SEGMENTATION OF T1-, T2-, AND PD-WEIGHTED MR Images

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ABSTRACT

Multimodal segmentation, like the physicians in practice, uses several images, representing different features of the object under investigation, to make segmentation decisions. In this paper, a multimodal two-dimensional segmentation method is introduced. The principle of this method is the combination of multimodal region growing and multimodal edge detection. The combining condition is universally valid, using neither object-specific nor imaging-specific knowledge, so that a variety of segmentation tasks can be worked on.

INTRODUCTION

Segmentation is an important step for every kind of medical image processing, such as 3D-visualization or volume measurements. Only after splitting an image into primitives (segmenting), it is possible to address and use these primitives, such as organs or tissues, separately. The idea of multimodal segmentation is to combine several object features and to use different imaging modalities as input signals for segmentation, like Computer Tomographie (CT) or Magnetic Resonance Imaging (MRI). The goal is to collect as much information as possible about the examined object. Multimodal segmentation, therefore, includes several properties of the object.

If images of different devices such as CT and MR are used as modalities in multimodal segmentation, the problem of slight variations in the object's location and orientation will arise. These varieties result from changing the device. The differences in modalities are eliminated by a preprocessing step called Matching. The development of methods for exact matching of different data sets is actually still the object of research activities.

In magnetic resonance imaging, it is possible to take three different kinds of weighted images. These T1 relaxation, T2 relaxation and proton density images can be used as modalities in multimodal segmentation. Because the three different weighted images are taken by the same device, variations in the object's location and orientation are negligible. Thus Matching, a step which is costly and susceptible to errors can be avoided.

Magnetic resonance images are very suitable for examining multimodal segmentation techniques, because the error-susceptible and costly preprocessing step of matching can be avoided.

This paper introduces a technique for multimodal two-dimensional image segmentation used on T1 weighted, T2 weighted and PD weighted MR images.

STATE OF THE ART

Several methods of multimodal segmentation have already been developed. The principal segmentation can be categorized into two groups. The first group's methods use *only intensity values* for segmentation decisions. The methods of the second group simultaneously use intensity values with *pixel's neighborhood* as a guideline for segmentation decisions.

The commonly used methods for unimodal signal segmentation were transferred to the multimodal case. *Multimodal methods not using local information* are e.g. *cluster analysis*, *nonparametric histogram method* [1] or the *topological map* [2], whereas *methods using local information and pixel's neighborhood* are, for example, the *cluster analysis of topological features*, methods of *multimodal region growing* [3], or *multimodal edge detection* [4]. Realizing that every method mentioned above has its drawbacks and uncertainties, systems were developed that *combine different basic methods for segmentation*, to compensate one method's drawbacks by another method's advantages.

NEW METHOD

The segmentation method developed by the authors is a combination of multimodal two-dimensional region growing and multimodal two-dimensional edge detection. Combining these techniques utilizes the advantages of any method to compensate for the drawbacks of the other. The combining technique aims at using a common relation between regions and edges in order to keep the method suitable for general multimodal segmentation tasks. It is a general segmentation method using neither imaging specific nor object specific knowledge.

MULTIMODAL REGION GROWING

The multimodal region growing method used, follows the principle of Nagoa/Matsuyama [5] for segmenting a multimodal signal. A first preprocessing step produces a smoothed version of the image by using an *edge preserving smoothing* method as described in [5]. Another step is the *determination of a threshold* (TH) used in the region-growing process to decide whether a neighboring pixel is accepted as a member of the region under examination. Finally, the image is segmented by a *region growing process*. The multimodal region growing process results in an image divided into several connected regions. Every region is uniquely characterized by a different label. The labels are given continuously with the region growing process, i.e. they have no reference to any feature of the region they belong to.

Threshold Determination

The idea of threshold determination is to find a fixed value TH of intensity difference that has the following features: intensity differences smaller than TH result from irrelevant signal deviations, whereas intensity differences larger than TH result from real inter-object transition (see [5]).

In this method the threshold is determined by a process developed by Nagao/Matsuyama [5]. The principle of this process is to detect the minimum valley in the histogram of the differential values calculated in the image. The result of this process is a threshold TH_m for every modality which fits the conditions above.

Region Growing Condition

The region growing process uses the different thresholds TH_m for each modality in the acceptance condition to decide whether a pixel neighboring the growing region can be accepted as new member of this region.

In the method developed by Nagao/Matsuyama [5] the use of intensity differences to make the decision has the advantage that regions with slightly changing intensity values (caused by either noise or the object) are segmented correctly. In general the used region growing process follows the steps described by Nagao/Matsuyama [5]. The main difference between the region growing of Nagao/-Matsuyama [5] and the region growing used in this method is the acceptance condition.

While in the region growing of Nagao/Matsuyama [5] the acceptance condition considers every modality separately and finally makes an acceptance decision by building the conjunction of all single decisions:

$$\bigwedge_{i=1}^{m} \left((s_i(x_s,y_s) - s_i(x_n,y_n))^2 < TH_i^2 \right) \tag{1}$$

the acceptance condition was modified to make a real parallel decision, regarding the distance between the vectors spanned by all modalities:

$$\sum_{i=1}^{m} (s_i(x_s,y_s) - s_i(x_n,y_n))^2 < \sum_{i=1}^{m} TH_i^2 \tag{2}$$

with m = number of used modalities, $s_i(x_s,y_s)$ = seed point's intensity in modality i, $s_i(x_n,y_n)$ = neighbor's intensity in modality i and TH_i = threshold of modality i.

Neighbors satisfying this condition are accepted as a member of the region under investigation.

