

An Algorithm for Segmentation of Blood Vessels in Images

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Introduction

In medical image applications, such as radiological diagnostic systems, segmentation algorithms are of crucial importance. Despite the abundance of various techniques and algorithms, much research effort is still devoted to creating faster, more accurate, and more autonomous algorithms.

Segmentation is a process of partitioning an image into separate regions until the ones of interest are singled out. The mechanism of this process is critical as segmentation constitutes the front end of the image processing chain leading to such high-level capabilities as automated scene analysis and object recognition [1, 2, 3].

Regions can be found indirectly by finding the boundaries between them, or directly by *thresholding* the image with reference to the distribution histogram of the gray levels (see, e.g., [4] for a review). In this paper, we shall focus on the latter approach, with similarity of gray levels used as a criterion for splitting an image into regions.

One of the methods frequently employed is *region growing*. Starting with a few so-called seeds, regions are formed by merging the seeds with the pixels in their neighborhood having similar gray levels.

Proposed Algorithm

Fig. 1 illustrates a rather straightforward case where the blood vessels can be clearly identified on the original MRI image. In the figure, the profile of the gray-level values is shown superimposed on the image. The white horizontal line indicates the location where the profile was derived (close to 500). The x axis on the plot corresponds to the abscissa of the image, and y axis represents the gray-level values.

Meanwhile, Fig. 2 presents a more complicated case where the blood vessels are hidden in the background. As shown by the noisy profile of the gray-level values, automatic detection of the blood vessels would be impossible, if only global thresholding were used. To tackle this problem, additional processing is required in the vicinity of the blood vessels. This involves using a local

threshold that narrows down the scope to the relevant region in the image.

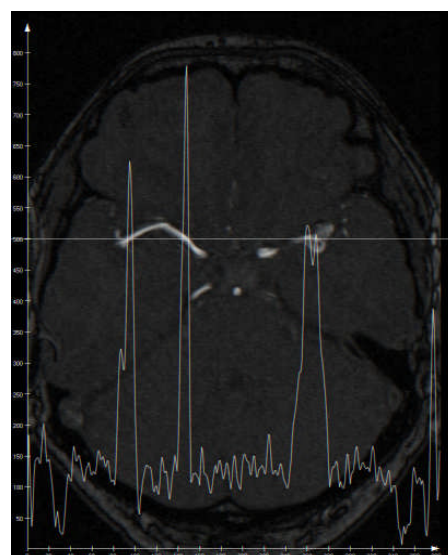


Fig. 1. Simple case of detecting blood vessels

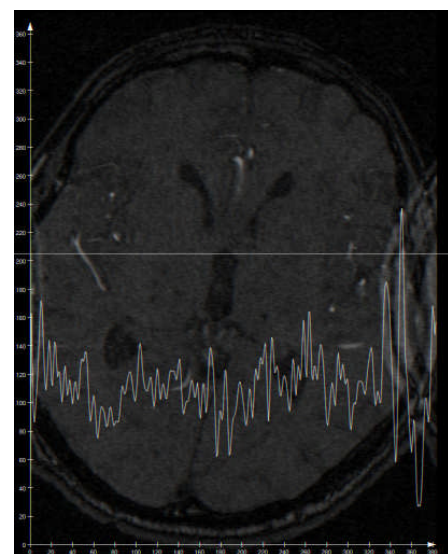


Fig. 2. Complicated case of detecting blood vessels

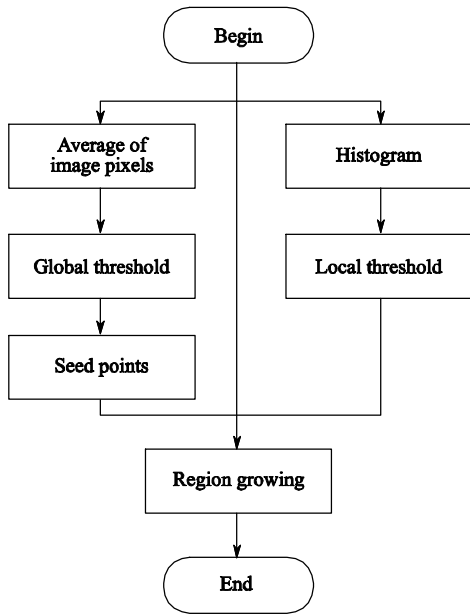


Fig. 3. Algorithm of thresholding and region growing combined

To segment a vessel tree, we thus combine the approaches of thresholding and region growing similarly to [5]. Applying global threshold to the original image yields the seed points. These points initiate the region growing procedure that continues until the stop condition is met (as determined by the local threshold). The algorithm is depicted in Fig. 3.

