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STUDIES IN IMAGE SEGMENTATION AND DATA EXTRACTION

M. Noor Moyeen[1], Dr. Durgam Kumaraswamy[2]

[1]Research Scholar, OPJS University, Churu, Rajasthan
[2]Professor, OPJS University, Churu, Rajasthan

Abstract

Segmenting a picture is the first step in doing image analysis and data extraction. This is a well-studied area that nonetheless presents researchers with a number of interesting problems. This study aims to explain some of the fundamentals of picture segmentation techniques. This paper explains the reasoning behind commonly used techniques. The developed algorithms for image segmentation fall into one of two general categories: the semi-interactive method and the completely automated approach. Segmenting a picture is a vital process since it has a direct bearing on how well the image can be understood as a whole.

Keywords: Segmentation Methods, Image, Pixon, Hybrid Methods.

INTRODUCTION

The intensity of a picture may be thought of as the amplitude of a two-dimensional function of spatial coordinates, f(x, y), at a certain coordinate. Illumination and reflection functions may be multiplied to provide an expression for the picture.

$$f(x,y) = i(x,y) \,.\, r(x,y)$$

where the intensity function i(x,y) and the reflectivity function r(x,y) are denoted

The goal of digital image processing is to enhance a picture by applying different algorithms to it in order to fix problems like noise and undesired pixels and to learn more about the image.

One of the most important steps in analysing any given picture is the process of image segmentation. This study focuses mostly on this approach, its variations, and a small set of often used algorithms. Test photos are captured in an effort to compare the two approaches. MatLab software is used to manipulate the photos.

IMAGE SEGMENTATION

Segmenting an image involves first clustering pixels with similar attributes into a zone of homogeneity, and then splitting that zone into individual segments. This technique is employed in intermediate-level image analysis. Information gleaned from segmentation substantially aids in the scene annotation of an object. [10]. The goal of image segmentation is to divide a picture into sections that seem similar to one another yet share certain characteristics, regardless of the domain in which the picture was taken. [29]. Separating an image's foreground item from its background is the primary objective of segmentation.

Segmenting a picture is as easy as dividing the image's representation, R, into smaller parts, R1, R2, and so on up to Rn.

$$R = \bigcup_{i=1}^{n} R_i$$

and is governed by following set of rules:

a) Ri is a connected set, i=1,2,…..n.

b) Ri ∩ Rj = Ø for all i and j, i ≠ j

c) Q(Ri) = True for i= 1,2,…n.

d) Q(Ri U Rj) = False for adjoint regions, Ri and Rj

where the predicate Q(Rk) is a logical one [42]. According to the aforementioned guidelines, the pixels should maintain their continuity, one-to-one relationships, homogeneity, and uniqueness following segmentation.

We provide a short overview of these techniques to help you grasp the underlying ideas and extrapolate the relevant features from the study area. Although Markov Random Field segmentation is considered in some publications as a distinct segmentation method, its omission from this paper's focus and subsequent reference when necessary belies the importance it has been accorded in other works.

Separating a picture into its constituent "meaningful" pieces is what image segmentation is used for. It's been studied since at least the 1970s, but no concrete answers have been found. There are two primary causes for this: first, the vast amount of diversity present in visual content; and second, the absence of a reliable performance benchmark. Figure 1.1 displays an original picture with two segmented images produced using various image segmentation techniques. Figure 1.1 (b) divides the sky into numerous sections, while Figure 1.1 (c) omits certain information from the original. It's tough to say which method is superior since they all have their pros and cons.

Numerous studies have already been done on the topic of picture segmentation, and good overview materials can be found in [1, 2, 3]. Based on the results of these studies, we are able to categorize image segmentation approaches into three groups: (1) feature-space based method, (2) image-domain based method, and (3) edge-based method. The two components of the feature-space based technique are feature extraction and clustering. Pixel values, color components, average pixel values, variances, windowed averages, Law's filters, Tamura features, Gabor wavelet features, etc. are all examples of features that may be extracted from an image. As soon as we have gathered symbolic characteristics around each pixel, we may use a clustering method to divide the picture into distinct "meaningful" sections. Using Law's feature together with the K-means clustering technique, like we did in DIP assignment 4, is quite similar to this. There is a wide variety of clustering methods to choose from, such as the Gaussian mixture model, mean shift, and the "normalized cut" approach we developed.

