A Survey on Image Segmentation through Clustering Algorithm

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Abstract: ***The goal of this survey on different clustering techniques is to achieve image segmentation. Clustering can be termed here as a grouping of similar images. The purpose of clustering is to get meaningful result, effective storage and fast retrieval in various areas. The goal is to provide a self-contained review of the concepts and the mathematics underlying clustering techniques. Then the clustering methods are presented, divided into: hierarchical, partitioning, density-based, model-based, grid-based, and soft-computing methods. The goal of this survey is to provide a comprehensive review of different clustering and image segmentation techniques. Due to the importance of image segmentation and clustering a number of algorithms have been proposed but based on the image that is inputted the algorithm should be chosen to get the best results.***

Keywords: Clustering, Image segmentation, Hierarchical, K-means, Spectral Clustering, Histogram-based

1. Introduction

Segmentation is the process of partitioning a digital image into multiple segments based on pixels. It is a critical and essential component of image analysis system. The main process is to represent the image in a clear way. The result of image segmentation is a collection of segments which combine to form the entire image. Real world image segmentation problems actually have multiple objectives such as minimize overall deviation, maximize connectivity, minimize the features or minimize the error rate of the classifier etc.

Image segmentation is a multiple objective problem [1]. It involves several processes such as pattern representation, feature selection, feature extraction and pattern proximity. Considering all these objectives is a difficult problem, causing a gap between natures of images. To bridge this gap multi-objective optimization approach is an appropriate method. Clustering in image segmentation is defined as the process of identifying groups of similar image primitive. Clustering techniques can be classified into supervised clustering-demands human interaction to decide the clustering criteria and the unsupervised clustering- decides the clustering criteria by itself. Supervised clustering includes hierarchical approaches such as relevance feedback techniques and unsupervised clustering includes density based clustering methods. These clustering techniques are done to perform image segmentation.

1.1 Segmentation

Segmentation is the process of partitioning a digital image into multiple segments .The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images [2]. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image [3]. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s). When applied to a stack of images, typical in medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like marching cubes.

Image segmentation is defined as the process of partitioning the digital image into different sub regions of homogeneity. The objective of image segmentation is to cluster pixels into salient image regions i.e., regions corresponding to individual surfaces, objects or natural parts of objects. A segmentation might be used for object recognition image compression, image editing, etc[4]. The quality of the segmentation depends upon the digital image. In the case of simple images the segmentation process is clear and effective due to small pixels variations, whereas in the case of complex images, the utility for subsequent processing becomes questionable.

Image segmentation is one of the best known problems in computer vision. Graph based methods were earlier considered to be too insufficient in practice. Recent advances in technology and algorithm have negated this assumption. Histogram based methods are very effective while compared to other image segmentation methods because they typically require only one pass through the pixels. In this method a histogram is computed from all of the pixels in the image and the peaks and valleys in the histogram are used to locate the clustering of the image. Intensity can be used as the measure. This process is repeated with smaller and smaller clusters until no more clusters are formed [5]. This approach can be quickly adapted to multiple frames which is done in multiple fashion.

Segmentation can also be done based on spatial coherence. This includes two steps: Dividing or merging existing regions from the image and growing regions from seed points. All image processing operations generally aim at a better recognition of objects of interest, i. e., at finding suitable local features that can be distinguished from other objects and from the background. The next step is to check each individual pixel to see whether it belongs to an object of interest or not. This operation is called segmentation and produces a binary image. A pixel has the value one if it belongs to the object; otherwise it is zero. Segmentation is the operation at the threshold between low-level image processing and image analysis. After segmentation, it is known that which pixel belongs to which object. The image is parted into regions and we know the discontinuities as the boundaries between the regions [6]. The different types of segmentations are;

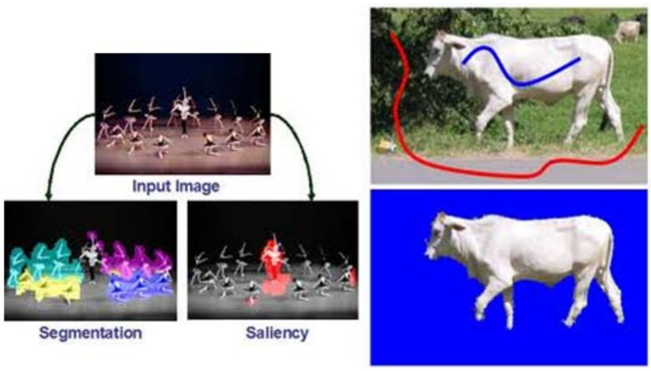


Figure 1: Segmentation

1.2 Pixel – Based segmentation Schemes

1.2.1 Mode Method

The most widely used segmentation technique is the mode method which is applicable to images with bimodal histograms, as shown in figure I. One mode of the histogram corresponds to the gray levels of the object pixels while the other mode captures the gray levels of the background pixels [7]. It is assumed that a fixed threshold level exists that separates the background area from the objects. The threshold level is chosen to be the gray level in between the two modes using any of a number of different methods. The two most popular methods are Gaussian filtering (Jain and Dubuisson.1992) and Otsu's method based on discriminate analysis (Otsu, 1979).

