

Segmentation of MRI Data to Extract the Blood Vessels Based on Fuzzy Thresholding

Jan Kubicek¹, Marek Penhaker¹, Karolina Pavelova¹, Ali Selamat²,
Radovan Hudak³, and Jaroslav Majernik⁴

¹ VSB–Technical University of Ostrava, FEECS, K450
17. listopadu 15, 708 33, Ostrava–Poruba, Czech Republic

{jan.kubicek, marek.penhaker, karolina.pavelova.st}@vsb.cz
² UTM-IRDA Center of Excellence, UTM and Faculty of Computing, University
Teknologi Malaysia, 81310 UTM Johor Bahru, Johor, Malaysia
aselamat@fsksm.utm.my

³ Department of Instrumental and Biomedical Engineering,
Faculty of Mechanical Engineering, Technical University of Košice,
Letná 9, Košice, 042 00, Slovakia
radovan.hudak@tuke.sk

⁴ Department of Medical Informatics, Faculty of Medicine,
Pavol Jozef Šafarik University in Košice, Slovakia
jaroslav.majernik@upjs.sk

Abstract. The article discusses the design of appropriate methodology of segmentation and visualization of MRI data to extract the blood vessels. The main objective of the proposed algorithm is effective separation individual vessels and adjacent structures. In clinical practice, it is necessary to assess the progress of the blood vessels in order to assess the condition of the vascular system. For physician who performs diagnosis is much more rewarding to perform analysis of an image that contains only vascular elements. The proposed method of image segmentation can effectively separate the individual blood vessels from surrounding tissue structures. The output of this analysis is the color coding of the input image data to distinguish contrasting behavior of individual vessels that are at the forefront of our concerns, the structures that we need in the picture.

Keywords: Image segmentation, MRA, Fuzzy thresholding, Color mapping.

1 Introduction

Current methods for noninvasive imaging of the vascular system include Doppler ultrasonography, CT angiography (CTA) and MR angiography (MRA). MR angiography provides examination with absence of risks that are associated with exposure to ionizing radiation. The main disadvantages of this diagnostic method may include higher cost of examinations and difficult accessibility. A major problem is the inability perform examination of people with pacemakers, implanted defibrillators, because these devices are not exclusively from non-magnetic material. MRA offers

contrasting view of blood vessels without contrast fluid. Currently native MRA examination is intended for intracranial arterial and venous circulation. Currently, it is one of the most elaborate techniques, which gives very good results [6, 7].

2 MR Angiography (MRA)

Method angiography allows examination of the blood vessels by imaging methods. This method is normally considered non-invasive examination method. This method allows perform examination of different body parts (e.g.. Limbs or brain). This method can be divided into angiography with administration of contrast fluid and without its use [10].

This contrast fluid is to enhance the contrast of the individual structures. For example it is possible to highlight pathology, or dynamic processes. These contrast fluids normally contain paramagnetic chelates. Subsequent contrast-enhanced examination is appropriately timed to contrast agent was present mainly in the arterial blood stream, or in the venous system [11].

The resulting MRA image is given by subtraction image without contrast and image with contrast. Non-contrast MRA is used to display the bloodstream is only flowing blood in the investigated area. Signal of surrounding stationary tissues is intentionally suppressed [8, 9, 10, 11].

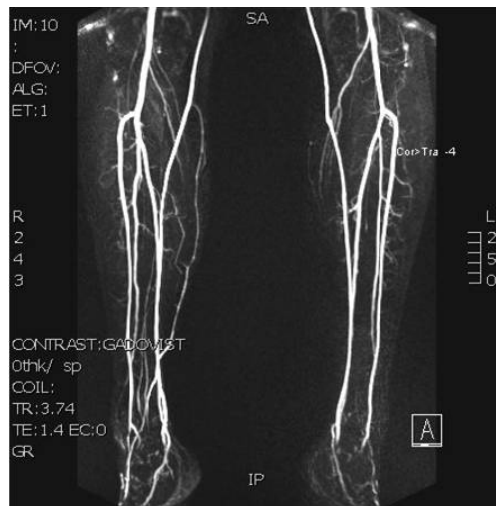


Fig. 1. MRA of lower limbs [9]

3 The Proposed Segmentation Algorithm

Segmentation methods play a key role in the processing of medical imaging data. We often solve the task of extracting parts of the image that exhibit specific properties. Image data from the MRA are represented by gray-levels.

