Region Growing: A New Approach

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Abstract

Accurate segmentation of images is one of the most important objectives in image analysis. The two conventional methods of image segmentation, region based segmentation and boundary finding, often suffer from a variety of limitations. Many methods have been proposed to overcome the limitations but the solutions tend to be problem specific. Here we present a new region growing method with the capability of finding the boundary of a relatively bright/dark region in a textured background. The method relies on a measure of contrast of the region which represents the variation of the region gray level as a function of its evolving boundary during the growing process. It helps to identify the best external boundary of the region. The application of a reverse test using a gradient measure then yields the highest gradient boundary for the region being grown. A number of experiments have been performed both on synthetic and real images to evaluate the new approach. The proposed scheme can be categorized as a region based segmentation method which uses gradient information to specify the boundary of a region. The main strength of the method is its ability to segment out from a textured background a bright/dark region with fuzzy boundaries as well as its simplicity and immunity to intensity changes.

1 Introduction

The segmentation of regions is an important first step for a variety of image analysis and visualization tasks. There is a wide variety of image segmentation techniques in the literature, some considered general purpose and some designed for a specific class of images. Segmentation techniques for monochromatic images can be categorized into two different approaches [2]. One is region based, which relies on the homogeneity of spatially localized features, whereas the other is based on boundary finding, using discontinuity measures. The two methods exploit two different definitions of a region which should ideally yield identical results. Homogeneity is the characteristic of a region and nonhomogeniety or discontinuity is the characteristic of the boundary of a region.

If a region is homogeneous with relatively high contrast, the detection of the region boundary becomes a simple task using any of the two conventional methods. But the problem arises when the high frequency information characteristic of a boundary is missing or is unreliable, with the consequence that the region is not well defined and an uncertain boundary exists. In such situations, boundary finding methods fail, especially in the presence of noise. Although, region based techniques are less affected by noise, they commonly suffer from the problem of over-growing into neighbouring regions or background specially when these are textured. Furthermore, since conventional boundary finding methods rely on changes in gray level, rather than on their actual values, they are less sensitive to changes in image contrast than the region based segmentation methods. Also boundary finding methods in general do a better job of boundary localization [2, 5].

Many studies investigating the properties of the two approaches for image segmentation have been reported [1, 3, 4, 6, 7, 12, 14, 15]. As the two methods use complementary information, they involve conflicting objectives and therefore their direct comparison is not straightforward. Most of the reported techniques rely on a region growing method and use some discontinuity measures as a stopping criterion to avoid the problem of merging two neighbouring regions or over-growing into the background. The quality of these techniques is highly dependent on the edge operator used [7, 8] as a measure of discontinuity. Other approaches use the slope of a local planar approximation of the image surface. The idea is to test the hypothesis that the slope of the plane has changed which would be characteristic of the boundary between two neighbouring regions. Fitting a plane to image intensities over a set of pixels requires information about the region which is not always accessible in real situations. Consequently, the methods often exhibit poor performance in defining the boundary. A good survey of different approaches to region growing, their capabilities and limitations is presented by Haralick [8].

We present here a new idea for region growing by pixel aggregation which uses new similarity and discontinuity measures. A unique feature of the proposed approach is that in each step at most one candidate pixel exhibits the required properties to join the region. This makes the direction of the growing process more predictable which is the most important characteristic of our method. The novel growing procedure offers an ideal framework in which any suitable measurement can be applied to define a required characteristic of the segmented region. We use "contrast" and "gradient" as sequential discontinuity measurements derived by the region growing process whose locally highest values identify the external boundary and the highest gradient boundary of each region, respectively. The method first finds the location of the highest contrast boundary which is the external boundary of a region. Then a reverse test using the "gradient" measure is applied to produce the highest gradient region. Since the two measurements are based on gray level difference, the method is not sensitive to intensity changes. This contrasts with the existing region growing techniques [8, 10, 14]. The method is very effective in defining the boundary of a region with fuzzy edges located in a textured background.

Like the existing procedures, the proposed method in this paper has not a universal capability, but, on the other hand, it does appear to have a fairly wide application potential, especially in medical image analysis, where the areas corresponding to a tissue of interest appear as bright/dark objects relative to the surrounding tissues and both the foreground and background tissues exhibit textural variations.

The concept of the method is presented in the next two sections. The similarity measure used by the method is presented in Section 2. Section 3 introduces the two different discontinuity measures, "contrast" and "gradient" and considers their behaviour on a Gaussian shape image. Section 4 considers the behaviour of the measurements on noisy or textured images and illustrates that our method is independent of the choice of a starting point. Section 5 demonstrates the capability of our method on a set of real images.

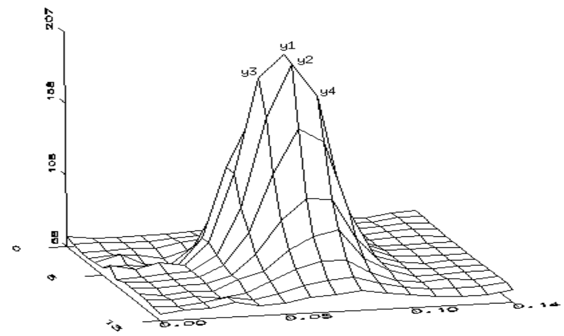
2 Growing Process

The concept of our method, like other region growing methods by pixel aggregation, is to start with a point that meets a detection criterion and to grow the point in all directions to extend the region. The choice of the starting point will be discussed later.

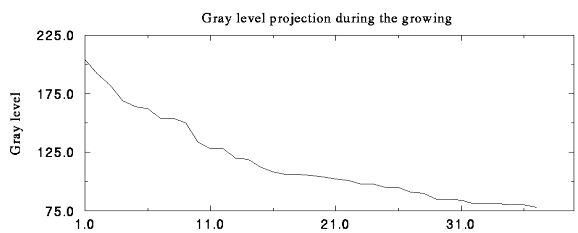
Let us assume that the process starts from an arbitrary pixel. The pixel is labeled as a region which grows based on the similarity measure used. In our approach, a boundary pixel is joined to the current region provided it has the highest gray level among the neighbours of the region. This induces a directional growing such that the pixels of high gray level will be absorbed first. Then the pixels with monotonically lower and lower gray levels will join the region. When several pixels with the same gray level jointly become the candidates to join the region, the first-come first-served strategy is used to select one of them. This makes the region more compact, particularly in situations where the gray levels of the background or the region pixels are very homogeneous.