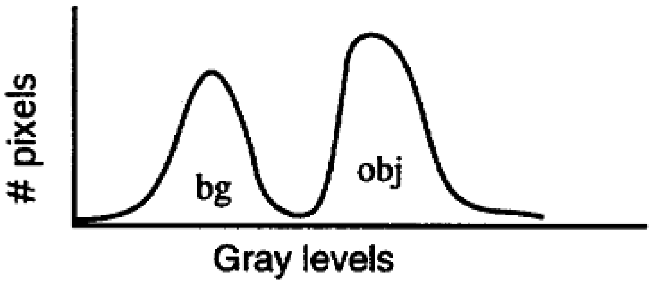


Figure 2: A Bimodal histogram, one mode represents the background pixels while the other represents the object pixels

1.2.2 Gaussian filtering algorithm

The simplest segmentation method is based on the Bayes decision theory in pattern recognition. The gray level histogram of the image is computed and then two component densities are extracted (corresponding to the object and the background) from the mixture density associated with the histogram [8]. It is commonly assumed that both the background and the object densities are Gaussian.

Algorithm

1. Compute the mean (μ) and standard deviation (σ) of the histogram:

$$\mu = \frac{1}{N}\sum F(i) * i$$

$$\sigma = \sqrt{\frac{1}{N}\sum F(i) * (i-\mu)^2}$$

2. Find a least-squares fit of the histogram F(i) by adjusting the parameters P1, μ1, σ1, P2, μ2,σ2..
3. After the parameters of the mixture density have been estimated, a pixel with gray level x is assigned to the Object.

1.2.3 Otsu's algorithm

Otsu's method of determining a threshold in a bimodal histogram is based on discriminate analysis in which thresholding is regarded as the partitioning of the pixels of an image into two classes C_o and C_1 at gray level t [9].

Algorithm

1. The gray level histogram is normalized and regarded as a probability distribution
2. Dichotomize pixels into two classes C_0 and C^1 by a threshold at level k.
3. Calculate the probabilities of class occurrence.
4. Calculate the class means levels
5. Calculate class variances
6. In order to evaluate the "goodness" of the threshold k,

we can use the following discriminate criterion.

7. The problem is now reduced to an optimization problem to search for a threshold k that maximizes one of the object functions (the criterion measures) [10].

Note that σ_W^2 and σ_B^2 are functions of threshold level k, whereas σ_T^2 is independent of k, Further, σ_W^2 is based on second order statistics while σ_B^2 is based on first-order statistics. Thus, we use η since it is the simplest measure with respect to k

The threshold determination methods discussed above work well the object size is large enough to make a distinct mode in the histogram, the gray level noise distribution (intensity noise) is independent of the gray level, and the noise is spatially uncorrelated [11]. The methods fail when it is difficult to detect the valley bottom, as in images with extremely unequal peaks or in those with board and flat valleys. Since peaks tend to become wider and lower with an increasing amount of intensity noise, some sharpening of the peaks and valleys can be accomplished by applying noise reduction preprocessing procedures.

Another approach to sharpening peaks and valleys is to weigh the influence of individual pixels and not count them all equally when calculating the histogram, as in the gradient-guided methods. Gradient guided histograms take one of two forms, interior only or boundary only. The interior-only methods (Mason et al., 1975; Panda and Rosenfeld, 1978) take into background (i.e., those pixels having low gradient values), disregarding pixels belonging to boundaries where the gray level varies rapidly. This should yield a histogram with sharper peaks and deeper valleys. In contrast, the boundary – only methods (Weszka, Nagel, and Rosenfeld, 1974; Watanabe et al., 1974) take into account only pixels having high gradient vales). This should yield a well-defined unimodal histogram, the peak value of which is a proper constant threshold level.

Finally, instead of computing a ID histogram of gray level values, a 2D histogram or "scatter" diagram can be computed with gray level and gradient as its coordinates. In this case, a good threshold can be selected using clusters of points rather than the modes of a histogram (Katz, 1965; Weszka and Rosenfeld, 1979).