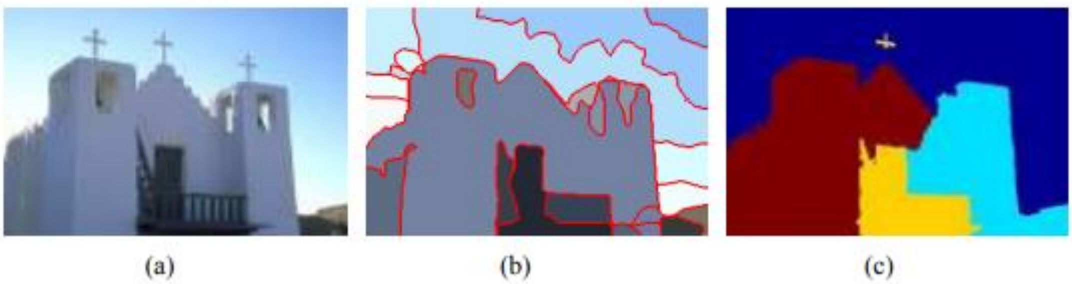

Figure 1.1: (a) is the original image, (b) is the segmentation result based on [6], and (c) is the result from [7].

The image-domain based technique examines the picture and uses predefined criteria to locate the segment boundary. Since the pixel value difference is the primary factor used to divide an image into segments, this kind of approach is not well-suited for dealing with textures. In this context, the split-and-merge, region-growing, and watershed tactics stand out as the most common options. To segment pictures along their edges, methods like edge detection and edge linking fall under the third heading.

Many different approaches have been developed over the years, but unfortunately, there are still certain widespread issues that have not been addressed. Due to the fact that features collect properties surrounding each pixel rather than directly on it, class boundary detection remains difficult. Over-segmentation of texture regions is possible if Class just uses the pixel value information. The over-segmentation problem will persist in class as long as we continue to collect edge information in the same manner. Using the "normalized cut framework" for image segmentation, our research hopes to get better segmentation results. This methodology uses a global view, rather than relying on local criteria, to decide the best path for making cuts.

LITERATURE REVIEW

Kumar, A. (2022), When it comes to diagnosing and learning more about brain tumors, one of the most trusted imaging techniques is magnetic resonance imaging (MRI). Segmentation is the process of separating the suspicious area from pre-processed MRI scans in order to create a simpler, more relevant, and more easily analyzed picture. Each of the several segmentation techniques that include detection tools yields a unique result. Several image segmentation algorithms, including Otsu's, watershed, level set, K-means, HAAR Discrete Wavelet Transform (DWT), and Convolutional Neural Network, are compared in this article to see which one is most suited for diagnosing brain tumors (CNN). Data from the 2018 iteration of the Brain Tumor Image Segmentation Benchmark (BRATS) dataset are used to run simulations of each approach in MATLAB. The efficiency of these methods is measured by several parameters, such as reaction times, recall, precision, F-measures, and accuracy. Accuracy for Otsu's method is at 71.42%; for watershed and level set at 78.16%; for K-means at 80.445%; for DWT at 86.95%; and for CNN at 91.39%. Under the conditions of the MATLAB simulation environment, the CNN response time is 2.519 s for the planned method. The original contribution of this study is the demonstration that CNN is superior to previously used approaches for segmenting brain tumor images. In the fight against brain tumours, businesses are on the lookout for cutting-edge CNN and deep learning-based hardware models; the computed parameters let scientists choose the right algorithm for embedded hardware solutions and develop the most effective machine-learning models possible.

The authors Bhanu and Lee (2014), Image segmentation may be accomplished in a number of ways. Methods such as edge detection, area splitting, region merging, clustering, surface fitting, rule-based expert systems, relaxation, and integrated approaches are all included. This chapter begins with a brief introduction to picture segmentation techniques such as edge detection, area splitting, and region expansion before diving into the intricacies of the Phoenix algorithm used in this research.