We generate gray level, gradient and contrast mappings during the growing process. The mappings are very similar to the mapping used in the mode separating (MODESP) procedure proposed by Kittler [11] for cluster analysis. MODESP method is a clustering procedure based on the mapping of data points from an N-dimensional feature space onto a sequence in which each cluster in the space appears as a mode in the mapping. Separating surfaces between the modes in the N-dimensional space are derived from the points associated with distinct modes in the one-dimensional mapping function. MODESP has never been used for the segmentation of spatially indexed data and the only similarity of our method with MODESP is the mapping used to monitor the growing process.

Consider Figure 1(a) which shows a small subimage with a single bright blob. To present the concept of the growing process on this data, let us assume that its starting point y_1 is the pixel with the maximum gray level of the subimage and defines a nucleus of the blob region. The sequence of pixels joining the region is y_2, y_3, y_4 and so on. The graph of gray levels associated with the sequence of candidate pixels for the region generated by the growing process is shown in Figure 1(b). The mapping shows that the



(a)



(b)

Figure 1: (a) Topographical surface of a microcalcification in a homogeneous background and (b) Mapping of gray levels of the region during the growing process.

gray levels decreases from the highest value in the region to the background.

A similar mapping can be obtained for any measurement defined on the growing region. The mapping function defined on the sequence of pixels joining the growing region characterizes the variation of each measurement in the spatial domain. Different criteria can be used to stop the growing process and to apply a reverse check on the relevant measurements to detect the region boundary. We use the maximum possible size N of a region to stop the process. However, other criteria, such as minimum size of neighbouring region or maximum difference between the current candidate and the maximum gray level inside the region can also be applied to stop the growing process. We used the latter criterion for the segmentation of calcifications in mammographic images [9]. The size of a region is simply measured by counting the number of pixels in the mapping. This can be formalized by the following rule: consider the current pixel generated by the similarity measure as a region candidate provided its index number i satisfies:

$$i < N \tag{1}$$

where N is the maximum expected size (number of pixels) of the region of interest.

In the next section we consider the use of two measurements as characteristic features of a region to find its best boundary among all the candidate boundaries considered during the growing process. The applied measurements are not sensitive to the selected threshold N. Hence, the check against the threshold is introduced only to avoid unnecessary growing into a neighbouring region or homogeneous background.

3 Discontinuity Measures

For segmentation purposes we define region of interest as a gray level blob, exhibiting a high contrast relative to its background. The best boundary for a region is a connected boundary of the highest gradient. Thus we search for the highest gradient boundary where the contrast is also high. Two different measurements called "contrast" and "gradient" are used as criteria to characterize the properties of the current region and its boundary during the growing process.

In the description of the proposed algorithm, four different boundaries are mentioned which are defined as follows: *Current boundary* is the set of pixels adjacent to the current region during the growing process. *Internal boundary* is defined as the boundary produced by the set of connected outermost pixels of current region. The current region and the two boundaries are dynamically changing during the growing process. *Gradient boundary* is the boundary of the final output region produced by the region growing method. *External boundary* is the outermost boundary at which the growing process stops.

The contrast measure $c(i)$ for a region containing i pixels is defined as the difference between the average gray level of the region and the average of its *current boundary*. This is expressed by:

$$c(i) = \frac{1}{i}\sum_{t=1}^{i} y_t - \frac{1}{k-i}\sum_{t=i+1}^{k} y_t \qquad (2)$$

where $y_1, y_2, ..., y_i$ is the sequence of pixels forming the current region and $y_{i+1}, y_{i+2}, ..., y_k$ is the set of its *current boundary* pixels. This measurement captures the local contrast of the region based on all the gray levels inside the region and its boundary.

Let us recall that the algorithm always searches for the highest gray level in the boundary. The pixel with the highest gray level is then added to the growing region which systematically replaces the region boundary with pixels of lower intensity values. The region growing will produce increasing contrast measure values as long as the growing region continues subsuming high intensity pixels of the bright blob. Once it starts growing into the background, the rate of gray level decrease for the boundary will be less than that for its region, and consequently the contrast will commence decreasing. Hence, the maximum of this measurement during the growing process corresponds to the point when the process starts to grow into the background. The result of the segmentation based on the maximum contrast is the *external boundary* of the region.

We approximate the gradient of a region using the difference between gray level average of the current *internal boundary* and the average of the *current boundary*. The mapping of this measurement during the growing process shows the pixel by pixel variation of the boundary gradient of the evolving region. If the region is smooth the gradient is a reliable measurement to define the point where the growing process should be stopped.

One could say that contrast is equal to the gradient measure biased by the gray level average of its internal pixels. This becomes apparent by rearranging Equation (2) as:

$$c(i) = g(i) + \frac{1}{l}\sum_{t=1}^{l} y_t \qquad (3)$$

where $g(i)$ is the mean of the *internal-current boundary* pixel pair gradients and $y_1, y_2, ..., y_l$ are the gray levels of the pixels inside the region excluding the *internal boundary* pixels.

The measurement is a very sensitive approximation of the gradient, because only the difference between two neighbouring boundaries is used to define it. If the region is very noisy or textured the gradient could exhibit false peaks. It is particularly affected by noise or texture when the size of the region is very small and therefore the number of pixels in the boundary is low. Hence, we use the contrast measurement to find the *external boundary* and the last local maximum of the gradient to determine the highest gradient region to terminate the growing process.

However, every local peak of the gradient can be used to segment out a distinct region which meaningfully corresponds to the information conveyed by the internal parts of the region. Furthermore, for a relatively homogeneous region, the global maximum of the gradient is uniquely defined so that without using the contrast measure, the region can be segmented.

Commonly the *external boundary* and the actual boundary are not very far away from each other. The difference is especially low when a bright region has a vary sharp edge and it is very high for fuzzy edge regions. We used a Gaussian shape image which has a very extensive *external boundary* as compared to its *gradient boundary*, to show the effect of the two measurements. However in applications where strong edges exist the difference is not significant.

Theoretically the highest gradient of a Gaussian shape is located one standard deviation from the mean. Equation (4) defines a two dimensional Gaussian shape:

$$g(x,y) = M \exp^{-\frac{1}{2}[\frac{(x-m_x)^2}{\sigma_x^2}+\frac{(y-m_y)^2}{\sigma_y^2}]} \tag{4}$$

where m_x,m_y specify the x, y location of the centre of the Gaussian blob and σ_x, σ_y specify the spread of the gray level function. Constant M is used to normalize the output to the maximum gray level range. However the effect of quantization is that only an approximation of the Gaussian image is obtained. For the sake of simplicity identical spread parameters are used, $\sigma_x = \sigma_y$. Hence in polar coordinates the shape can be represented by Equation (5).

$$g(r) = M \exp^{-\frac{1}{2}[\frac{(r-r_0)}{\sigma}]^2} \tag{5}$$

where $r_0 = \sqrt{(m_x^2 + m_y^2)}$, $r = \sqrt{(x^2+y^2)}$ and $\sigma = \sigma_x = \sigma_y$. Maximum gradient for a Gaussian shape is a circle with radius σ, centred on r_0.