Detection of blood vessels was solved by more approaches, in particular on the basis of edge operators. With edge detection is possible to find various objects in the image, but it is difficult to identify them. Significant benefit of the proposed solution is recognition of individual image elements based on the color spectrum and clearly distinguish the image structures.

The main objective of our analysis is the separation of gray levels in the output sets, so in order to create a contrasting color map, which represents the individual tissue structures. For this purpose fuzzy classifier was used, which has sufficient sensitivity to even slight contrasting shades of gray were distinguished. The histogram of the input image is divided into K different regions, which is the first key stage segmentation procedure, because there we specify what the difference image, we are able to separate from each other. We assume that we have a number of recognizable areas:

$$k = \{n\}_{n=1}^K \quad (1)$$

Subsequently, histogram normalization is solved in order to eliminate outliers and scaling of the image. The resulting histogram is restricted to the interval $[0, 1]$.

$$\bar{h}(i) \rightarrow [0;1] \quad (2)$$

Number of output areas is determined by the number of distinguishable peaks of the histogram. The number of local extremes (N_{\max}) can be defined by:

$$K = N_{\max} \quad (3)$$

The final step of data preprocessing is image smoothing of lowpass filter, which is used to remove unwanted high frequency noise [3].

For the classification of each pixel in the output sets is used fuzzy logic rules. There it is necessary to first define the membership function for each output region R_n .

For the n - th classifier is used expression $\mu_n(f(x))$. There are many kinds of membership functions, but not all are suitable classifiers. The optimum properties have function of triangular shape (TS). Based on these facts, we have used for our algorithm pseudo trapezoidal shape membership function (PTS).

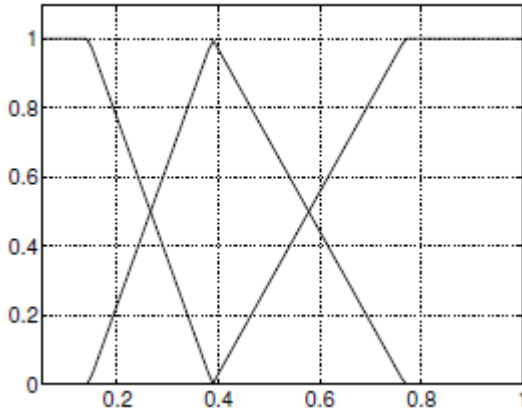


Fig. 2. The shape of the PTS function [4]

Individual blood vessels is segmented in successive iteration steps. The first step of the iteration is defined by:

$$S = \max_n \mu_n(f(x)) \quad (4)$$

The output of this procedure is to determine the maximum individual classification sets. This output is often insufficient, because the image data are suppressed noise that is transmitted to the output of segmentation, which degrades the quality of the entire segmentation process. For this reason, we have to evaluate the competence of pixels intended use of the operator, which is invariant to noise. For each channel of segmentation, we used the median, which is invariant to noise. The output of the segmentation procedure using the median is defined as [1], [3], [4]:

$$S = \text{med}(\mu_n(f(x))) \quad (5)$$

3.1 Structure of the Proposed Algorithm

The structure of the proposed algorithm segmentation of MRA data to extract the blood vessels can be summarized in three basic steps:

Data preprocessing - there is performed histogram normalization and the definition of each output regions. The number of regions is determined by the number of distinguishable peaks of the histogram. This phase determines how deep we are able to perform the final segmentation and how many objects we are able to distinguish from the input data.

Process of Filtration – for filtration is used low-pass filter. This phase is in the structure of the proposed methodology optional. It is used especially when the image data are suppressed by high frequency noise. Noise has a negative impact on the

quality of the segmented images, after removing noise we are able to achieve a smooth contour segmentation.

The process of segmentation - in this key phase of segmentation individual pixels are grouped into output sets on the basis of their properties using the membership function. The aim is the separation of shades gray that represent the blood vessels and the removal of remaining tissues that belong to the background of images.

