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Objective Evaluation Parameters of Image Segmentation Algorithms

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Abstract- Image segmentation is the process of partitioning an image into multiple segments, so as to change the representation of an image into something that is more meaningful and easier to analyze. Several general-purpose algorithms and techniques have been developed for image segmentation. However ,evaluation of segmentation algorithms thus far has been largely subjective , leaving a system designer to judge the effectiveness of a technique based only on intuition and results in the form of few example segmented images .This is largely due to image segmentation being a ill defined problem-there is no unique ground truth segmentation of an image against which the output of an algorithm may be compared .There is a need for researchers to know on what parameters there suggested techniques can be evaluated .In this paper we have surveyed 100 papers to present various evaluation parameters. This paper presents 13 performance evaluation parameters that can be used to perform a quantitative comparison between image segmentation.

Keywords- Segmentation, MRI,

I. INTRODUCTION

This paper surveys various researchers on image segmentation and presents 13 evaluation parameters that can be used for evaluating image segmentation techniques. 13 evaluation parameters are rand index, variation of information, global consistency error ,boundary displacement error, segmentation accuracy, precision recall measure ,convergence rate ,mean absolute error, peak signal to noise ratio, hamming distance ,local consistency error, structural similarity index measure and entropy.

Images are considered as one of the most important medium of conveying information, which can be used for navigation of robots, extracting malign tissues from body scans, detection of cancerous cells, and identification of an airport from remote sensing data. Now there is a need of a method, with the help of which, we can understand images and extract information or objects, image segmentation fulfill above requirements. Thus, image segmentation is the first step in image analysis. Sometimes image denoising is done before the segmentation to avoid from the false contour selection.

This paper is organized as follows; section 2 introduces the term image segmentation. Section 3 describes the current image segmentation techniques and section 4 gives different evaluation parameters used for comparing the quality of image segmentation. In section 5 conclusions are drawn.

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II. IMAGE SEGMENTATION

Image segmentation refers to the process of partitioning a digital image into multiple segments i.e. set of pixels, pixels in a region are similar according to some homogeneity criteria such as color, intensity or texture, so as to locate and identify objects and boundaries in an image [1]. Practical application of image segmentation range from filtering of noisy images, medical applications (Locate tumors and other pathologies, Measure tissue volumes, Computer guided surgery, Diagnosis, Treatment planning, study of anatomical structure), Locate objects in satellite images (roads, forests, etc.), Face Recognition, Fingerprint Recognition, etc. Many segmentation methods have been proposed in the literature. The choice of a segmentation technique over another and the level of segmentation are decided by the particular type of image and characteristics of the problem being considered.

III. CURRENT SEGMENTATION TECHNIQUES

The Research on Image segmentation for many years has been a high degree of attention. Thousands of different segmentation techniques are present in the literature, but there is not a single method which can be considered good for different images, all methods are not equally good for a particular type of image [7].Thus, algorithm development for one class of image may not always be applied to other class of images. Hence, there are many challenging issues like development of a unified approach to image segmentation which can be applied to all type of images, even the selection of an appropriate technique for a specific type of image is a difficult problem. Thus, in spite of several decades of research, there is no universally accepted method for image segmentation and therefore it remains a challenging problem in image processing and computer vision. Based on different technologies, image segmentation approaches are currently divided into following categories, based on two properties of image.

- **Detecting Discontinuities**

It means to partition an image based on abrupt changes in intensity [1], this includes image segmentation algorithms like edge detection.

- **Detecting Similarities**

It means to partition an image into regions that are similar according to a set of predefined criterion [1]; this includes image segmentation algorithms like Thresholding, region growing, region splitting and merging.

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IV. PERFORMANCE EVALUATION PARAMETERS:

We still lack reliable ways in performance evaluation for quantitatively positioning the state of the art of image segmentation. In many prior works, segmentation performance is usually evaluated by subjectively or objectively judging on several sample images. Such evaluations on a small number of sample images lack statistical meanings and may not be generalized to other images and applications [13].Segmentation evaluation metrics can be divided into boundary –based and region –based methods. The analysis of various research papers indicate that 13 evaluation parameters can be used for evaluating the image segmentation techniques based on applications. Various performance evaluation parameters used for evaluation of image segmentation are as follows.

4.1. The Rand index (RI):

Rand index counts the fraction of pairs of pixels who's labeling are consistent between the computed segmentation and the ground truth averaging across multiple ground truth segmentation [21]. The Rand index or Rand measure is a measure of the similarity between two data clusters. Given a set of n elements and two partitions of S to compare, we define the following(a), the number of pairs of elements in S that are in the same set in X and in the same set in Y. (b), the number of pairs of elements in S that are in different sets in X and in different sets in Y. (c), the number of pairs of elements in S that are in the same set in X and in different sets in Y.(d), the number of pairs of elements in S that are in different sets in X and in the same set in Y The Rand index I is,

$$R = \frac{a+b}{a+b+c+d} = \frac{a+b}{(\frac{n}{2})}$$

Where, a + b is the number of agreements between X and Y and c + d is the number of disagreements between X and Y. The Rand index has a value between 0 and 1, with 0 indicating that the two data clusters do not agree on any pair of points and 1 indicating that the data clusters are exactly the same.

