques perform better than others for particular types of images indicating better performance can be obtained by selecting suitable algorithm or combination of suitable methods.

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