In a study by Liu, Tian, Wang, et al (2022), Insulator segmentation in highly dynamic settings has emerged as a pressing issue because to the growing use of power inspections. Based on adaptive region growth and the adaptive Otsu algorithm, a technique is provided for segmenting insulator images. Segmentation findings are generated using morphological processing, with the help of the 8 neighboring pixels utilized for region growth. Finally, We do a statistical evaluation on the initial segmented image, as well as on the results of subsequent iterations of dynamic threshold segmentation, global threshold segmentation, and adaptive region growth. By using adaptive region expansion, the accuracy of segmenting photographs taken in natural light increases by 14.23% when compared to the original segmentation result. The accuracy of adaptive region expanding segmentation for infrared image findings is increased by 8.13 percentage points when compared to the initial segmentation. The experimental findings demonstrate the superiority of adaptive region growth threshold segmentation over conventional threshold segmentation in the extraction of contour information. This work lays a vital foundation for future research into insulator defect identification and the extraction of temperature field features from infrared insulator images.

Researchers Liang, M. Zhang, and W.N. Browne all contributed to this work (2014), Segmenting images is a common initial step in solving problems with computer vision and image processing. Its accomplishments have far-reaching effects on what happens afterwards. Because of EC's powerful search capabilities, it has been used to the area of image segmentation. It would be helpful for researchers to have access to systematic reviews of EC-based image segmentation methods so that they may quickly familiarise themselves with the area and assess the many methods currently in use, but this is not often the case. This paper therefore provides a survey of existing EC-based image segmentation methods and investigates some of the unanswered concerns in this area. In terms of EC techniques, genetic algorithms (GAs) are by far the most common, followed by GP, DE, and PSO. It is pointed out that one of the most typical issues with EC approaches used for picture segmentation is their limited generalization ability and high computational cost.

Tairi, H.; Ramadan, H.; Lachqar, C.; (2020), Segmenting images is still often the first step in computer vision applications despite being one of the field's most fundamental jobs. Interactive image segmentation (IIS), often known as foreground-background separation or object extraction, is a branch of image processing that we investigate here. With more than 150 articles included, including several new papers that have not been examined before, we aim to give a comprehensive overview of the IIS literature. Additionally, we make an effort to provide a thorough categorization of them according to various points of view and offer a broad and brief comparison of the most current works to be released. As an added bonus, we take a look at some of the most popular statistics, assessment measures, and resources in the area of IIS.

INTENSITY BASED SEGMENTATION

Threshold-based segmentation, which uses thresholds based on intensity levels, is one of the simplest methods available. Threshold-based methods partition an image into two groups on the premise that pixels falling within a certain range of intensity values represent one class, while the remaining pixels represent the other. Thresholding may be set on a global or regional scale. Using a threshold value and a binary partition, global thresholding separates foreground and background pixels. Pixels that make it over the threshold are labeled as objects, given the binary value 1, while those that don't are given the value 0 and regarded to be part of the backdrop. When combined with dedicated hardware, the threshold-based segmentation techniques may be used in real-time scenarios, and they are cheap and computationally quick.

$$g(x,y) = \begin{cases} 1 & \text{for } \mathrm{i}(x,y) \geq \mathrm{t} \\ 0 & \text{for } \mathrm{i}(x,y) < t \end{cases}$$

In this formula, g(x,y) represents the final picture, i(x,y) represents the input image, and t represents the threshold.

One name for local thresholding is adaptive thresholding. This method divides a picture into smaller parts, each of which has its own unique threshold value based on the local characteristics of those smaller regions.

In global thresholding, the selected threshold value is applied uniformly throughout the whole picture, functioning as a "cutoff" point. To do local thresholding, a picture is first segmented into smaller images, and then each segment's threshold is individually selected based on the characteristics of its constituent pixels. Band thresholding, multi-thresholding, and semi-thresholding are all ways in which the threshold value may be adjusted. Depending on the threshold value, the outcome may be achieved by either global or local thresholding. As a result, settling on a threshold is a difficult and important decision. Several techniques are used to identify the threshold value, the optimal thresholding, multispectral thresholding, the edge maximisation technique, the mean method, the bimodal histogram, and the ptile- thresholding method. [43] Most threshold-based segmentation methods employ a variant of the histogram-based threshold selection proposed by Nobuyuki Otsu in 1979. [31]. When it comes to distinguishing massive objects from the backdrop, the Otsu technique excels. The discriminant criteria maximizes the discriminant measure,, to determine the best threshold to use.