Estimating Global Threshold

Three statistics were considered as candidates for the best automatic indicator of the global threshold. These were the average, the sum, and the standard deviation of all the gray-level values in the image. As seen from Table 1, the average correlated best ($r = 0.89$) with the threshold value obtained experimentally.

Fig. 4 plots the global threshold points ($N = 20$) against the average of all the gray-level values in the image.

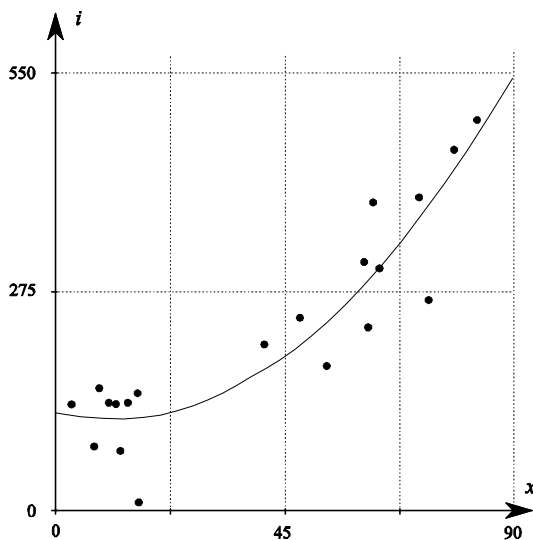


Fig. 4. Global threshold as a function of the average intensity

Table 1. Correlation of statistics with experimental threshold

Parameter	r
Average	0.89
Sum	0.09
Standard deviation	0.79

Fitting the data with a quadratic polynomial gives:

$$y = 0.1116x^2 - 8.314x + 388.4, \quad (1)$$

where y – the threshold, x – the average of all the gray-level values in the image:

$$x = \frac{1}{n+1} \sum_{j=0}^n I(j). \quad (2)$$

$I(j)$ denotes the gray-level value of pixel j .

Estimating Local Threshold

The majority of histogram plots shown in Fig. 5 reveal a bimodal nature of distribution of gray-level values in the image. That is, blood vessels appear as light objects on a dark background. Even though a typical histogram has no clear valley, gray-level values of pixels belonging to the vessels and those of the background group into two dominant modes. Therefore, a single threshold is sufficient for extracting areas containing the blood vessels from the background. These areas can then be used as seed points.

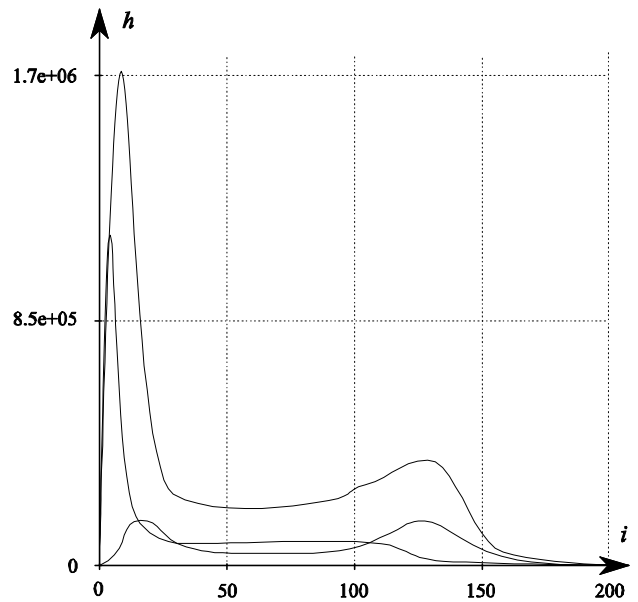


Fig. 5. Histogram of gray-level values

The next step is determining the local threshold that serves as the stop condition for the region-growing procedure. In other words, the local threshold determines the limits within which the seed points are allowed to expand. The value of the local threshold can be obtained from the histogram. The goal is to find the point of maximum curvature on the falling slope of the histogram's second hill. Fig. 6 schematically shows the rationale behind this.

