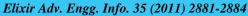


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Comparison of medical image and video segmentation using various algorithms N.J.R.Muniraj

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ABSTRACT

Image segmentation is an essential but critical component in low level vision image analysis, pattern recognition, and in robotic systems. It is one of the most difficult and challenging tasks in image processing which determines the quality of the final result of the image analysis. Image segmentation is the process of dividing an image into different regions such that each region is homogeneous. The problem of segmenting the image and/or the video content into meaningful pieces of information is of crucial importance for further steps such as 3-D shape reconstruction, object and event recognition, etc. Video segmentation is different from segmentation of a single image. While several correct solutions may exist for segmenting a single image, there needs to be a consistency among segmentations of each frame for video segmentation. Various image segmentation algorithms are discussed. Some examples in different image formats are presented and overall results discussed and compared considering different parameters.

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Introduction

Scene complexity.

The most basic attribute for segmentation is image luminance for monochrome image and colour components for the colour image. Segmentation is required to distinguish objects from background. Some of the practical applications of image segmentation include Medical imaging such as locating tumors and other pathologies, measuring tissue volumes, locating objects in satellite images, face recognition, Traffic control systems, Fingerprint recognition and Machine vision etc. Video segmentation refers to partitioning video into spatial, temporal, or spatiotemporal regions that are homogeneous in some feature space. It is an integral part of many video analysis and coding problems, including (i) video summarization, indexing, and retrieval, (ii) advanced video coding, (iii) video authoring and editing, (iv) 3D motion and structure estimation with multiple moving objects, and (v) video surveillance/understanding. Different features and homogeneity criteria generally lead to different segmentations of the same video, for example, colour, texture, or motion segmentation. Factors that affect the choice of a specific segmentation method include the following:

≻ Real-time performance

- > Precision of segmentation
- \triangleright Scene complexity

Segmentation Algorithms

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 different image segmentation algorithms are K-means clustering. Ostuthresholding, Active contour, FCM, Improved FCM, Edge detection techniques (Sobel, Roberts cross, Prewitt, Canny). **Edge Detection**

tool in image Edge detection is a fundamental processing and computer vision, particularly in the areas of feature detection and feature extraction, which aim at identifying points in a digital image at which the image brightness changes sharply or, more formally, has discontinuities. The purpose of detecting sharp changes in image

brightness is to capture important events and changes in properties of the world. It can be shown that under rather general assumptions for an image formation model, discontinuities in image brightness are likely to correspond to:

- \succ discontinuities in depth,
- ≻ discontinuities in surface orientation,
- ➤ changes in material properties and
- ▶ variations in scene illumination.

In the ideal case, the result of applying an edge detector to an image may lead to a set of connected curves that indicate the boundaries of objects, the boundaries of surface markings as well as curves that correspond to discontinuities in surface orientation. Thus, applying an edge detection algorithm to an image may significantly reduce the amount of data to be processed and may therefore filter out information that may be regarded as less relevant, while preserving the important structural properties of an image.

An edge is a jump in intensity. The cross section of an edge has the shape of a ramp. An ideal edge is a discontinuity (*i.e.*, a ramp with an infinite slope). The first derivative assumes a local maximum at an edge. For a continuous image f(x, y), where x and y are the row and column coordinates respectively, we typically consider two directional the derivatives $\partial_x f(x, y)$ and $\partial_y f(x, y)$. Of particular interest in edge detection are two functions that can be expressed in terms of these directional derivatives: the gradient magnitude and the gradient orientation. The gradient magnitude is defined as

$$|\nabla f(x, y)| = \sqrt{(\partial_x f(x, y))^2 + (\partial_y f(x, y))^2}$$

And the gradient orientation is given by

Local maxima of the gradient magnitude identify edges $in^{f(x, y)}$. When the first derivative achieves a maximum, the second derivative is zero. The four steps of edge detection

- (1) Smoothing
- (2) Enhancement

(3) Detection

(4) Localization

There are different types of edge detection techniques used in image processing. They are:

Sobel:

Sobel is a discrete differentiation operator, computing an approximation of the gradient of the image intensity function. At each point in the image, the result of the Sobel operator is either the corresponding gradient vector or the norm of this vector. The Sobel operator is based on convolving the image with a small, separable, and integer valued filter in horizontal and vertical direction and is therefore relatively inexpensive in terms of computations.

Roberts Cross:

The Roberts' Cross operator is used in image processing and computer vision for edge detection. It was one of the first edge detectors and was initially proposed by Lawrence Roberts in 1963. As a differential operator, the idea behind the Robert's Cross operator is to approximate the gradient of an image through discrete differentiation which is achieved by computing the sum of the squares of the differences between diagonally adjacent pixels. The Roberts operator performs a simple, quick to compute, 2-D spatial gradient measurement on an image. It thus highlights regions of high spatial gradient which often correspond to edges.