Methods based on histograms, clustering, mutual information, attributes, and local adaptive segmentation are also used to determine a suitable threshold value. The following findings evaluate both methods.

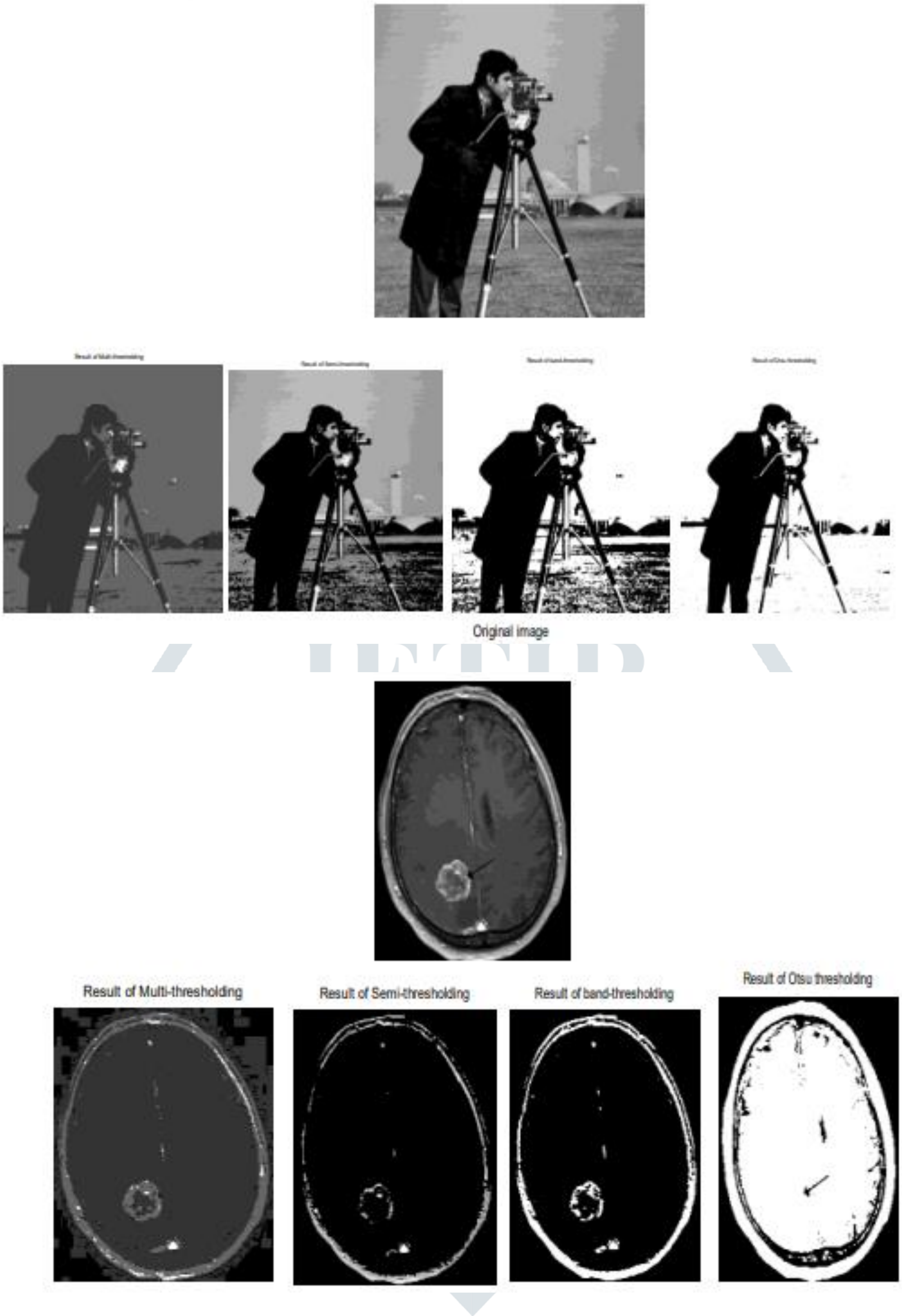

Figure 1.2: Intensity Based Segmentation

DISCONTINUITY BASED METHODS

These strategies are founded on the idea that individual pixels may vary in intensity. Boundaries exist and may be used to segment a picture if it contains two or more items. Edges are created when an object's boundaries are traversed. Edges are created when there are large, sudden variations in intensity levels between adjacent pixels in a given direction, leading to a break in the continuity of the image. To identify edges, a picture must first be smoothed, after which edges may be detected and their locations pinpointed.