A Gaussian shape image with a variance of 25 pixels, $\sigma = 25$, Figure 2(a), is used to demonstrate the relationship of the two boundaries. Let the growing process starts at the highest gray level in the region, 255. The gray level, contrast and gradient mappings during the growing process are shown in Figure 2(e). The gray level mapping shows that the gray levels of the sequence of pixels joining the region from the starting point monotonically decrease to zero corresponding to the background. As a result of the directional growing process, the shape of the region for the Gaussian shape is circular even when the process continues to absorb the zero gray levels in the background. This is apparent by considering Figure 2(d) and noting that the gray level of all the candidate pixels beyond pixel number 21772 is zero. As one might expect, contrast commences from a minimum and smoothly increases to a maximum at point 6685 and then decreases. The maximum contrast point corresponds to a circular region with the radius of 46.13 pixels which is approximately 1.85σ in the Gaussian image. The result of segmentation using this point is shown in Figure 2(c). As can be seen, the segmented region based on the contrast matches with the *external boundary* of the Gaussian shape at 1.85σ.

The mapping of gradient starts from low values increasing to a maximum at pixel number 2000 and then decreasing again to zero. The maximum gradient point corresponds to a circular region with the radius of 25.23 pixels which is approximately 1.009σ in the Gaussian image. This result agrees well with the maximum gradient region of an analog Gaussian shape. The slight difference is caused by the effect of quantization and the fact that our method uses the difference between the mean of two completely closed contour boundaries to calculate the contrast, so the effect of diagonal pixels the distance of which is $\sqrt{2}$ is the same as that of pixels located in the neighbouring position with distance 1. The result of segmentation using this criterion is shown in figure 2(b).

We advocate the use of gradient as the final result of segmentation and apply the contrast measure to find the *external boundary* of the region of interest. Note that for sharp edge regions, the results of segmentation using the contrast and gradient measures are similar. In Section 4, we consider the effect of noise and texture on the results produced by applying the two complementary measurements.

4 Textured Image

In this section, the aim is to consider the performance of the procedure in situations where a noisy textured region is located in a textured background. A part of a road centre line shown in figure 3(a) is used as the input. As can be seen, the dynamic gray level range of the region is quite high.

A point located at $(60, 108)$ with the gray level of 175 is used as a starting point to segment the region. The gray level mapping is shown in figure 3(e)-top. Note that, the mapping exhibits fluctuations during the growing process two of which are particularly noticeable at pixel numbers $1100 - 1400$ and $7100 - 7700$. The artifact of each peak is a distinct valley in the contrast and gradient mappings which occur in our example at pixel numbers 1300 and 7465, respectively, see Figure 3(e)-bottom. These two measures decrease inside the area of locally high gray level and increase after it has been covered (based on the gray level changes in the region and its boundary). The maximum contrast measure defines the *external boundary* of the region containing 18240 pixels, see figure 3(b). Region's texture produces more fluctuations in the gradient measure than in the contrast measure. The gradient mapping shows that the difference between the global maxima which specifies the boundary of the region and local maxima which are created by texture and noise is not high enough to rely fully only on the gradient measure. In contrast, the global peak of the contrast measure is not affected by the texture in the region. Hence, as mentioned before, a reliable maximum gradient point is the last gradient peak which is located before the global peak of the contrast measure. This is located at pixel number 12031, see figure 3(e)-bottom. The segmented region based on this point is shown in figure 3(c). This region is in a full agreement with the result of human visual segmentation.

If the growing process terminates at any local gradient peak, a region which is particularly acceptable by human visual system will be segmented. Figure 3(d) shows a region segmented out based on the first local maximum of the gradient of value 37.44 containing 511 pixels. The region can be characterized as a subregion of region shown in Figure 3(c).

Gray level, contrast and gradient mappings obtained from any starting point inside the region will eventually start appending the same pixels once all the brighter pixels are absorbed by the growing process. This happens as a result of the strategy of always appending the pixels of the largest gray level in the boundary to the current region. Hence, the segmentation results are the same regardless of which starting point is used inside the region. Figure 4 shows the mapping produced during the growing process on the road centre line image using two different starting points located at $(362, 90)$ and $(60, 108)$ with the gray levels of 171 and 175, respectively. The two starting points are marked on the image, Figure 3(a). The effect of non-homogeneity of the region is noticeable in the mappings. Note that, the mappings for different starting points are different while the growing process absorbs brighter pixels inside the region. But, after these pixels have been assigned, the mean of the gray levels inside the current region starts decreasing with a lower rate than that of the boundary gray levels. Hence, as expected, both the sequence and the corresponding measurements will converge to the same point and the mapping will exhibit the same behaviour thereafter. For the road centre line, the mapping functions become identical after pixel number 1000, Figure 4. The highest contrast for the region is always located at pixel number 18240 with the gray level of 77. The highest gradient region containing 12031 pixels with the minimum gray level of 112 is specified by the gradient measure maximum of 41.72.

The use of the two contrast measures produces a unique region independent of the starting point. This will be further clarified in the next section when we consider the region growing procedure on another real image.

5 Experiments on Real Images

This section shows the performance of our method on medical images where each region can be categorized as a bright blob separated from its neighbour by a low gray level boundary. First we show that our method is not sensitive to threshold N of rule (1). We then give an interpretation of the gray level mapping when N is very high in comparison to the size of the region of interest. The segmentation result obtained for Magnetic Resonance Imaging (MRI) and Computer Tomography (CT) Scan images of a head are presented and discussed. For each region we specify an arbitrary internal starting point.

Figure 5 shows an MRI of head. The aim is to outline the corpus callosum, brain stem and cerebellum. As we can see edges are very fuzzy at the boundaries of these regions. Consequently, neither boundary finding methods nor region based methods can reliably determine the boundaries.

We first start with the segmentation of brain stem. A very high threshold, $N = 20000$, in comparison to the size of the region is used to provide an opportunity to consider the behaviour of the different discontinuity measurements in relation to the neighbouring regions. The gray level, contrast and gradient mappings obtained during the growing process are shown in Figure 6. As can be seen, the highest contrast measure determines the location of the *external boundary* and the last gradient measure maximum before the maximum contrast point specifies the best boundary for the region. The region segmented out using the method is shown in figure 5(b).