Curvature σ is evaluated according to the following formula:

$$\sigma = \sum_{j=a}^b h_j - \mu \frac{h_a + h_b}{2} \quad (3)$$

where $\mu = b - a$ – the width of the window, h_a and h_b – the values of the histogram at the edges of the window, h_j – the value of the histogram at point j .

The first term in Equation 3 denotes the area under the plot that is approximated by the sum of the samples. The second term in Equation 3 is the area of the trapezium formed by μ , h_a , and h_b . Result of the deduction is a gap having the largest area where the plot's curvature is at its maximum.

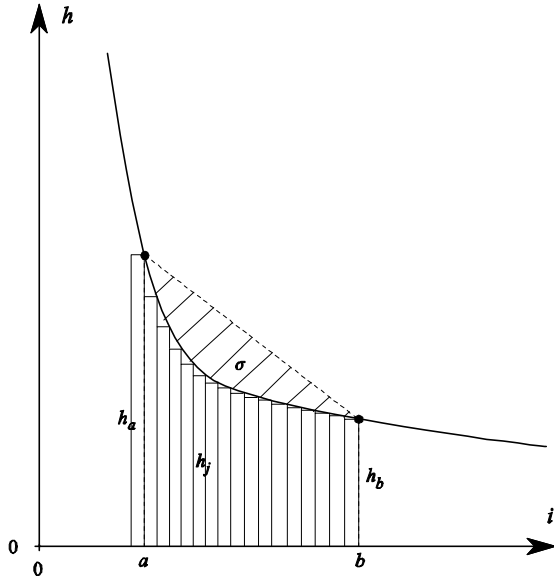


Fig. 6. Finding the point of maximum curvature

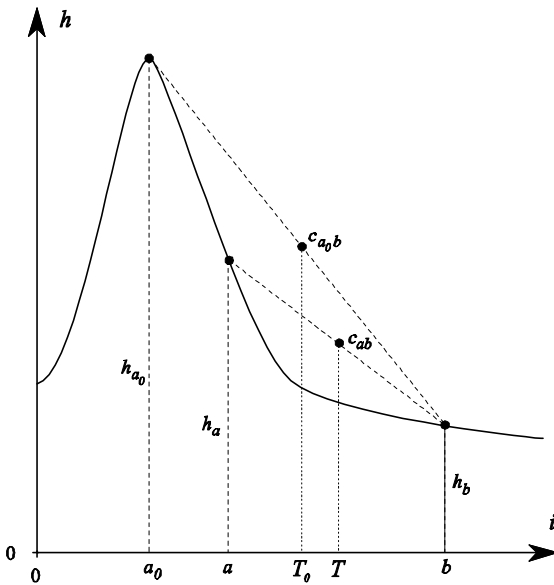


Fig. 7. Effect of choosing different windows

It must be emphasized that the algorithm is quite sensitive to μ , the width of the window chosen. As demonstrated by Fig. 7, windows of different widths may produce estimates for the maximum curvature that vary dramatically in size. Therefore, some experimentation is required on the actual data to decide on the appropriate size of the window.

Algorithm's Performance

After application of the global threshold only small groups of pixels (i.e., seed points) remain. In Fig. 8, the seed points are shown in black. The remaining pixels belonging to blood vessels (shown in gray) are obtained after performing the region-growing procedure.



Fig. 8. Output from algorithm



Fig. 9. Aneurysm observed in blood-vessel tree

The proposed algorithm can potentially be a valuable tool for clinicians as the blood-vessel network is automatically segmented and visualized along with the associated pathologies, such as aneurysms. Fig. 9 illustrates a case with an aneurysm present in the blood-vessel tree (the big round blob on the left).

Conclusions

The algorithm's processing times for various dimensions of data arrays were as follows. For the smallest images tested (384 x 512 x 68), it took on the average 19 seconds to segment blood vessels. Meanwhile, for the two bigger sizes of images (384 x 512 x 90 and 384 x 512 x 115) the processing lasted almost identically (24 and 25 seconds, respectively). As expected, there was a marked increase in processing time with significant increase in image size: 79 and 102 seconds for images sized 768 x 1024 x 72 and 768 x 1024 x 90, respectively.