In order to prepare the test picture for segmentation, we use an appropriate smoothing filter to eliminate the noise in the image. After the "possible" edges are clustered for candidacy testing, "true" edges are identified by focusing on the candidates for those edges. Figure A shows a step-edge, figure B shows a ramp-edge, figure C shows a ridge-edge, and figure D shows a ramp-edge.

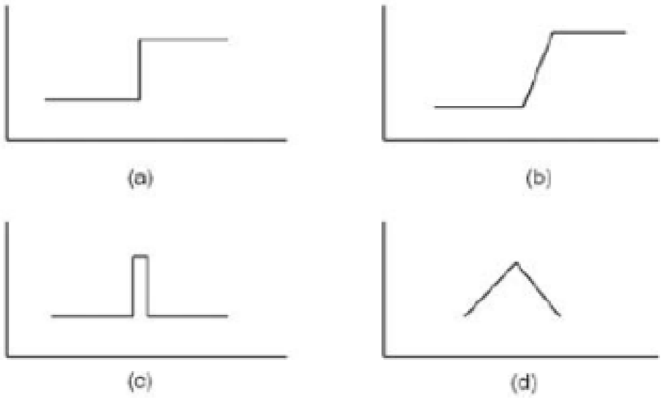

Fig 1.3: Figure A shows a step-edge, figure B shows a ramp-edge, figure C shows a ridge-edge, and figure D shows a ramp-edge.

To locate edges in a picture, masks are often used. When looking for the image's edges, we use either the gradient or zero crossing method. An image's edge set is calculated using a convolution operation involving the mask and the input image.

REGION BASED SEGMENTATION

Using the idea that nearby pixels within an area have similar features and are distinct from surrounding pixels in other regions, this approach operates on the concept of homogeneity. The goal of region-based segmentation is to create a single, large area from an image, rather than several smaller ones. Though the zones are assumed to be homogenous, there is a mechanism in place to flag any striking differences in the characteristics of adjacent pixels.

Segmenting a picture on the basis of similarities between pixels is easiest when each pixel is checked against its neighbors for similarities (in terms of gray level, texture, color, and shape)[24]. A zone is expanded by one pixel whenever the result is positive. When the likeness test fails, growth is halted.

Region based methods are fundamentally divided as

1. Region growing methods

2. Region split and merge methods

In addition, several segmentation strategies based on regional analysis of the image have been proposed, including the use of Similarity measures among neighbours, comparisons of pixels to original seeds, comparisons of pixels to neighbours within the same region, comparisons of pixels to region statistics, the use of multiple seeds, the calculation of cumulative differences, and the use of counterexamples.

Fig 1.4: Results of region growing algorithms for segmenting images.

The segmentation techniques mentioned here are compared in the following table. In order to provide a fair comparison, we utilise randomly generated values for the parameters under consideration. The relevant items were derived through close examination of the aforementioned result photos.

Table 1: Image Segmentation Methods: A Comparative Study

Parameter	Threshold Based Segmentation	Edge Based Segmentation	Region Based Segmentation
Nature of the Output Image	Black-White	Black-White	Black-White
Spatial Information	Neglected	Neglected	Considered
Region-Continuity	Moderate	Moderate	High
Computation Complexity	Less	Moderate	High
Speed	Fast	Moderate	Slow
Noise Immunity	Less	Less	Less
Detection of Multiple objects	Poor	Poor	Moderate
Automaticity	Interactive (Semi-Automatic)	Interactive	Interactive (Semi-Automatic)
Accuracy	Moderate	Moderate	Good

CLUSTERING BASED METHODS

Clustering is a method of categorizing entities according to shared characteristics. [santhanu&viki]. Clustering methods are used to locate clusters within a dataset. Similar pixels from one location (as opposed to pixels from other regions) make create a cluster. Cluster analysis, automated categorization, numerical taxonomy, botrology, and typological analysis are all terms that may be used interchangeably with "data clustering." This is a madhulatha (). The content of an image may be used to categorize it. The pixels in a content-based clustering are categorized according to their shared properties, such as form and texture.