Prewitt

The basic criterion for using Prewitt edge detector for detection of edges in digital images is that image should contain sharp intensity transition and low noise of Poisson type is present. When using Prewitt edge detection the image is convolved with a set of (in general 8) convolution kernels, each of which is sensitive to edges in a different orientation.

Canny:

The Canny edge detection operator was developed by John F. Canny in 1986 and uses a multi-stage algorithm to detect a wide range of edges in images. Canny's aim was to discover the optimal edge detection algorithm.

 \triangleright The first and most obvious is low error rate.

 \triangleright The second criterion is that the edge points be well localized.

> A third criterion is to have only one response to a single edge.

K-Means Clustering

The main idea is to define k centroids, one for each cluster. These centroids should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early groupage is done. At this point we need to re-calculate k new centroids as barycenters of the clusters resulting from the previous step. After we have these k new centroids, a new binding has to be done between the same data set points and the nearest new centroid. A loop has been generated. As a result of this loop we may notice that the k centroids change their location step by step until no more changes are done. In other words centroids do not move any more.

The algorithm is composed of the following steps:

> Place K points into the space represented by the objects that are being clustered. These points represent initial group centroids.

Assign each object to the group that has the closest centroid.

> When all objects have been assigned, recalculate the positions of the K centroids.

> Repeat Steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups from which the metric to be minimized can be calculated.

Ostu thresholding:

In computer vision and image processing, Otsu's method is used to automatically perform histogram shape-based image thresholding, or, the reduction of a graylevel image to a binary image. The algorithm assumes that the image to be thresholded contains two classes of pixels (e.g. foreground and background) then calculates the optimum threshold separating those two classes so that their combined spread (intra-class variance) is minimal. The extension of the original method to multi-level thresholding is referred to as the Multi Otsu method.

This method, as proposed in, is based on discriminate analysis. The threshold operation is regarded as the partitioning of the pixels of an image into two classes C0 and C1 (e.g., objects and background) at grey-level t, i.e., $C0 = \{0, 1, 2, ..., t\}$ and $C1 = \{t + 1, t + 2, ..., L-1\}$. Let $\sigma 2$ w, $\sigma 2$ B and $\sigma 2$ T be the within-class variance, between-class variance, and the total variance, respectively. An optimal threshold can be determined by minimizing one of the following (equivalent) criterion functions with respect to:

$$\eta(t) = \frac{\sigma_b^2}{\sigma_d^2}$$

The complete expressions for σ_b^2 and σ_a^2 can be found.

The algorithm for the proposed method is prescribed as follows: 1. I=Input Image.

2. Obtain the histogram values (h) of the image I.

3. Set the initial Threshold value:

 $T_{in} = \frac{\sum (h * total shades)}{\sum h}$

4. Segment the using Tin. This will produce two groups of pixels: C1 and C2.

5. Repeat step-3 to obtain the new threshold values for each class. (TC1 &TC2).

6. Compute the new threshold value:

$$T = \frac{(T_{c1} + T_{c2})}{2}$$

7. Repeat the steps 3-6 until the difference in T in successive iterations is not tends to zero.

8. Now apply the Otsu method for the obtained threshold value for further segmentation process.

Active Contour

An active contour is an energy minimizing spline that detects specified features within an image. It is a flexibile curve (or surface) which can be dynamically adapted to required edges or objects in the image (it can be used to automatic objects segmentation).

It consists of a set of control points connected by straight lines. The active contour is defined by the number of control points as well as sequence of each other.

Fitting active contours to shapes in images is an interactive process. The user must suggest an initial contour, which is quite close to the intended shape. The contour will then be attracted to features in the image extracted by internal energy creating an attractor image.

Basic Definition

Active contour (a set of the coordinates of control points on the contour) is defined parametrically as [1, 3, and 5]:

$$\vec{v}(s) = (\vec{x}(s), \vec{y}(s)),$$

Where x(s) and y(s) are x, y coordinates past the contour and s is the normalized index of the control points. **FCM**

Data clustering is the process of dividing data elements into classes or clusters so that items in the same class are as similar as possible, and items in different classes are as dissimilar as possible. Depending on the nature of the data and the purpose for which clustering is being used, different measures of similarity may be used to place items into classes, where the similarity measure controls how the clusters are formed.

In hard clustering, data is divided into distinct clusters, where each data element belongs to exactly one cluster. In fuzzy clustering (also referred to as soft clustering), data elements can belong to more than one cluster, and associated with each element is a set of membership levels. These indicate the strength of the association between that data element and a particular cluster. Fuzzy clustering is a process of assigning these membership levels, and then using them to assign data elements to one or more clusters.

One of the most widely used fuzzy clustering algorithms is the Fuzzy C-Means (FCM) Algorithm (Bezdek 1981). It is based on minimization of the following objective function, with respect to U, a fuzzy c-partition of the data set, and to V, a set of K prototypes:

$$J_m(U, V) = \sum_{j=1}^n \sum_{l=1}^c u_{ll}^m ||X_j - V_l||^2, \quad 1 \le m < \infty$$

Where m is any real number greater than 1, u_{ij} is the

degree of membership of X_j in the i, X_j is the jth of ddimensional measured data, is the d-dimension center of the cluster, V_i and ||*|| is any norm expressed the similarity between any measured data and the center.