1.2.4 Local methods

Global segmentation techniques such as the mode method are notoriously sensitive to parameters like ambient illumination, object shape and size, noise level, variance of gray levels within the object and background, and contrast (Taxt et al., 1989). When there is a large of gray levels within the object and background, and contrast (Tax et al., 1989). When there is a large range of variation in gray values from one part of the image to the other, a single threshold value cannot be used [12]. Further, objects may legitimately have widely different albedos and, as a result, an object in one part of an image may be lighter than the background in another part. Local methods attempt to eliminate these disadvantages by partitioning the image into sub images, determining a threshold for each of these sub images, and then smoothing between sub images to eliminate discontinuities. An example of this group of methods is the Chow-Kaneko adaptive thresholding method (Chow and Kaneko, 1972). This method assigns a different threshold value to each pixel [13].

1.2.5 Chow-Kaneko adaptive thresholding algorithm

1. Subdivide the image into several sub images.
2. For each sub image, compute the histogram, smooth it, and determine a threshold using the method.
3. Smooth the thresholds' among the neighboring sub images.
4. Determine a threshold for each pixel by interpolation.
5. Threshold the image using the threshold value assigned to each pixel.

1.3 Edge Based Segmentation Schemes

Edge-based segmentation schemes also the local information into account but do it relative to the contents of the image, not based on an arbitrary grid. Each of the methods in this category involves finding the edges in an image and then using that information to separate the regions. The most direct method is to detect and link method in which local discontinuities are first detected and then connected to form longer, hopefully complete, boundaries. The disadvantage of this approach is that the edges are not guaranteed to form closed boundaries and thus the subsequent thresholding scheme merges regions which may not be uniform (relative to the uniformity predicate discussed in the introduction).

An improvement over this method is Yanowitc and Bruckstein's adaptive thresholding method (Yanowitz and Bruckstein, 1989). Similar to detect and link method, the adaptive thresholding method locates objects in an image by using the intensity gradient [14]. These edges are used as a guide to determine an initial threshold level for various areas of the images. Local image properties are then used to assign thresholds to the remainder of the image.

Another improvement of detect and link method is the local intensity gradient (LIG) method (Parker, 1991). It is similar to Yanowitz and Bruckstein's algorithm and works well in practice. We present each algorithm below.

1.3.1 Yanowitz and Bruckstein's Adaptive Thresholding Algorithm

1. Smooth the image, replacing every pixel by the average gray – level values of some small neighborhood of it.
2. Derive the gray-level gradient magnitude image from the smoothed original. In discrete images, the gradient is actually computed as an intensity difference over a small distance.
3. Thin the gradient image, keeping only points in the image which have local gradient maxima. His should produce a one – pixel wide edge.
4. Sample the smoothed image at these maximal gradient (or edge) points. These points are assumed to be correct.
5. Interpolate the sampled gray levels over the image. The result is a threshold surface, with a (possibly) different threshold value for each pixel.
6. Using the obtained threshold surface, we segment the image. If the original pixel value is greater than or equal to the threshold value at that location, set the threshold value to 1 (or white). Otherwise, set the value to 0 (or black). Thus, objects will be set to white and background to black.

1.3.2 Local Intensity Gradient Method Algorithm

The local intensity gradient method (Parker, 1991) is based on the fact that objects in an image will produce small regions with a relatively large intensity gradient (at the boundaries of objects) whereas other areas ought to have a relatively small gradient. It uses small sub images of the gradient image to find local means and deviations. As in the local mode techniques, these regions must be small enough so that the illumination effects can be ignored.

1. Compute a smooth gradient of the image.
2. Find the object pixels in the gradient image. Object pixels are defined as outliers in the smoothed image. That is, pixel [I,j] is an object pixel if IM2[I,j] ≤ QIM[I,j]+ 3*QDEV [i,j]. Otherwise [I,j] is unclassified.
3. After sample object pixels are found, thresholds can be identified for the remaining pixels. This can be done using a region growing procedure based on gray levels in known to belong to the object.
   - For all unclassified pixels [i,j], select a gray level threshold by finding the smallest gray level value in an 8-neighborhood (pixel aggregation). If IM 1 [I,j] is less than this value, it is an object pixel. Repeat until no more object pixels are found.
   - (Optional) For all still unclassified pixels, compute a threshold as the mean of at least four neighboring object pixels (region growing). Repeat until no new object pixels are found.
   - (Optional) For all still unclassified pixels, compute a threshold as the minimum of at least six neighbors (region growing). Repeat until no new object pixels are found.
   - Set all object pixels in IMI to the value 0 and all unclassified pixels to a positive value. IMI now contains the threshold image.