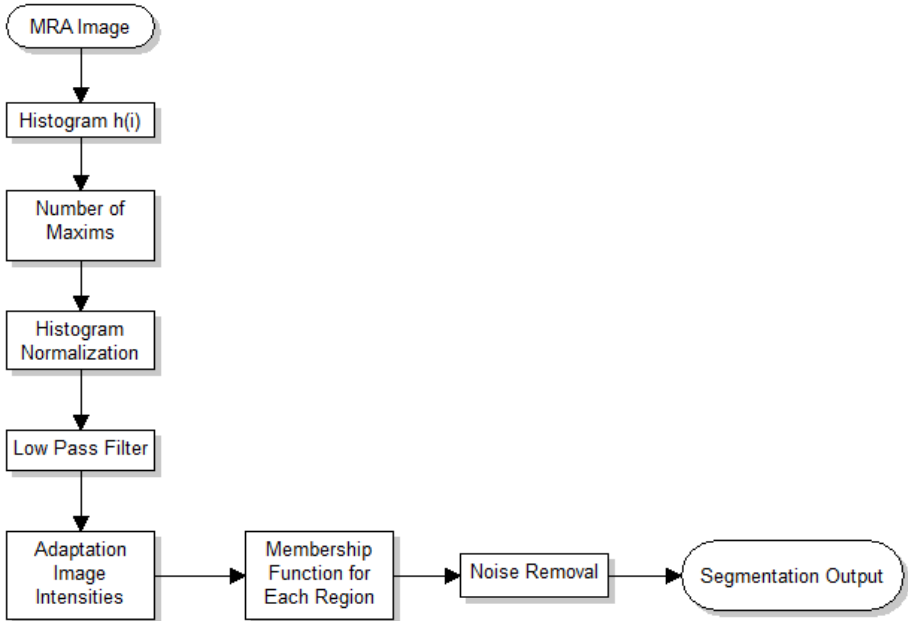


Fig. 3. The structure of the proposed segmentation procedure

4 Testing of the Proposed Algorithm

For testing of the algorithm, we used a series of MRA images 60 patients. The main requirement is approximation of vessels by the color model that separates the blood-stream from the background and subsequent filtering to display only vascular structures. Benefit of the proposed solution is the choice of output sets, which allows in-depth analysis even tissues that are poorly recognized. In the first part of the analysis we performed mapping of carotid arteries in order to detect the main trunk of the carotid artery.



Fig. 4. MRA image of carotid arteries

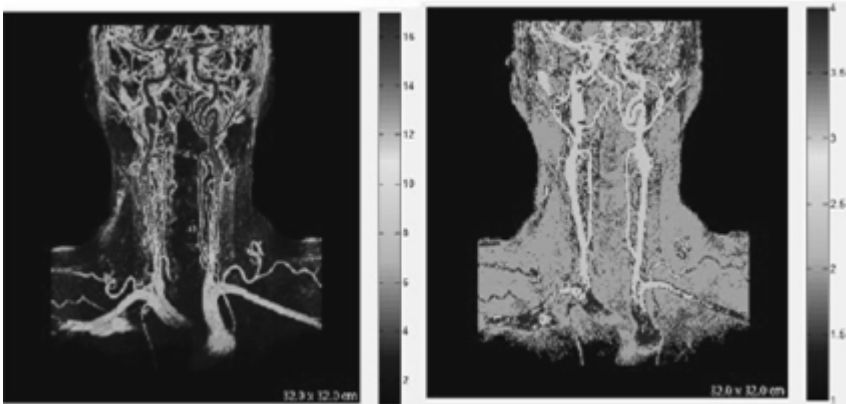


Fig. 5. Evaluation of the number output sets - 18 (maximum) on the left and 4 on the right

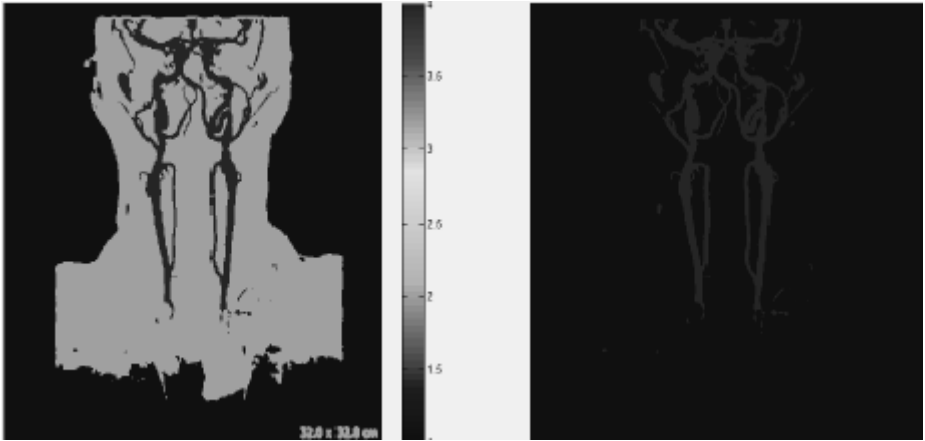


Fig. 6. Filtered image of carotid arteries -18 sets (left) and thresholded image (right)