4.2 Variation of Information (VOI):

The Variation of Information (VOI) metric defines the distance between two segmentations as average conditional entropy of one segmentation given the other, and thus measures the amount of randomness in one segmentation which cannot be explained by the other [21]. Suppose we have two clustering (a division of a set into several subsets) X and Y where X = {X1, X2... Xk}, pi = | Xi | / n, n = Σ k | Xi |. Then the variation of information between two clustering is:

VI(X; Y) = H(X) + H(Y) – 2I(X, Y)

Where, H(X) is entropy of X and I(X, Y) is mutual information between X and Y. The mutual information of two clustering is the loss of uncertainty of one clustering if the other is given. Thus, mutual information is positive and bounded by {H(X), H(Y)} _ $\log_2(n)$

4.3 Global Consistency Error (GCE):

The Global Consistency Error (GCE) measures the extent to which one segmentation can be viewed as a refinement of the other [21, 13]. Segmentations which are related are considered to be consistent, since they could represent the same image segmented at different scales. Segmentation is simply a division of the pixels of an image into sets. The segments are sets of pixels. If one segment is a proper subset of the other, then the pixel lies in an area of refinement, and the error should be zero. If there is no Subset relationship, then the two regions overlaps in an inconsistent manner. The formula for GCE is as follows,

$$GCE = \frac{1}{n}\min\{\sum_i E(S1,S2,pi), \sum_i E(S2.S1,pi)\}$$

Where, segmentation error measure takes two segmentations S1 and S2 as input, and produces a real valued output in the range [0::1] where zero signifies no error. For a given pixel pi consider the segments in S1 and S2 that contain that pixel.

4.4. Boundary Displacement Error (BDE):

The Boundary Displacement Error (BDE) measures the average displacement error of one boundary pixels and the closest boundary pixels in the other segmentation [21, 4].

$$\mu_{LA}(u,v) = \{\frac{u-v}{L-1} 0 < u-v$$

4.5 Segmentation Accuracy:

The percentage of segmentation accuracy [1] can be defined as, %Segmentation accuracy=Number of correctly classified pixels for segmented area /Total number of pixels

4.6 Precision-Recall Measures:

Martin in his thesis [6, 32], propose the use of *precision* and *recall* values to characterize the agreement between the oriented boundary edge elements (termed *edgels*) of region boundaries of two segmentations. Given two segmentations, *S* and *R*, where *S* is the result of segmentation and *R* is the ground truth, precision is proportional to the fraction of edgels from *S* that matches with the ground truth *R*, and recall is proportional to the fraction of edgels from *R* for which a suitable match was found in *S*. Precision measure is defined as follows:

$$P = \frac{Matched(S,R)}{|S|} \qquad \mathrm{Re}call = \frac{Matched(R,S)}{|R|}$$

Where |*S*| and |*R*| are the total amount of boundary pixels In probabilistic terms, Precision is the probability that the result is valid, and recall is the probability that the ground truth data was detected. A low recall value is typically the result of under-segmentation and indicates failure to capture salient image structure. Precision is low when there is significant over-segmentation, or when a large number of boundary pixels have greater localization errors than some threshold δmax. The two statistics may be distilled into a single figure of merit:

$$F = \frac{PR}{\alpha R + (1-\alpha)P}$$

Where α determines the relative importance of each term, α is selected as 0.5, expressing no preference for either. The main advantage of using precision and recall for the evaluation of segmentation results is that we can compare not only the segmentations produced by different algorithms, but also the results produced by the same algorithm using different input parameters. However, since these measures are not tolerant to refinement, it is possible for two segmentations that are perfect mutual refinements of each other to have very low precision and recall scores.

4.7 Convergence rate or Execution time:

Convergence rate is defined as the time period required for the system to reach the stabilized condition. The lesser the execution time better is the segmentation technique.

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4.8. Mean absolute error (MAE):

Mean absolute error is the average of the difference between predicted and actual value in all test cases; it is the average prediction error. MAE indicates that higher the values of MAE mean the image is of poor quality.

4.9 Peak signal to noise ratio (PSNR):

It gives quality of image in decibels (db).and is given as

$$PSNR = 20\log_{10}\left(\frac{255^2}{MAE}\right)$$

4.10. Hamming Distance

Huang and Dom [3] introduced the concept of directional Hamming distance between two segmentations, denoted by *DH* (*S*1 $\Rightarrow$ *S*2). Let *S* and *R* be two segmentations. They began by establishing the correspondence between each region of *S* with a region of *R* such that $s_i \cap r_j$ is maximized. The directional Hamming distance from *S* to *R* is defined as:

$$D_H(S \to R) = \sum_{ri \in R} \sum_{Sk \neq Sj, Sk \cap ri \neq 0} |ri \cap sk|$$

Where |.| denote the size of a set, Therefore, *DH* (*S* $\longrightarrow$ *R*) is the total area under the intersections between all $r_i \in R$ and their non-maximal intersected regions from *S*. A region-based evaluation measure based on normalized Hamming distance is defined as

$p = 1 - DH\,(S \Rightarrow R) + DH\,(R \Rightarrow S)\ 2 \times |S|$, where $|S|$ is the image size and $p \in [0, 1]$. The smaller the degree of mismatch, the closer the *p* is to one.