1.4 Region – Based Segmentation Schemes

Region based segmentation schemes attempt to group pixels with similar characteristics (such as approximate gray level quality) into regions. Conventionally, these are global hypothesis testing techniques. The process can star at the pixel level or at an intermediate level. Generation and filtering of good seed regions of high confidence is essential. Given initially poor or incorrect seed regions, these techniques usually do not provide any mechanism for detecting and rejecting local gross errors in situations such as when an initial seed region spans two separate surfaces. These techniques can also fail if the definition of region uniformity is too strict, such as when we insist on approximately constant brightness while in reality brightens may vary linearly [14]. Another potential problem with region growing schemes is their inherent dependence on the order in which pixels and regions are examined. Usually, however, differences caused by scan order are minor.

There are two approaches in region-based methods: region growing and region splitting. In the region growing methods, the evaluated sets are very small at the start of the segmentation process. The iterative process of region growing must then be applied in order to recover the surfaces of interest. In the region growing process, the seed region is expanded to include all homogeneous neighbors and the process is repeated. The process ends when there are no more pixels to be classified. Because initial seeds are very small, the processing time can be minimized by minimizing the number of times an images element is used to determine the homogeneity of a region.

In region splitting methods, on the other hand, the evaluation of homogeneity is made on the basis of large sets of image elements. The process starts with the entire image as the seed. If the seed is inhomogeneous, it is split into a predetermined number of sub regions, typically four. The region splitting process is then repeated using each sub region as a seed. The process ends when all sub region are homogeneous. Because the seeds being processed at each step contain many pixels, region spitting methods are less sensitive to noise than the region growing methods. In both approaches, their iterative structure leads to computationally intensive algorithms.

In the late 70s, Horowitz and Pavlidis developed a hybrid algorithm, the split, merge, and group (SMG) algorithm (Horowitz and Pavlidis, 1976; Chen and Lin, 1991), which incorporates the advantages of both approaches. Because the SMC algorithm begins at an intermediate resolution level, it is more efficient than either the pure split algorithms or the pure merge algorithms. The major disadvantage, however, is that the resulting image tends to mimic the data structure used to represent the image (a quadtree for 2D images or an octree or K-tree for 3D images) and comes out too square.

1.4.1 Split, Merge, and Group Algorithm

- Initialization phase
- Merge phase
- Split phase
- Conversion from quad tree to RAG phase
- Grouping phase
- Post processing of the RAG phase

2. Model Based Segmentation

All segmentation techniques discussed so far utilize only local information. The human vision system has the ability to recognize objects even if they are not completely represented. It is obvious that the information than can be gathered from local neighborhood operators is not sufficient to perform this task. Instead specific knowledge about the geometrical shape of the object is required, which can then be compared with the local information [15]. This train of thought leads to model based segmentation. Only utilize gray – level information cannot extract the target from background; we must by means of color information. According, with the rapidly improvement of computer processing capabilities, the color image processing is being more and more concerned by people. The color image segmentation is also widely used in many.

3. Color Image Segmentation algorithm

The human eyes have adjustability for the brightness, which can only identified dozens of gray - scale at any point of complex image, but can identify thousands of colors, in cases multimedia applications.

3.1 Seed Region Growing Algorithm Watershed Algorithm

The basic idea of region is collection of pixels [16] with similar properties to form a region. The steps are as follows:

1. Find a seed pixel as a starting point for each of needed segmentation.
2. Merge the same or similar property of pixel (Based on a pre-determined growing or similar formula to determine) with the seed pixel around the seed pixel domain into the domain of seed pixel.
3. These new pixel act as a new seed pixel to continue the above process until no more pixels that satisfy the condition can be included.

4. Gray Scale Image Segmentation

The segmentation of image raster data into connected regions of common gray - scale has long been as a basic operation in image analysis. In texture analysis, just this type of segmentation is possible after individual pixels in an image have been labeled with a numeric classifier. In preparing images for used in geographic information systems (Gls) this segmentation is usually followed by the production of a vector representation for each region. The original algorithm for segmentation, developed by Rosenfeld –pfaltz [3], described a two pass sequential algorithm' for the segmentation of binary images. The key feature of the Rosenfeld-pfaltz algorithm is that the image is raster-scanned, first the forward direction, from top left to bottom right, them backwards, During the forward pass, each pixel is located a region label, based on information scanned through; the regions so demarcated may have pixels with more than one label therein. During the backwards pass, a unique label is assigned to each pixel. Hence this classic algorithm can be described as two pass algorithms can be described as two pass algorithm. In a previous paper Cohen [4] presented a one-pass algorithm was presented for the segmentation of gray-scale images. Cohen's single pass algorithm proceeds to label pixels on a forward pass, background contrast.