While many other methods of cluster analysis are available, the K-means algorithm and the fuzzy C-means algorithm are now the most used approaches. Methods for cluster analysis are often categorized as either hierarchical algorithms or partitioning algorithms.

A. Agglomerative clustering:

With this hierarchical method, we first label each data point as its own cluster and then combine like clusters into larger ones. For hierarchical algorithms, calculating the distance is the most important phase. Dendograms provide a useful framework for visualizing this procedure. This strategy produces many divisions as an end result. The dissimilarity matrix is utilized to make these decisions, with the lowest entry indicating the clusters whose data points are the least dissimilar and hence the most promising candidates for merging.

Algorithm: Agglomerative Hierarchical clustering

1. Select the biggest similarity value from the input similarity matrix and its session is Si, Sj and combine and form its composition Si, j.

2. Form a matrix with Si, j.

3. Find the cell value of matrix as Similarity (Si,j, Sk) = min { similarity (Si,Sk), Similarity(Sj,Sk)}

4. Repeat step 2 until single cluster in matrix cell.

B. **Partitional clustering:**

These methods are able to converge groups by repeatedly decreasing the number of groups until convergence is achieved. The data is partitioned into clusters with the smallest possible average distance to the cluster centers using a method called partitional clustering. Kmeans clustering is a kind of algorithm used for this purpose. One division of the picture is produced using the partitional clustering method.

i. K-means algorithm: Points close to the centroid are grouped together using this method. The centroid's coordinates are those of the geometric mean of all the cluster's points, calculated independently for each dimension.

$d^2(x_k, v_i) =$ distance between object x_k and cluster center v_i

Algorithm:

1. Please fill in the values for c, q, and the threshold value The partition matrix U should also be initialised to [vik].

2. Center the clusters and start a counter.

3. Produce an array containing the calculated membership values.

4. Parameters must be calculated for each iteration. a_i^p and b_i^p till all pixels are processed where

$$a_i^p = a_i^p + v_i x_k$$
$$b_i^p = b_i^p + v_i$$

5. Cluster centre should be updated and compared to the previous value after each cycle (Ub – Ub-1)

6. The process is iterated until the difference between the two values is less than the threshold, at which point it is terminated.

There is also a combination of k-means and fuzzy c-means, which is referred to as fuzzy k-c means algorithm. This method is quite similar to fuzzy c-means in most cases, but it is more effective. In [1] we see a comparison of these two algorithms. An image's brightness (pixel intensity) and geometry information (pixel position) are only two examples of the various characteristics that may be employed by clustering algorithms. However, the success of a given approach is very feature and object dependant. This limits the generalizability of a clustering method since it creates doubt about which attributes to use to improve outcomes for a specific picture.

HYBRID METHODS

One or more of the standard segmentation techniques are brought together in hybrid approaches. These algorithms improve upon their parent algorithms' performance by absorbing their best features. In medical image segmentations, threshold-based and clustering techniques are often employed together, similar to region-based techniques, region-deformable models [Fresno et al], and region-based approaches with morphological watershed. Hybrid methods rely heavily on morphological image processing. Some of the most common methods are watershed segmentation, variable-order surface fitting, and active contour algorithms.

When all points "downhill" from a certain region drain into one central location, we say that area is a watershed. When applied to the magnitude of a picture's gradient, the watershed method draws on techniques from edge detection and mathematical morphology to segment the image into unified chunks. The gradational picture may be seen as a topographic map, with the ridges denoting the divisions between different areas. When the intensity or sharpness of the transition between sections varies, this strategy results in closed borders.

Let g(x, y) be the pixel value of coordinate x in image M1, x in image M2, y in image M3, etc., and let M1, M2,..., MR be sets indicating the coordinates in the regional minima of the picture (x, y). In this context, we will refer to C(Mi) as the catchment basin coordinates associated with the regional minimum Mi. Let T[n] be the set of (s, t) coordinates for which g(s, t) n, and then prove as

$$T[n] = \{(s, t) \mid g(s, t) < n\}$$

GRAPH BASED METHODS

There are several practical applications for graph-based picture segmentation methods. By formally organising the visual components into mathematically sound structures, it facilitates a more broad issue formulation and more efficient processing.