Improved FCM

Fuzzy c-means (FCM) algorithm is one of the most popular methods for image segmentation. However, the standard FCM algorithm is sensitive to noise because of not taking into account the spatial information in the image. An improved FCM algorithm is proposed to improve the antinoise performance of FCM algorithm. The new algorithm is formulated by incorporating the spatial neighbourhood information into the membership function for clustering. The distribution statistics of the neighbourhood pixels and the prior probability are used to form a new membership function. It is not only effective to remove the noise spots but also can reduce the misclassified pixels. Experimental results indicate that the proposed algorithm is more accurate and robust to noise than the standard FCM algorithm.

One of the important characteristics of an image is that neighbouring pixels are highly correlated. In other words, these neighboring pixels possess similar feature values, and the probability that they belong to the same cluster is great. This spatial relationship is important in clustering, but it is not utilized in a standard FCM algorithm. All samples are used as dispersive points when using the standard FCM algorithm to cluster. So the standard FCM algorithm is sensitive to noise. To overcome the defect of the standard FCM algorithm, we exploit the spatial information which is formed by using the distribution statistics of the neighborhood pixels and the prior probability to form a new membership function for clustering. It is not only effective to remove the noise spots but also reduce the misclassified pixel.

Implementation

The above discussed algorithms are implemented using MATLAB 7.4.0(R2009a). The different set of input medical images such as X-ray, MRI and CT are considered for experimentation. Also the different image file formats such as JPEG, TIFF, BMP, GIF, text and PNG are considered. The sample results are displayed for the discussion. Figure1 shows the input brain image.

This image is given as input to various image segmentation algorithms and the outputs are shown in the above table.Figure 2 shows the output of SOBEL edge detection technique. This is a high speed edge detection algorithm. The Sobel operator is slower to compute than the Roberts Cross operator, but its larger convolution mask smooth, the input image to a greater extent and so makes the operator less sensitive to noise. The operator also generally produces considerably higher output values for similar edges compared with the Roberts Cross.

Figure 3 shows the output of ROBERTS CROSS edge detection technique. The main reason for using the Roberts Cross operator is that it is very quick to compute. Only four input pixels need to be examined to determine the value of each output pixel, and only subtractions and additions are used in the calculation. In addition there are no parameters to set. Its main disadvantages are that since it uses such a small kernel, it is very sensitive to noise. It also produces very weak responses to genuine edges unless they are very sharp. Figure 4 shows the output of PREWITT edge detection technique. It gives good smoothing operation and reduces noise to a good level.

For that we have to select the threshold value. But it takes longer time to fix that value. Figure 5 shows the output of canny method. In this edges are marked as close as possible to the edge in real image. So it gives the clear output. Figure 6 shows the output of K-means clustering. K-Means is faster than other methods, and associated ground truth can be precomputed and stored, and assigned to new data sets. The result only depends on K value. But to find the K value is critical thing. Figure 7 OTSU method is based on discriminate analysis. The threshold operation is regarded as the partitioning of pixels of an image. It is very senstive to noise. But it is very time taking process. FCM algorithm corrects for noisy images without Figure 8 affecting the edges. Figure 9 Improved FCM is one of the popular algorithms for image segmentation. Computitional time of clustering is less.

Result

Image Segmentation

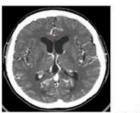
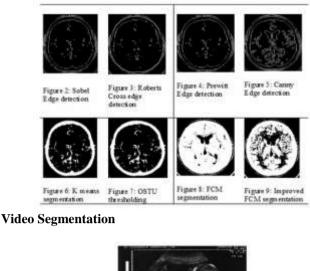


Figure 1: Input image of Brain



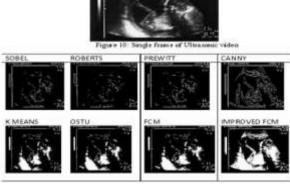


Figure 10 shows the frame of input ultrasorsic video. This video is given as input to various segmentation algorithms and the results are shown in the above. Based on the conjust obtained, we concluded that improved FCM as the best algorithm.

Conclusion

The image segmentation is a relevant technique in image processing. Numerous and varied methods exist for many applications. Now that we have described the algorithms, we can compare the outputs and check which type of segmentation technique is better for particular format. It is believed that there are two key factors which allow for the use of segmentation algorithm in a larger object detection system: correctness and stability. On an average parameter set of the edge detection techniques, The canny operator performed better than all other operators for all the formats of images, sample of which can be found in result. The same is reflected by higher value of entropy after segmentation. The clustering algorithm is guaranteed to converge but it may not return optimal solution. The quality of the solution depends on the initial set of clusters and value of k. An inappropriate choice of K yields very poor result. This algorithm can be directly applied for colour images. References

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