The gray level mapping shows local valleys which are induced by the gray levels at the boundary of two neighbouring regions. Each visible valley in the gray level mapping is the result of the switch between the absorption of decreasing gray levels of the pixels in the boundary of the region being grown and the absorption of pixels of increasing gray levels leading to the nearest local peak of the neighbouring region. As mentioned before, the gradient of the gray level mapping on the left side of the valley is related to the rate of gray level decrease in the boundary of the region and the size of its *current boundary*. The size of the region affects the rate, because the number of pixels in the boundary is a function of it. Hence, the bigger the size, the lower the gradient. The gradient on the right side of the valley is related to the rate of gray level increase along the pathway forged by the growing process forwards a local hill of a neighbouring region. The latter is very sharp because the growing process takes a single pixel wide path to the top of the hill and then continues to cover its surface. Thus, the difference between a valley minimum and the following peak in the gray level mapping shows the difference between the maximum gray level of the hill and the maximum gray level at which the two neighbouring regions meet. If the difference is quite high and the number of pixels in the new region is big enough, it is a strong clue for the existence of a new significant region. Otherwise the new hill is a local peak or noise in the region being grown.

The effect of these variations is even more clear is the contrast mapping. The growing into a neighbouring region causes a more rapid increase in the mean of the gray levels of the pixels in the region's boundary than that of the region itself. So, a local peak in the grey level mapping causes a local valley in the contrast mapping and consequently a local peak. The local peak in the contrast measure corresponds to the *external boundary* of its corresponding region. Its related gradient peak will then specify the best boundary to the region. The contrast mapping in Figure 6 shows the sequence of such peaks and valleys.

Figure 5(c) shows the boundary corresponding to the last local gradient maximum before the second distinct contrast peak which segments a region containing 5677 pixels. The two gradient maxima located before the second and third contrast peaks are located at point 11904 and 14448 (see Figure 6-bottom). The corresponding boundaries are shown in Figure 5(d) and (e), respectively. As mentioned before, each boundary has a meaningful information regarding different possible regions produced by the process which can be of interest in target detection.

Segmentation results of different parts of the MRI image are shown in Figure 7(a). For each segmented region in the image a starting point is selected. We tested many different starting points in different positions of each region but the segmentation results were similar. The independence of the segmentation results from the choice of a starting point is an important characteristic of our approach. Figure 7(b) shows the result of segmentation based on the contrast mapping. As can be seen, the *external boundary* of each region is well characterized. Figure 7(c) and (d) show the distinct regions produced by applying each of the two measurements separately.

All the considerations which are presented here are applicable to segmenting out a dark region if the whole process is reversed. In such a case, a region with the minimum gradient is the result of the segmentation method. We show this by applying the method to segment out the cavities in a CT-Scan image. Figure 8(a) shows a CT-Scan image. The segmentation results of our method using three arbitrary starting points, one in each cavity, are shown in Figure 8(b). The results are again in full agreement with the results of human visual segmentation.

6 Summary and Conclusions

We presented here a new idea for region growing by pixel aggregation, using novel similarity and discontinuity measures. A unique feature of the proposed approach is that in each step at most one candidate pixel will exhibit the required properties to join the region. This makes the direction of the growing process more predictable. Two new discontinuity measures named "contrast" and "gradient" which use gray level difference information to produce the final segmentation result are proposed and their properties analyzed.

Since the growing process is directional, i.e. pixels join the grown region according to a ranking list and moreover the discontinuity measurements are tested pixel by pixel, the method does not necessarily include all the pixels with the same gray level to the region. This contrasts with thresholding methods where all the pixels exceeding a certain threshold are included in the segmented region [13]. From an extensive experimental testing, our method appears to be more reliable and consistent than the thresholding methods.

The result of our method does not be appear to be effected by the presence of a reasonable amount of noise. Hence, it can be used for segmenting raw images without any need to apply a smoothing filter or perform preprocessing to improve the signal to noise ratio. This property of the proposed method is in sharp contrast to standard segmentation techniques which are commonly disturbed by noise.

As "contrast" and "gradient", which determine the segmentation result, are differential measurements, the method is unaffected by intensity changes which is the characteristic of conventional region growing techniques.

The most significant features of the method are:

- Independence from the starting point location.
- Insensitivity to a reasonable amount of noise, and to region and/or background being textured.
- Since the method uses two discontinuity measurements which delineate a region, it does not need any statistical information concerning the region.

We should mention that the method is applicable for the segmentation of bright/dark regions in a dark/bright background without using any priori knowledge about the region.