4.11 Local Consistency Error:

Based on this consistency, two metrics that can be used to evaluate the consistency of a pair of segmentations. The measures are designed to be tolerant to refinement, that is, if subsets of regions in one segmentation consistently merge into some region in the other segmentation the consistency error should be low. In order to compute the consistency error for a pair of images, they first define a measure of the error at each pixel pi

$$E(S_1, S_2, p_i) = \frac{|R(S_1, p_i) \setminus R(S_2, p_i)|}{|R(S_1, p_i)|}$$

Where R (S_j; p_i) is the region in segmentation j that contains pixel pi, \ denotes set difference, and |.| denotes set cardinality. This measure evaluates to 0 if all the pixels in S1 are also contained in S2 thus achieving the tolerance to refinement discussed above. It is important to note that this measure is not symmetric, so for every pixel it must be computed twice, once in each direction. Given the error measures at each pixel, segmentation error measure is defined as

$$LCE(S_1, S_2) = \frac{1}{n}\sum_i \min(E(S_1, S_2, p_i), E(S_2, S_1, p_i))$$

The Global Consistency Error (GCE) assumes that one of the segmentations must be a refinement of the other, and forces all local refinements to be in the same direction. The Local Consistency Error (LCE) allows for refinements to occur in either direction at different locations in the segmentation. When pairs of human segmentations of the same image are compared, both the GCE and the LCE are low; conversely, when random pairs of human segmentations are compared, the resulting GCE and LCE are high.

4.12 Entropy:

Entropy[12] of a discrete random distribution p(x) is defined as the entropy H of a discrete random variable X with possible values { $x_{1,\ldots,}x_n$ }is H(X)=E(I(X)) here E is the expected value , and I is the information content of X .I(X) is random variable. If p denotes the probability mass function of X then entropy can explicitly be written as

$$H(X) = \sum_{i=1}^{n} p(x_i) I(x_i) = -\sum_{i=1}^{n} p(x_i)\log_b p(x_i)$$

4.13 stimated as mean intensity:

$$\mu_x = \frac{1}{N}\sum_{i=1}^{N} x_i \quad \ldots\ldots\ldots\ldots..1$$

$$\sum_{i=1}^{N} x_i = 0 \quad \ldots\ldots\ldots.2$$

Standard deviation is used as estimate of the signal contrast. An unbiased estimate in discrete form is given by

$$\sigma_x = \left(\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu_x)^2\right)^{\frac{1}{2}} \quad \ldots\ldots\ldots3$$

The contrast comparison c(x, y) is conducted on these normalized signal $(x-\mu_x)/\sigma_x$ and $(y-\mu_y)/\sigma_y$.Finally the three components are combined to give overall similarity measure

S(x, y) =f (l(x, y), c(x, y), s(x, y))……….4

An important point is that the three components are relatively independent .In order to complete the definition of similarity measure of equation 4 we need to define the three functions l(x,y), c(x,y), s(x,y) as well as the combination of function f(.). For luminance comparison we define

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} \quad \ldots\ldots..5$$

Where constant c1 is included to avoid instability when µ 2 x +µ 2 y is very close to zero. c1 is choose as $C_1 = (k,l)^2$ …….6

Where l is dynamic range of pixel values (255 for 8 bit grey scale images) and k1<<1 is a small constant .Let R represent the size of luminance change relative to background luminance, we rewrite the luminance of distorted signal as µy=(1+R)µy substituting this in equation 5 gives

$$l(x,y) = \frac{2(1+R)}{1+(1+R)^2 + C_1/\mu_x^2} \quad \ldots\ldots\ldots.7$$

If we assume C1 small enough (relative to µ2x) to be ignored, then l(x, y) is function only of R1 contrast comparison function takes similar form

$$c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} \quad \ldots\ldots\ldots8$$

Where C2= (k2L) 2 and k2 <<1 the structure comparison function is defined as

$$s(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3}$$

Where $\sigma_{xy} = \frac{1}{N-1}\sum_{i}^{N-1}(x_i - \mu_x)(y_i - \mu_y)$ …………10

Set c3=c2 /2.Finally combining equation 5, 8, 9 and name the resulting similarity measure the SSIM between signal x and y

$$SSIM(x,y) = [l(x,y)]^{\alpha}[c(x,y)]^{\beta}[s(x,y)]^{\gamma} \quad \ldots\ldots\ldots11$$

This results in specific form of SSIM index

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$$SSIM(x,y)=\frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)}$$

The luminance comparison

or X on the h

V. CONCLUSION:

We present 13 evaluation parameters to evaluate the segmentation techniques. The analysis of various research work shows that for the unsupervised methods ie. Cluster based methods performance is measured using segmentation parameters like rand index, global consistency error, variation of information and boundary displacement error. For region based evaluation global consistency is widely used. For boundary based evaluation precision and recall are frequently used.

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