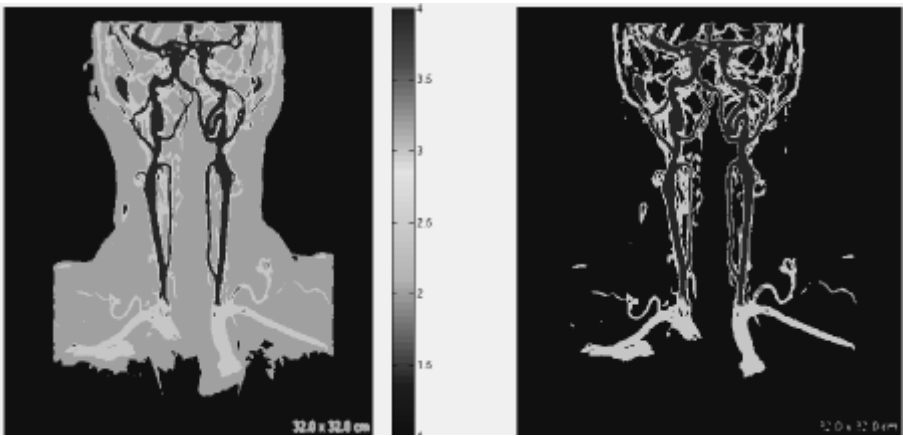


Fig. 7. Filtered image of carotid arteries - 4 sets (left) and thresholded image (right)

We used two segmentation outputs for 4 and 18 output sets. From this view, it appears that it is not always desirable to select the maximum number of output sets as the optimal solution. When comparing the number of output regions can be seen that the filter 18 suppresses the set portion of the structure that includes the blood stream and provides to the physician significant diagnostic information.

In the following part of the analysis, we focused on MRA sequences that generate areas of tibia and pelvis. There is the same requirement, and that separation of the bloodstream from the background.

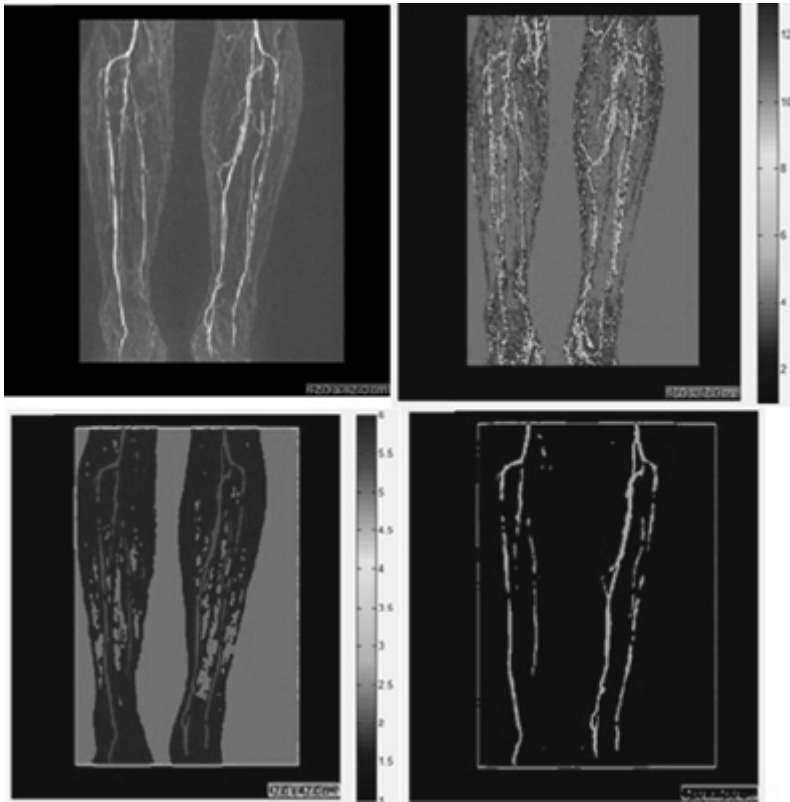


Fig. 8. MRA image of tibia (top left), 13 output sets (top right), filtered image (bottom left) and thresholded image (bottom right)