4.1 Mean Shift Segmentation

The mean shift based segmentation technique was introduced in [1] and has become widely- used in the vision community. it is one of many techniques under the heading of "feature space analysis". The mean shift technique is comprised of two basic steps. A mean shift filtering of the original image data (in feature space), and a subsequent clustering of the filtered data points. Below we will briefly describe each of these steps and then some of the strengths and weaknesses of this method.

4.1.1 Filtering

The filtering step of the men shift segmentation algorithm consists of analyzing the probability density function underlying the image data in feature space. Consider the feature space consisting of the original image data represented as the (L, y) location of each pixel, plus its color in L*u*v* space (L*,u*,v*). The modes of the pdf underlying the data in the space will correspondent to the locations with highest data density. In terms of segmentation, it is intuitive that the data points close to these high density points (modes) should be clustered together. Note that these modes are also far less sensitive to out less sensitive to outliers than the means of, say a mixture of Gaussians would be.

The mean shift filtering step consists of finding the modes of the underlying pdf and associating with them any points in their basin of attraction. Unlike earlier techniques, the mean shift is a non – parametric technique and hence we will need to estimate to find the modes. For a data point x in feature space, the density gradient is estimated as being proportional to the mean shift vector.

4.1.2 Clustering

After mean shift filtering each data point in the feature space has been replaced by its corresponding mode. As described above, some points may have collapsed to the same mode, but many have not despite the fact that they may be less than one kernel radius apart. In the original mean shift segmentation paper [1], clustering is described as a simple post – processing step in which any modes that are less than one kernel radius apart are grouped together and their basins of attraction are merged. This suggests using single linkage clustering, which effectively converts the filtered points into segmentation. This is the method used in the publicly available EDISON system, also described in [2]. The EDISON system is the implementation we use here as our mean shift segmentation system.

4.2 Efficient Graph based Segmentation

Efficient graph based image segmentation, introduction in [4], is another method of performing clustering in feature space. This method works directly on the data point in feature space, without first performing a filtering step, and uses a variation on single linkage clustering. The key to the success of this method is adaptive thresholding. To perform traditional single linkage clustering a minimum spanning tree of the data points is first generated (using Kruskal's algorithm), from which any edges with length greater than a given hard threshold are removed. The connected components become the clusters in the segmentation. The method in [4] eliminate the need for a hard threshold, instead replacing it with a data dependent term.

4.3 Hybrid Segmentation Algorithm

An obvious question en\merges when describing the mean shift based segmentation method [1] and the efficient graph based clustering method [4]; can we combine the two methods to give better results than either method alone? More specifically, can we combine the two methods to create more stable segmentations that are less sensitive to parameter changes and for which the same parameters give reasonable segmentations across multiple images? In an attempt to answer these questions, the third algorithm we consider is a combination of the previous two algorithms: first we apply mean shift filtering, and then we use efficient graph – based clustering to give the final segmentation. Several general-purpose algorithms and techniques have been developed for image segmentation. Since there is no general solution to the image segmentation problem, these techniques often have to be combined with domain knowledge in order to effectively solve an image segmentation problem for a problem domain.

5. Text Segmentation

It is well known that text extraction, including text detection, localization, segmentation and recognitions is very important for video auto – understanding. In this paper, we only discuss text segmentation, which is to separate text pixels from complex background in the sub – images from videos. Text segmentation in video images from videos, Text segmentation in video images is much more difficult than in scanning images. Scanning images generally has clean and white background, while video images often have very complex background without prior knowledge about the text color. Although there have been several successful systems of video text extraction, few researchers specially study text segmentation in video images deeply. The used strategies could be classified into two main categories: (1) difference (or top – down) and (2) similarly based (or bottom – up) methods. The first methods are based on the foreground.

6. Thresholding

The simplest method of image segmentation is called the thresholding method. This method is based on a clip-level (or a threshold value) to turn a gray-scale image into a binary image. The key of this method is to select the threshold value (or values when multiple-levels are selected).

Several popular methods are used in industry including the maximum entropy method, Otsu's method (maximum variance), and k-means clustering. Recently, methods have been developed for thresholding computed tomography (CT) images. The key idea is that, unlike Otsu's method, the thresholds are derived from the radiographs instead of the (reconstructed) image.