We may think of the image's components as vertices in a graph G = (V, E), where V = v1,..., vn, and E is the set of all possible edges in the picture. Some subset of the pairs of neighbouring vertices are connected by a set of edges, represented by E. Each edge (vi,vj) in the set E has an associated weight w(vi,vj), where w is a quantitative measure of some attribute shared by the connected vertices. Each edge's weight is a statistic that quantifies the degree of dissimilarity between its endpoints when segmenting an image using pixels as V's components.

Each half A of a partitioned picture is a linked graph G = (V, E) where V′ V, E′ E, and E' has only edges created from the nodes of V'. In other words, if AiAj = (i,j 1, 2,..., k, ij) and A1...Ak=G then the nonempty sets A1,..., Ak constitute a partition of the graph G.

Minimal spanning tree techniques, graph cut methods with cost functions, graph cut methods using Markov random field models, shortest route methods, and other methods that do not fit into the other four categories make up the graph-based approaches.

PIXON BASED METHOD:

Pixons are used in place of pixels in this nonlinear picture reconstruction technique. The linear spatial resolution and the sensitivity are both improved by many times using this technology. [puetter]. Pina and Puetter first presented this concept in 1993. Additionally, the computational speed of the pixon based technique is an advantage over other methods. Pixies may be selected using any number of techniques, including local convolution of the kernel with the pseudo image, anisotropic diffusion equations, and even a combination with Markov Random Fields. In reference to [Yang and Jiang] Combining the Fast Quad Tree Combination algorithm with an MRF model is one way to get a good pixon representation; alternatively, Hassanpour et al. utilise wavelet thresholding as a preprocessing step, then extract a good pixon representation using a suitable technique, and then segment using the Fuzzy-C Means algorithm. There are a few different ways to categorize Pixon-based approaches, but the most common ones are the "Traditional" approach, the "MRF model" approach, and the "Wavelet threshold" approach.

Creating pixons and then segmenting the picture are the only two stages involved in the conventional Pixon Based technique. In this approach, the pixon is formed in three stages: To create pixons, one must I create a false picture with the same resolution as the observed image, and (ii) filter using an anisotropic diffusion filter. (iii) Run the pixon extraction via a hierarchical clustering technique.

After the pixons have been extracted, the segmentation issue is recast as a problem of labeling pixons, and the pixon-based picture model is represented as a graph structure. Until the specified termination condition is reached, pixons are combined to produce the final segmented picture.

The picture is first represented as a pixon-based model in MPB. Attributes and adjacencies between the pixons are merged (pixons and edges). By using this pixon representation, an MRF model is introduced for image segmentation. In order to properly segment the picture, a Bayesian framework must be used. Good pixon representation may be extracted using a FQTC technique.

DISCUSSIONS

In order to extract information from the characteristics of a picture, the technique of image segmentation divides the image into homogenous sections. Therefore, the output of a successful segmentation should be areas where the picture components are of the same brightness, color, texture, etc. Despite the picture being divided up into sections, the large differences between them should still be easy to see. The quality of segmentation may be evaluated by comparing the similarities and differences between the items in each area.

Pixel intensity, homogeneity, discontinuity, cluster data, topology, and other parameters may be used to classify the segmentation process into several categories. There are good and bad points to each strategy. Different methods may provide different outcomes. When faced with a segmentation challenge, it might be challenging to decide on a solution since methods tailored to certain uses typically provide superior results.

CONCLUSION

Segmentation may be done either interactively or automatically. These two classes include the segmentation algorithms that have been created. Obtaining a single response for segmentation of a given picture is challenging because to the illposed nature of segmentation, which means that the interpretation of segmentation results might vary widely depending on the method used. Manual involvement to segment the picture may be error-prone (as in the case of seed selection), a completely automated technique may provide inaccurate results (as in the case of watershed segmentation), and interactive approaches may be time-consuming and arduous. That being the case, it may be impractical to develop a universal method for segmenting all possible picture types. Better results may be achieved with previous picture information, and the user is given agency over selecting the most appropriate approach for segmenting the image.

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