Acknowledgements

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M. Paulinas, D. Miniotas, M. Meilūnas, A. Ušinskas. An Algorithm for Segmentation of Blood Vessels in Images // *Electronics and Electrical Engineering*. – Kaunas: Technologija, 2008. – No. 3(83). – P. 25–28.

Segmentation is a process of partitioning an image into separate regions until the ones of interest are singled out. We present an algorithm that combines the approaches of thresholding and region growing to segment the vessel tree. First, the optimal global threshold is determined experimentally. We found that the ordinary mean of all the intensity values in the image yields the best estimate for the value of the global threshold. The mean correlated with the threshold value obtained experimentally better than the other two statistics investigated: the sum and the standard deviation of all the intensity values. Upon derivation of the global threshold, it is applied to the original image to yield the seed points. Those are the initial points for the region growing procedure. Then, the algorithm determines the local threshold that serves as the stop condition for the region-growing procedure. Next, the value for the local threshold is obtained from the histogram of the gray-level values. This is equivalent to finding the point of the maximum curvature on the right slope of the histogram's second hill. Il. 9, bibl. 5 (in English; summaries in English, Russian and Lithuanian).

М. Паулинас, Д. Миниотас, М. Мейлунас, А. Ушинскас. Алгоритм для сегментирования кровеносных сосудов в образах // *Электроника и электротехника*. – Каунас: Технология, 2008. – № 3(83). – С. 25–28.

Сегментирование – это процесс, в котором образ циклически разделяется в отдельные части, пока не выделяются интересные области. В настоящей работе предлагается алгоритм для сегментирования кровеносных сосудов, который объединяет в одно целое два метода: конвертирование пикселей в бинарный код посредством определённого порога и наращивание области. В начале экспериментально определяется оптимальный глобальный порог. Нами установлено, что наилучшую оценку для значения глобального порога даёт обычное среднее значений яркости всех пикселей образа. Для этого параметра коэффициент корреляции с экспериментально установленным значением порога был лучше чем для двух других исследованных параметров: сумме и стандартному отклонению значений яркости всех пикселей. После определения оптимального глобального порога пиксели исходного образа конвертируются в бинарный код. В результате этого процесса получаются так называемые „семена“, т.е., начальные точки для процедуры наращивания областей. Далее разыскивается подходящий локальный порог по гистограмме распределения значений яркости. Для этого определяется точка максимальной кривизны графика гистограммы на правом склоне его второго холма. Ил. 9, библи. 5 (на английском языке; рефераты на английском, русском и литовском яз.).

M. Paulinas, D. Miniotas, M. Meilūnas, A. Ušinskas. Kraujagyslių segmentavimo vaizduose algoritmas // *Elektronika ir elektrotechnika*. – Kaunas: Technologija, 2008. – Nr. 3(83). – P. 25–28.

Segmentavimas – tai procesas, kuriuo vaizdas cikliškai dalijamas į atskiras dalis tol, kol išskiriamos reikiamos sritys. Šiame darbe pristatomas kraujagyslių segmentavimo algoritmas, jungiantis du metodus: vaizdo elementų konvertavimą į dvejetainį kodą pagal tam tikrą slenkstį ir srities auginimą. Iš pradžių eksperimentiškai randamas optimalus globalusis slenkstis. Nustatyta, jog geriausią globaliojo slenkščio reikšmės įvertį duoda paprastas visų vaizdo elementų skaiščio reikšmių vidurkis. Šio parametro koreliacijos su eksperimentiškai nustatyta slenkščio reikšme koeficientas buvo didesnis nei kitų dviejų tirtų parametrų: visų vaizdo elementų skaičių sumos ir standartinio nuokrypio. Nustačius optimalų globalųjį slenkstį, pirminio vaizdo elementai paverčiami dvejetainiu kodu. Šio proceso rezultatas – vadinamieji „daigai“, t. y. pradiniai taškai sričių auginimo procedūrai. Toliau ieškoma tinkamo lokaliajo slenkščio iš skaiščio reikšmių pasiskirstymo histogramos. Tam tikslui randamas histogramos grafiko didžiausio linkio taškas jo antrojo kauburio dešiniajame šlaite. Il. 9, bibl. 5 (anglų kalba; santraukos anglų, rusų ir lietuvių k.).

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