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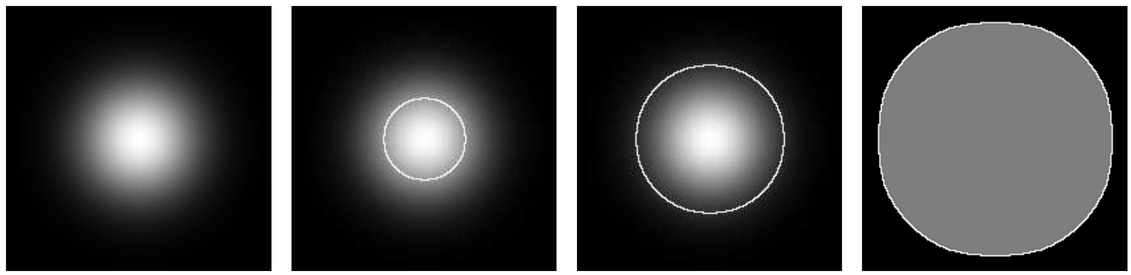
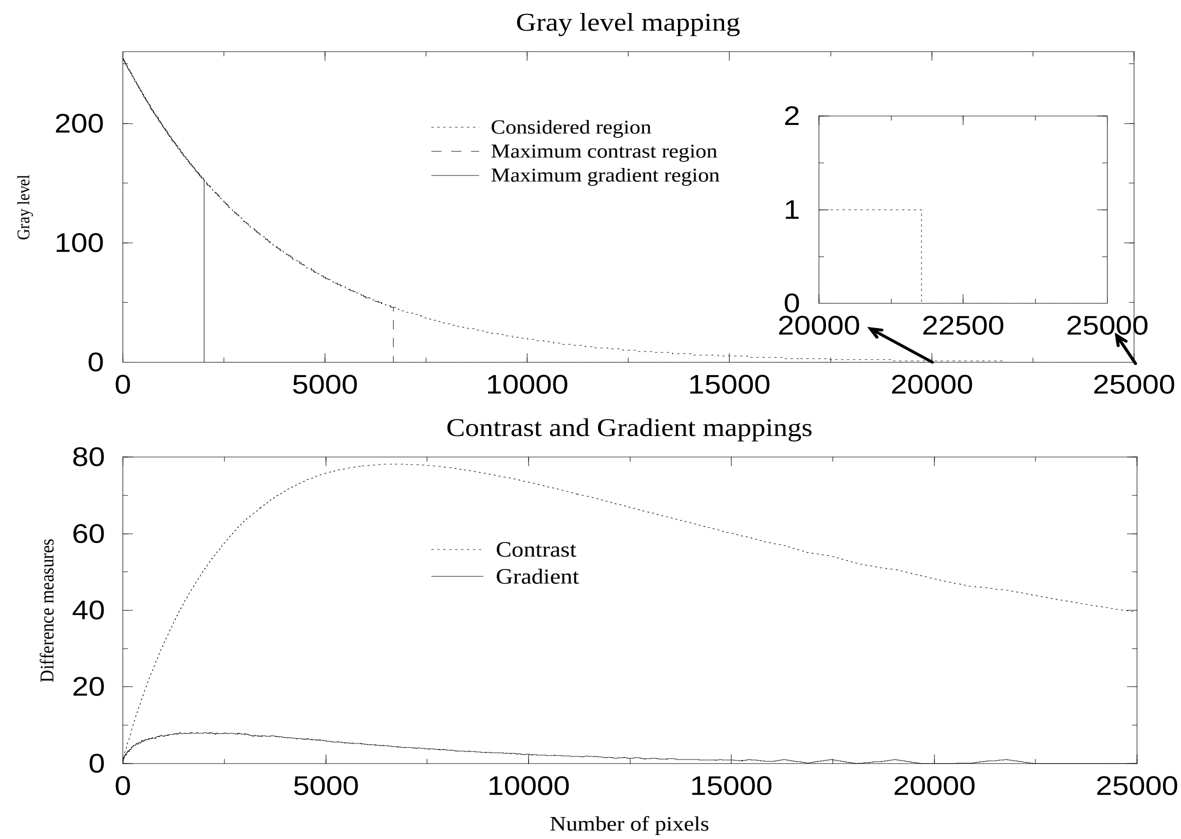
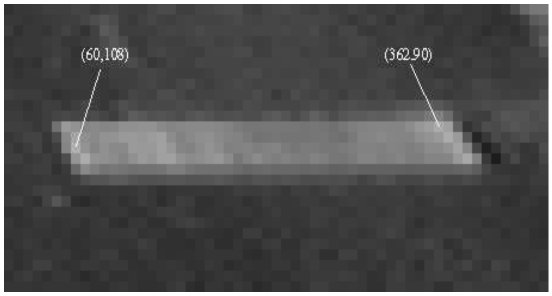


(a) (b) (c) (d)

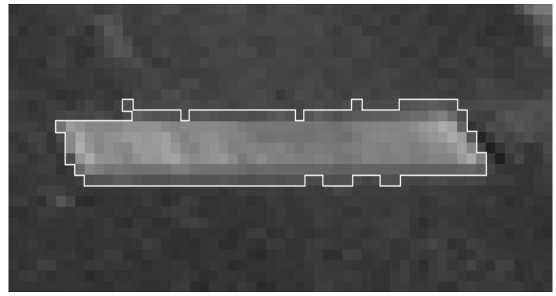


(e)

Figure 2: The segmentation results of a Gaussian shape image with $\sigma = 25$. The region size criterion used is $N = 25000$. (a) Original image. (b) Segmentation result based on the gradient measure. (c) *External boundary* segmented by the maximum contrast point. (d) The boundary produced by the region containing 25000 pixels. (e) Gray level, gradient and contrast mappings obtained during the growing process.



(a)



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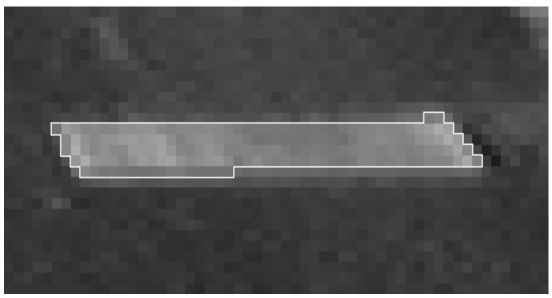

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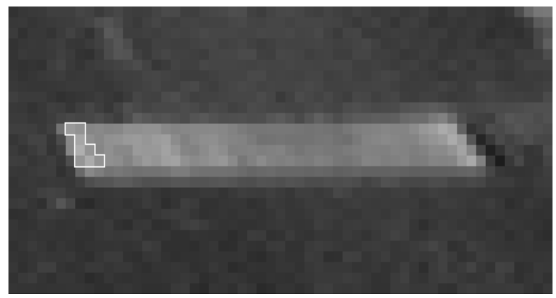
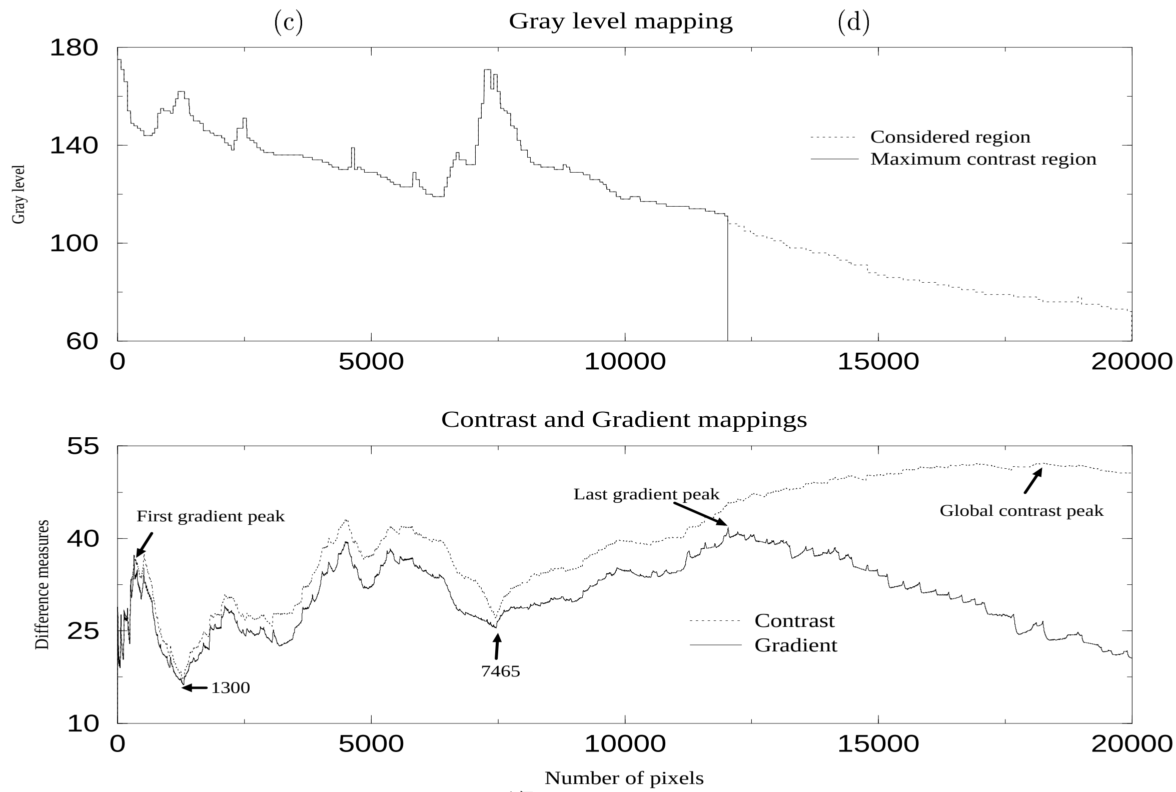