7. Compression based methods

Compression based methods postulate that the optimal segmentation is the one that minimizes, over all possible segmentations, the coding length of the data. The connection between these two concepts is that segmentation tries to find patterns in an image and any regularity in the image can be used to compress it. The method describes each segment by its texture and boundary shape. Each of these components is modeled by a probability distribution function and its coding length is computed Histogram-based methods Histogram-based methods are very efficient when compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image [1] Color or intensity can be used as the measure.

One disadvantage of the histogram-seeking method is that it may be difficult to identify significant peaks and valleys in the image. In this technique of image classification distance metric and integrated region matching are familiar.

The histogram can also be applied on a per pixel basis where the information results are used to determine the most frequent color for the pixel location. This approach segments based on active objects and a static environment, resulting in a different type of segmentation useful in Video tracking

8. Partial differential equation-based methods

Using a partial differential equation (PDE)-based method and solving the PDE equation by a numerical scheme, one can segment the image. Curve propagation is a popular technique in this category, with numerous applications to object extraction, object tracking, stereo reconstruction, etc. The central idea is to evolve an initial curve towards the lowest potential of a cost function, where its definition reflects the task to be addressed [14]. As for most inverse problems, the minimization of the cost functional is non-trivial and imposes certain smoothness constraints on the solution, which in the present case can be expressed as geometrical constraints on the evolving curve.

9. Parametric methods

Lagrangian techniques are based on parameterizing the contour according to some sampling strategy and then evolve each element according to image and internal terms. Such techniques are fast and efficient, however the original "purely parametric" formulation (due to Kass and Terzopoulos in 1987 and known as "snakes"), is generally criticized for its limitations regarding the choice of sampling strategy, the internal geometric properties of the curve, topology changes (curve splitting and merging), addressing problems in higher dimensions, etc.. Nowadays, efficient "discretized" formulations have been developed to address these limitations while maintaining high efficiency. In both cases, energy minimization is generally conducted using a steepest-gradient descent, whereby derivatives are computed using, e.g., finite differences.

10. Level set methods

The level set method was initially proposed to track moving interfaces by Osher and Sethian in 1988 and has spread across various imaging domains in the late nineties. It can be used to efficiently address the problem of curve/surface/etc. propagation in an implicit manner. The central idea is to represent the evolving contour using a signed function, where its zero level corresponds to the actual contour. Then, according to the motion equation of the contour, one can easily derive a similar flow for the implicit surface that when applied to the zero-level will reflect the propagation of the contour.

11. Fast marching methods

Fast marching method has been introduced by James A. Sethian. It has been used in image segmentation in 2006, and this model has been improved (permitting a both positive and negative speed propagation speed) in an approach called Generalized Fast Marching method.

12. Graph partitioning methods

Graph partitioning methods can effectively be used for image segmentation. In these methods, the image is modeled as a weighted, undirected graph. Usually a pixel or a group of pixels are associated with nodes and edge weights define the (dis)similarity between the neighborhood pixels [15]. The graph (image) is then partitioned according to a criterion designed to model "good" clusters. Each partition of the nodes (pixels) output from these algorithms are considered an object segment in the image. Some popular algorithms of this category are normalized cuts, random walker, minimum cut, isoperimetric partitioning and minimum spanning tree-based segmentation.[20]

13. Watershed transformation

The watershed transformation considers the gradient magnitude of an image as a topographic surface. Pixels having the highest gradient magnitude intensities (GMIs) correspond to watershed lines, which represent the region boundaries. Water placed on any pixel enclosed by a common watershed line flows downhill to a common local intensity minimum (LIM). Pixels draining to a common minimum form a catch basin, which represents a segment.

14. Model based segmentation

The central assumption of such an approach is that structures of interest/organs have a repetitive form of geometry. Therefore, one can seek for a probabilistic model towards explaining the variation of the shape of the organ and then when segmenting an image impose constraints using this model as prior. Such a task involves (i) registration of the training examples to a common pose, (ii) probabilistic representation of the variation of the registered samples, and (iii) statistical inference between the model and the image.

15. Multi-scale segmentation

Image segmentations are computed at multiple scales in scale space and sometimes propagated from coarse to fine scales; see scale-space segmentation. Segmentation criteria can be arbitrarily complex and may take into account global as well as local criteria. A common requirement is that each region must be connected in some sense.