When comparing the images of the carotid arteries and tibia is at first sight that the tibia images are suppressed by more noise. This negative image component is transferred to the segmentation result and acts as an artifact. These image series have lower resolution, which is reflected on the resulting color map that is not fluent in some places.



Fig. 9. MRA image of the pelvic bottom (top left), 5 output sets (top right), filtered image (bottom left), thresholded image (bottom right)

5 Conclusion

The main goal, which is described in the article is the development of a segmentation method that is able to reliably separate the blood vessels from the other structures. The proposed methodology is developed primarily for image data from MRA. The main requirement is only the detection of blood vessels, without the adjacent structures. This task is relatively easily implemented, because segmentation based on fuzzy logic is able to sharply demarcate the different tissue structures and choice of appropriate thresholding can be displayed only vessels that are at the forefront of our concerns. Another significant advantage is the high sensitivity of the algorithm even in places where there is only small changes in contrast. In a future time, we would like to focus on the calculation torturozity of vascular system from segmented data.

This parameter is very important because we get information about the curvature of the vessels, which corresponds with a vascular condition.

Acknowledgment. The work and the contributions were supported by the project SP2015/179 'Biomedicínské inženýrské systémy XI', and This paper has been elaborated in the framework of the project „Support research and development in the Moravian-Silesian Region 2013 DT 1 - International research teams“ (RRC/05/2013). Financed from the budget of the Moravian-Silesian Region.

References

1. Otsu, N.: A threshold selection method from gray-scale histogram. *IEEE Trans. on Sys., Man and Cyb.* 9(1), 62–66 (1979)
2. Szczepaniak, P., Kacprzyk, J.: *Fuzzy systems in medicine.* Physica-Verlag, New York (2000)
3. Ville, D.V.D., Nachtegael, M., Der Weken, D.V., Kerre, E.E., Philips, W., Lemahieu, I.: Noisereduction by fuzzy image filtering. *IEEE Trans. Fuzzy Sys.* 11(4) (2003)
4. Fernández, S., et al.: Soft tresholding for medical image segmentation. *IEEE EMBS* (2010)
5. Bezdek, J.C., Pal, S.K.: *Fuzzy Models for Pattern Recognition.* IEEE Press, New York (1992)
6. Falcao, A.X., Udupa, J.K., Samarasekera, S., Sharma, S.: User-steered image segmentation paradigms: live wire and live lane. *Graphical Models Image Process* 60, 233–260 (1998)
7. Eckstein, F., Tieschky, M., Faber, S., Englmeier, K.H., Reiser, M.: Functional analysis of articular cartilage deformation, recovery, and fluid flow following dynamic exercise in vivo, pp. 419–424. *Anat Embryol, Berl* (1999)
8. McWalter, E.J., Wirth, W., Siebert, M., Eisenhart-Rothe, R.M., Hudelmaier, M., Wilson, D.R., et al.: Use of novel interactive input devices for segmentation of articular cartilage from magnetic resonance images, *Osteoarthritis Cartilage*, pp. 48–53 (2005)
9. Graichen, H., Al Shamari, D., Hinterwimmer, S., Eisenhart-Rothe, R., Vogl, T., Eckstein, F.: Accuracy of quantitative magnetic resonance imaging in the detection of ex vivo focal cartilage defects, *Ann Rheum Dis*, pp. 1120–1125 (2005)
10. Schmid, M., Conforto, S., Camomilla, V., Cappozzo, A., Alessio, T.D.: The sensitivity of posturographic parameters to acquisition settings. *Medical Engineering & Physics* 24(9), 623–631 (2002)
11. Severini, G., Conforto, S., Schmid, M., Alessio, T.: D': Novel formulation of a double threshold algorithm for the estimation of muscle activation intervals designed for variable SNR environments. *Journal of Electromyography and Kinesiology* 22(6), 878–885 (2012)