EDGE DETECTION

The multimodal edge detection method developed, generalizes the edge detection operator presented by Canny [6] to the multimodal case. The principle of this operator is to identify the second derivation's zero-crossing pixels as edge pixels in the original image. A first preprocessing step produces a smoothed version of the image using a *gaussian smooth*. As a next step, the *second derivation* of the signal (either unimodal or multimodal) is computed. Finally, the *zero-crossing pixels* of the second derivation are marked as edge pixels of the image. The multimodal edge detection process results in a binary image, with all identified edge pixels marked uniquely by 1. To reduce the usually very high number of identified edge pixels, a *threshold* is passed as a postprocessing step, to mark only those edge pixels with intensity changes exceeding a fixed value TH.

Multimodal Second Derivation Method

Canny presented in [6] the development of a second derivation operator to detect edge pixels. He established that using a smoothed version of the image

$$S = G * I \tag{3}$$

with S = smoothed image, G = symmetric Gaussian and I = image,

the formula

$$\nabla S \cdot \nabla(\nabla S \cdot \nabla S) = 0$$

determines the edge pixels of an image.

In the multimodal case, Dreschler-Fischer [4] presented the computation of the first derivation as follows:

$$\nabla S = \begin{pmatrix} \dfrac{\lambda \cdot B}{\sqrt{B^2 + (\lambda - A)^2}} \\ \dfrac{\lambda \cdot (\lambda - A)}{\sqrt{B^2 + (\lambda - A)^2}} \end{pmatrix} \tag{5}$$

$$\lambda = \frac{A+C}{2} + \sqrt{\left(\frac{A-C}{2}\right)^2 + B^2},$$

$$A = \sum_{i=1}^{m} \left(\frac{\delta S_i}{\delta x}\right)^2, \quad B = \sum_{i=1}^{m} \frac{\delta S_i}{\delta x} \frac{\delta S_i}{\delta y}, \quad C = \sum_{i=1}^{m} \left(\frac{\delta S_i}{\delta y}\right)^2$$

with m = number of used modalities and S_i = intensity of smoothed image in modality i.

Using this first derivation of a multimodal signal in the edge detecting method developed by Canny [6], a multimodal edge detection method was developed.

COMBINATION

Region growing and edge detection result in two different segmented images. Theoretically, both representations correspond, i.e. a segmented region can be described as either an area (region growing) or a border (edge detection) enclosing the area. However, practically, the results of both segmentation methods differ widely. The differences between the results are caused by segmentation faults and uncertainties in determining the thresholds. To compensate for these errors, the two images are combined to form a resulting image.

Fig. 1 T1 weighted MRI

Fig. 2 T2 weighted MR

In detail, the combination method merges two neighboring regions of the region growing result, if their joint border has not been recognized characteristically by the edge detection method.

The characteristics of the combination method are evident. Regions formed in the region growing process are only merged, never split. The edges identified in the edge detection process guide the merging process. Detecting too many edges leads to incomplete merged regions, while identifying too few edges results in merging regions belonging to different objects.

RESULTS AND DISCUSSION

To show the effects of the method introduced in this paper, we used the three weightings T1 relaxation (Fig. 1), T2 relaxation (Fig. 2) and proton density (Fig. 3) of a MR image as a three-modal signal. The MRI is a routinely taken transversal image of the head, i.e. no special imaging sequence was used to enhance the contrast.

Fig. 3 Protondensity

In Fig. 4, the result of the region growing process is shown. It is easy to see that the segmented regions are generally smaller than the objects they belong to. By changing the threshold, the segmentation result of region growing also changes - a higher threshold results in larger regions, a smaller threshold results in smaller regions. The automatically determined threshold results in a segmentation that turns out to be satisfying for the later combination process.

Fig. 5 shows the thresholded edge detection result. Again the choice of the threshold has drastic effects. Using a threshold that is too large results in an image with only few unconnected edges. A threshold chosen too small however, leads to an image with too many edges. The automatic choice of an adequate threshold is actually still under investigation. An idea is to use the histogram of all edge strengths to choose the threshold according to the condition that only a percentage of the strongest edges appear in the thresholded version.

In Fig. 6 the result of combining the basic methods is shown. The regulator of this process is the choice of a threshold that determines whether a border is "characteristical" enough to prevent two regions from merging. The value of the chosen threshold determines the degree of correspondence between the regions' border and the identified edge pixels.

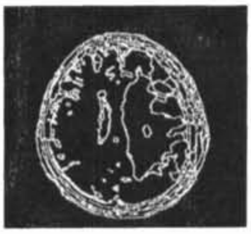

Fig. 4 Region growing

A threshold chosen too high has the effect that only regions separated by a very clear edge in the edge detection's result are accepted as separate regions. That is, many regions belonging to different objects are merged, because the edges, in edge detected results, show a lack of connectivity. Choosing the threshold too low has the opposite effect, i.e. nearly all neighboring regions remain separated, although they belong to the same object.

Fig. 5 Edge detection

CONCLUSION

The segmentation method introduced in this paper results in a satisfactory image segmentation. The drawbacks of the basic segmentation methods, such as incomplete region detection in the case of region growing and lack of connectivity in the case of edge detection, can be compensated. Moreover, the combination method uses the universally valid complementary feature of the basic segmentation methods.

A segmented region can always be represented by either the area or the border of the region. Using this feature, the regions' borders of the areas detected by region growing algorithms and the edges identified by edge detection algorithms must correspond to some extent. This feature is universally valid for both basic segmentation methods. The combination therefore does not use object-specific or imaging- specific knowledge. The edge detection and the region growing both use a real multimodal principle. They use all modalities in parallel and have no limitations concerning the number of modalities.

Fig. 6 Combination

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