16. One-dimensional hierarchical signal segmentation

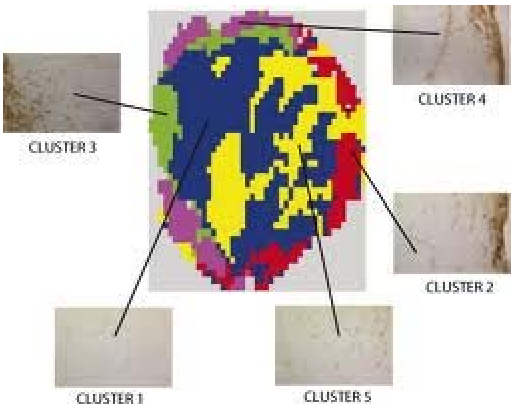
Witkin's seminal work in scale space included the notion that a one-dimensional signal could be unambiguously segmented into regions, with one scale parameter controlling the scale of segmentation. A key observation is that the zero-crossings of the second derivatives (minima and maxima of the first derivative or slope) of multi-scale-smoothed versions of a signal form a nesting tree, which defines hierarchical relations between segments at different scales[16]. Specifically, slope extrema at coarse scales can be traced back to corresponding features at fine scales. When a slope maximum and slope minimum annihilate each other at a larger scale, the three segments that they separated merge into one segment, thus defining the hierarchy of segments.

17. Image segmentation and primal sketch

There have been numerous research works in this area, out of which a few have now reached a state where they can be applied either with interactive manual intervention (usually with application to medical imaging) or fully automatically.

18. Clustering

Clustering is process of organizing the objects into groups based on its attributes. A cluster is therefore a collection of objects which are "similar" between them and are "dissimilar" to the objects belonging to other clusters. An image can be grouped based on keyword (metadata) or its content (description). A variety of clustering techniques have been introduced to make the segmentation more effective. The clustering techniques which are included in this paper [17] are relevance feedback (13), log based clustering (14), hierarchical clustering (15), graph based, retrieval-dictionary based, filter based clustering etc.



19. Clustering Techniques

An image may contain than one object and to segment the image in line with object features to extract meaningful object has become a challenge to the researches in the field. Segmentation can be achieved through clustering. This paper reviews and summarizes different clustering techniques.

19.1 Relevance feedback

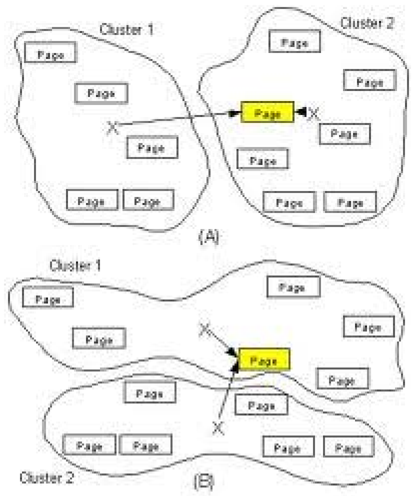
A relevance feedback approach allows a used to interact [18] with the retrieval algorithm by providing the information of which images user thinks are relevant to the query. Keyword based image retrieval is performed by matching keyword according to user input and the images in the database.

19.2 Log-Based Clustering

Images can be clustered based on the retrieval system logs maintained by an information retrieval process [11]. The session keys are created and accessed for retrieval. Through this the session clusters are created. Each session cluster generates log – based document and si8milarity of image couple is retrieved. Log – based vector is created for each session vector based on the log – based documents [19]. Now, the session cluster is replaced with this vector. The uncaused documents create its own vector.

19.3 Hierarchical Clustering

One of the well – known technologies in information retrieval is hierarchical clustering (15). It is the process of integrating different images and building them as a cluster in the form of a tree and then developing step by step in order to form a small cluster.



19.4 Retrieval dictionary Based Clustering

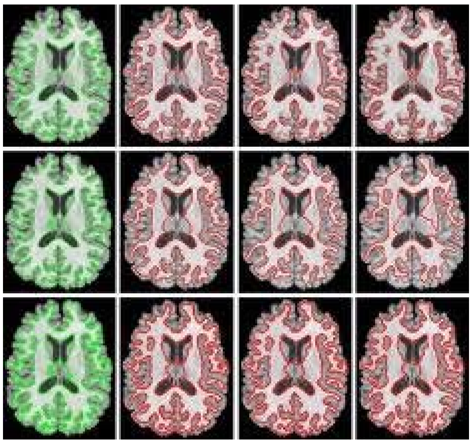
A rough classification retrieval system is formed. This is formed by calculating the distance between two learned patterns and these learned patterns are classified into different clusters followed by a retrieval stage. The main drawback addressed in this system is the determination of the distance. To overcome this problem a retrieval system is developed by retrieval dictionary based clustering 933). This method has a retrieval dictionary generate learned patterns into plural clusters and draw renewal dictionary using the clusters.