(d)



(e)

Figure 3: The segmentation results of a part of road centre line. (a) Input image. (b), (c) Boundary produced by applying contrast and gradient measures, respectively. (d) Segmentation results based on the first local gradient maximum at pixel number 511. (e) Gray level, contrast and gradient mappings during the growing process.

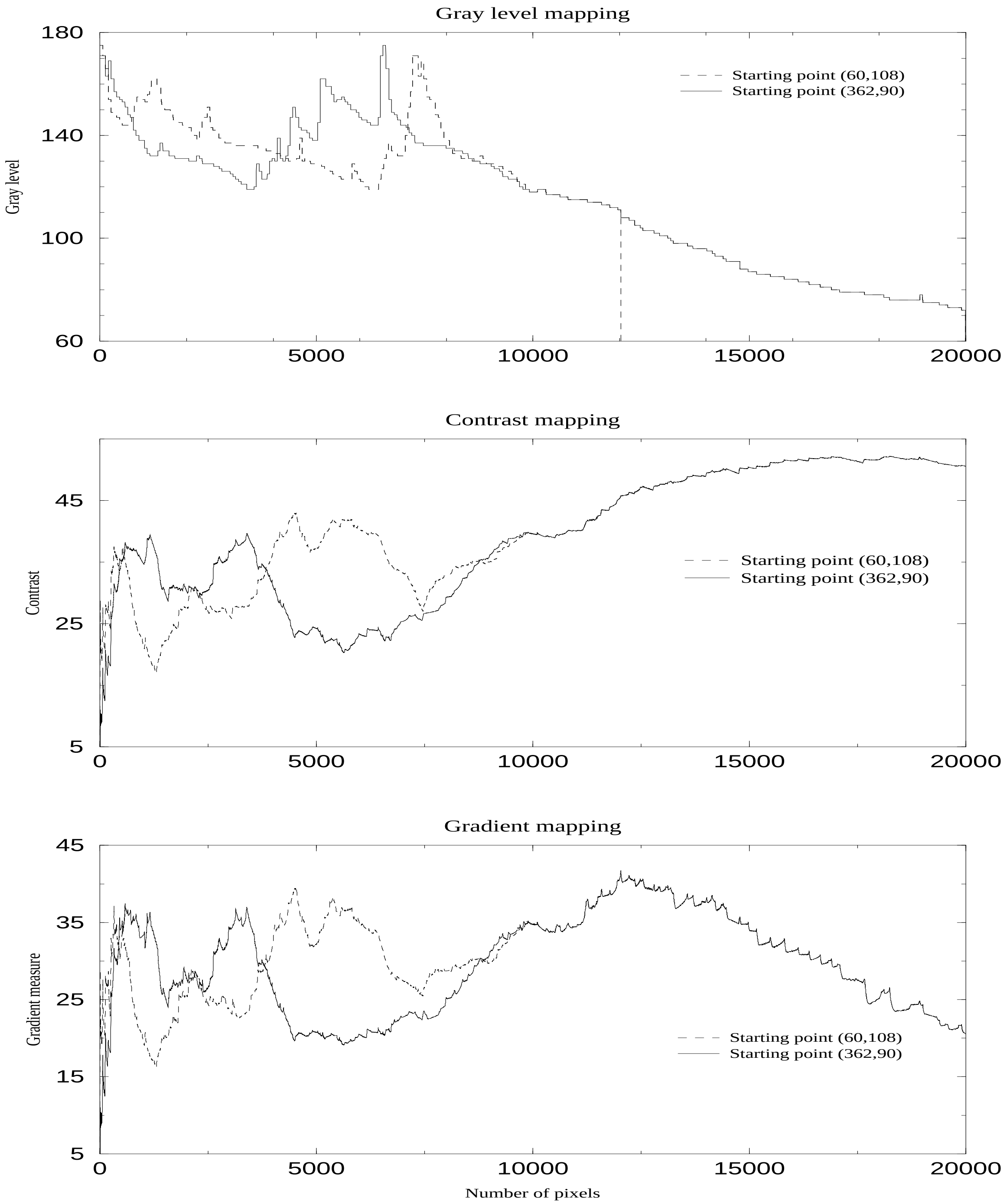
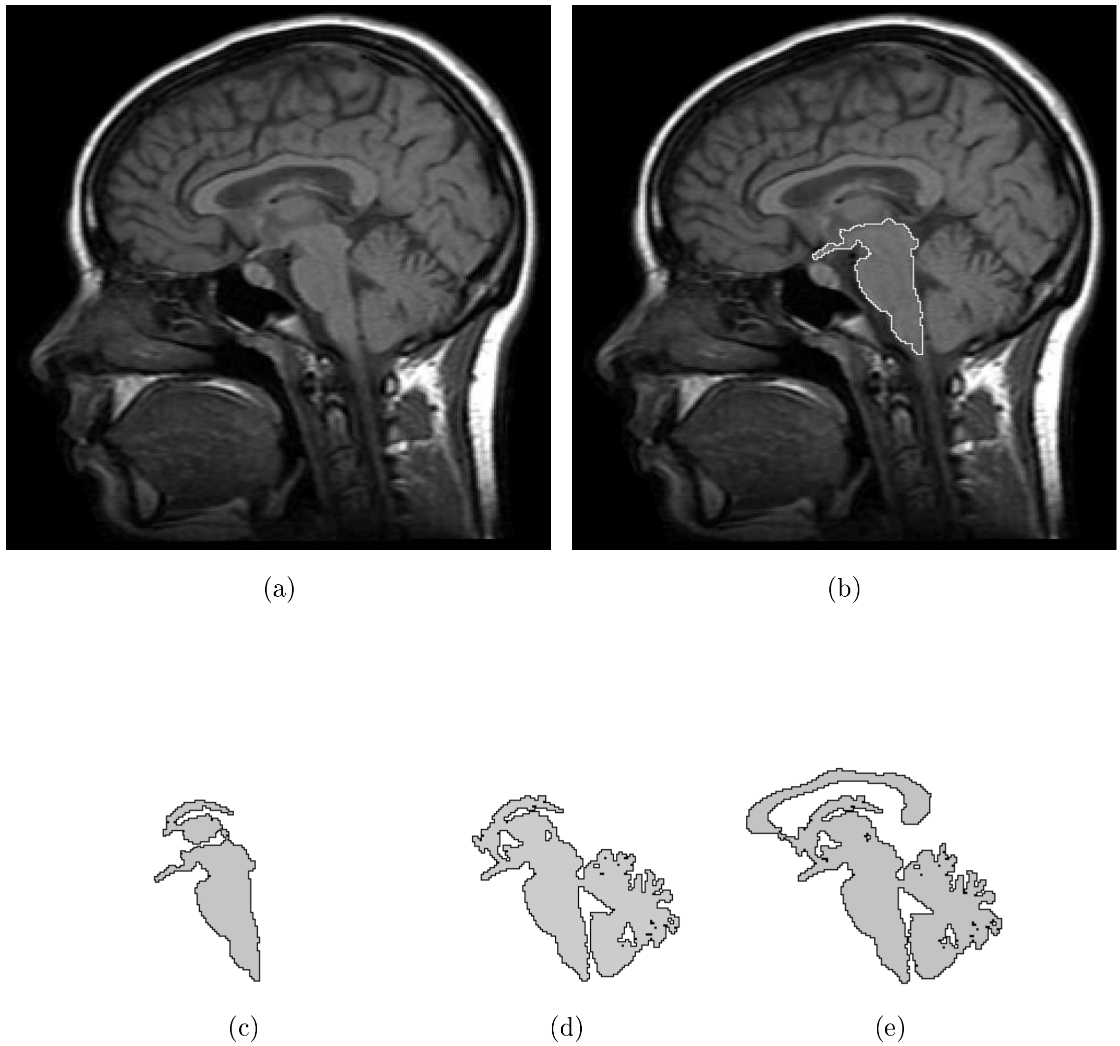
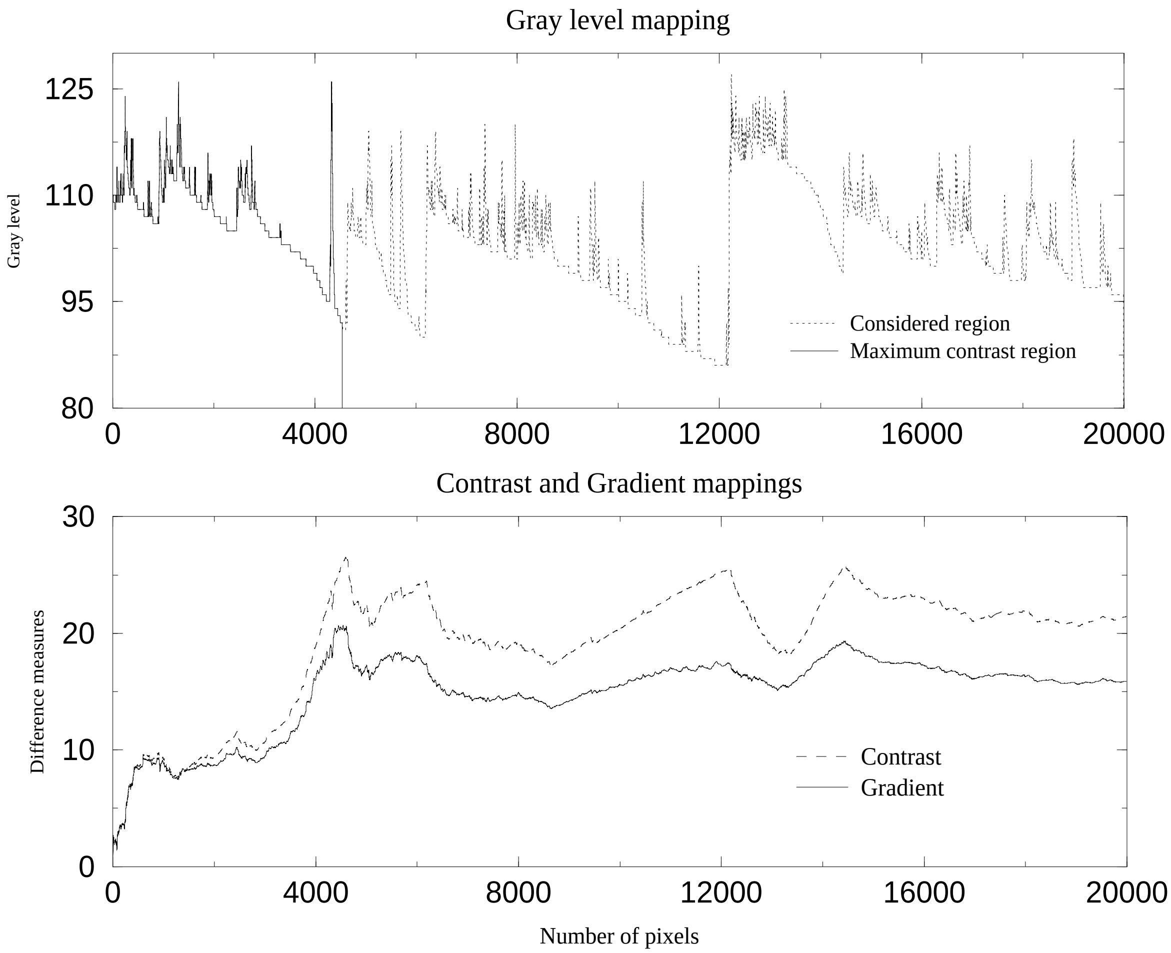


Figure 4: Mapping of gray level, contrast and gradient measures during the growing process for two starting points at $(362, 90)$ and $(60, 108)$.