19.5 K-Means Algorithm

In K-means algorithm data vectors are grouped into predefined number of clusters. At t he beginning the centroids of the predefined clusters is initialized randomly. The dimensions of the centroids are same as the dimension of the data vectors. Each pixel is assigned to the cluster based on the closeness, which is determined by the Euclidian distance measure. After all the pixels are clustered, the mean of each cluster is recalculated. This process is repeated until no significant changes result for each cluster mean or for some fixed number of iterations.

19.6 NCut Algorithm

Ncut method attempts to organize nodes into groups so that the within the group similarity is high, and/or between the groups similarity is low. This method is empirically shown to be relatively robust in image segmentation [20]. This method can be recursively applied to get more than two clusters. In this method each time the sub graph with maximum number of nodes is partitioned (random selection for tie breaking). The process terminates when the bound on the number of clusters is reached or the Ncut value exceeds some threshold T.



20. Clustering Methods

20.1 Hierarchical Methods

- Agglomerative hierarchical clustering
- Divisive hierarchical clustering
- Single-link clustering
- Complete-link clustering
- Average-link clustering

20.2 Partitioning Methods

5.2.1. Error Minimization Algorithms.
5.2.2. Graph-Theoretic Clustering.

20.3 Density-based Methods

5.4.1. Decision Trees
5.4.2. Neural Networks.

20.4 Grid-based Methods
20.5 Soft-Computing Methods

5.6.1. Fuzzy Clustering.
5.6.2. Evolutionary Approaches for Clustering
5.6.3. Simulated Annealing for Clustering

20.6 Incremental Clustering

21. General types of Clusters

21.1 Well-separated clusters

A cluster is a set of points such that any point in a cluster is closer (or more similar) to every other point in the cluster than to any point not in the cluster.

21.2 Center-based clusters

A cluster is a set of objects such that an object in a cluster is closer (more similar) to the "center" of a cluster, than to the center of any other cluster. The center of a cluster is often a centroid, the average of all the points in the cluster, or a medoid, the most "representative" point a cluster.

21.3 Contiguous clusters

A cluster is a set of points such that a point in a cluster is closer (or more similar) to one or more other points in the cluster than to any point not in the cluster.

21.4 Density-based clusters

A cluster is a dense region of points [21], which is separated by low-density regions, from other regions of high density. Used when the clusters are irregular or intertwined, and when noise and outliers are present.

21.5 Shared Property or Conceptual Cluster

Finds clusters that share some common property or represent a particular concept.

21.6 Described by an objective function

Finds clusters that minimize or maximize an objective function.

22. Cluster Analysis

22.1 Scalability
22.2 Analyze mixture of attribute types
22.3 Find arbitrary-shaped cluster
22.4 Minimum requirements for input parameters
22.5 Handling of noise
22.6 Sensitivity to the order of input records
22.7 High dimensionality of data
22.8 interpretability and usability

23. Distance Measures

Since clustering is the grouping of similar instances/objects, some of measure that can determine whether two objects are similar or dissimilar is required. There is main type of measures used to estimate this relation: distance measures and similarity measures. Many clustering methods use distance measures to determine the similarity or dissimilarity between any pair of objects. It is calculated for Numeric Attributes, Binary Attributes, Nominal Attributes, ordinal Attributes, and Mixed-Type Attributes.

24. Similarity Functions

24.1 Cosine Measure
24.2 Pearson Correlation Measure
24.3 Extended Jaccard Measure
24.4 Dice Coefficient Measure

25. Evaluation Criteria Measures

25.1 Internal Quality Criteria
25.1.1 Sum of Squared Error (SSE)
25.1.2 Other Minimum variance Criteria
25.1.3 Scatter Criteria
25.1.4 Condorcet's Criterion
25.1.5 The C-Criterion
25.1.6 Category Utility Metric
25.1.7 Edge Cut Metrics.

Some of the practical applications of image segmentation are Medical imaging , Face recognition ,Iris recognition , Fingerprint recognition , Traffic control systems , Brake light detection , Machine vision , Agricultural imaging – crop disease detection . Clustering lies at the heart of data analysis and data mining applications [25]. The ability to discover highly correlated regions of objects when their number becomes very large is highly desirable, as data sets grow and their properties and data interrelationships change. At the same time, it is notable that any clustering "is a division of the objects into groups based on a set of rules – it is neither true nor false".

26. Conclusion

The goal of image segmentation is a domain-independent decomposition of an image into distinct regions. Clustering concepts and image segmentation concepts have been analyzed. Image segmentation has become a very important task in today's scenario. In the present day world computer vision has become an interdisciplinary field and its applications can be found in any area. Thus, to find an appropriate segmentation algorithm and clustering algorithm based on your application and the type of inputted image is very important.

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