(a) (b) (c) (d) (e)

Figure 5: (a) Original MRI image. (b) Segmentation result of brain stem. (c), (d) and (e) Segmentation results based on different locally highest gradient regions at pixel numbers 5677, 11904 and 14448, respectively.



(a)

Figure 6: The mappings for brain stem during the growing process starting at pixel $(304, 165)$, $N = 20000$.

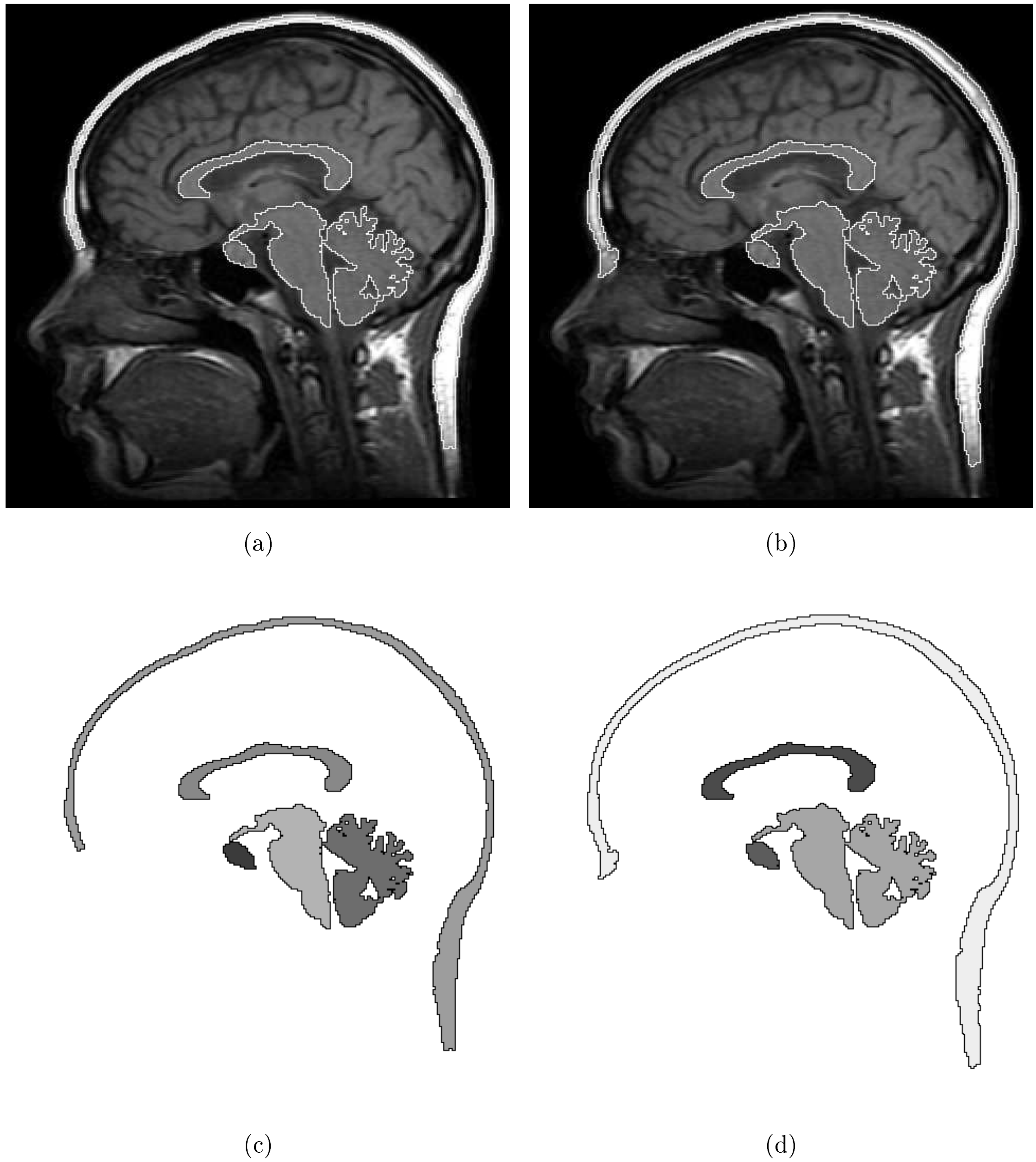
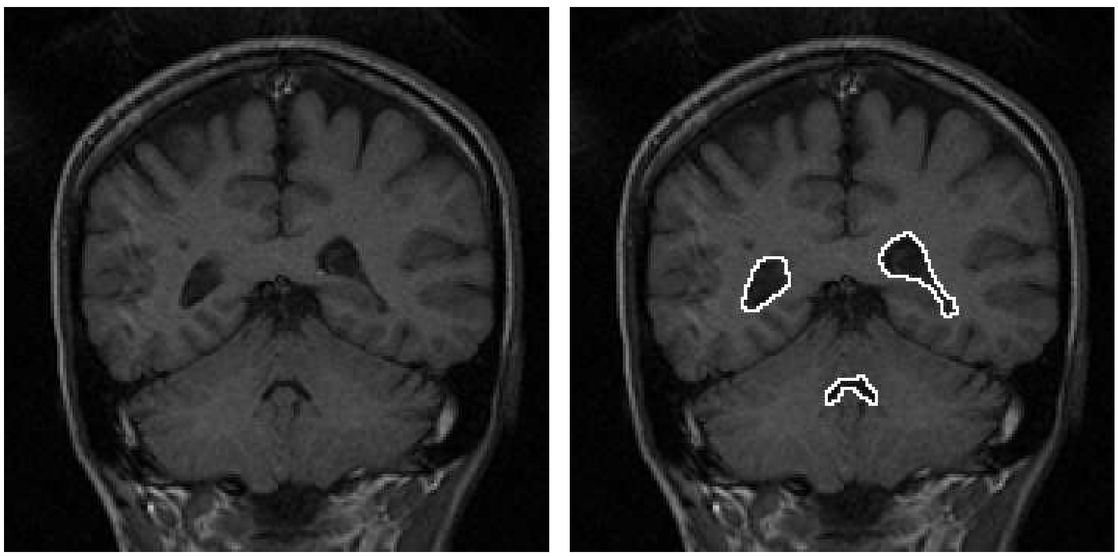


Figure 7: (a) segmentation results based on the highest contrast measurement. (b) The *external boundary* of each region specified by the contrast measurement. (c) and (d) Labeled regions based on the two measurements.



(a) (b)

Figure 8: The segmentation results of a part of CT-Scan Image.