PAPER REF: 7293

VESSEL DETECTION IN CAROTID ULTRASOUND IMAGES USING ARTIFICIAL NEURAL NETWORKS

Catarina F. Castro^(*), Carlos C. António, Luisa C. Sousa

Faculty of Engineering of the University of Porto and INEGI Porto, Portugal ^(*)*Email:* ccastro@fe.up.pt

ABSTRACT

Carotid Doppler ultrasound and imaging are focused on the visualization, identification and measurement of vessels and blood flow providing critical diagnostic information on symptomatic or asymptomatic stenotic or embolic accidents. Ultrasound imaging is a complicated interplay between physical principles and signal processing methods. In this work the development of a new algorithm for vessel identification and image segmentation in ultrasound images is reported. A fully automatic technique based on pixel intensity distribution alleviates the laborious and time consuming manual measurement and classification of the carotid artery.

Keywords: ultrasound images, vessel detection, image segmentation, artificial neural networks.

INTRODUCTION

Carotid sonography, a fast and inexpensive technique, is extremely useful in medical applications such as deep venous thrombosis detection, anesthesia guidance and catheter placement. The goal of vessel detection in carotid ultrasound images is to identify the position and size of blood vessels in the image. Previous methods developed for detection and measurements of carotid arteries in longitudinal ultrasound images has been reported and successfully considered for medical purposes (Sousa *et al.*, 2014). Detection and measurements of carotid arteries in transversal ultrasound images is the main issue having problems distinguishing vessels from non-vessels when varying user settings, such as gain, on the ultrasound scanner, or due to increased amounts of reverberation artifacts (Castro *et al.*, 2017). The new proposal is to use an ellipse fitting method to find vessel candidate regions which are passed on to a neural network classifier which determines if the region contains a vessel or not. The proposed methodology enables detection of multiple vessels and also it can be used as vessel measurement tool assuming the vessel presents an elliptical shape.

METHODOLOGY

Segmentation of acquired B-mode transversal images is due to identify cross sectional lumen areas of the carotid arteries. These complex images introduce a further challenge of poorly defined discontinuous walls as they present more artefacts caused by speckle noise. Images suffer from a refractive phenomenon of ultrasound (US) waves caused by the wall which distorts and impoverishes their quality (low contrast and noise). Moreover, transverse acquired images have different topologies and different cross-sections different branches of the carotid artery and bifurcation. The difficulty associated to analyze US transversal images is one reason why there is almost no published research work on cross sectional segmentation of acquired B-mode transversal the carotid arteries (Pinho *et al.*, 2017). Figure 1 provides an overview of the steps involved in the previous method. An elliptic vessel model is used to find vessel candidate regions in the ultrasound image creating individual sub-images from the ultrasound image for each vessel candidate.

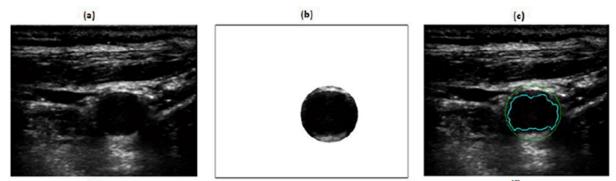


Fig. 1 - Lumen segmentation main steps: (a) Selection of the region of interest; (b) Circle imposition and contrast enhancement; (c) Identification and lumen segmentation.

The vessel model used in the proposed method assumes that the vessels are elliptical which often holds true for arteries. Vessels usually are compressed in the vertical direction, due to pressure from the ultrasound probe applied by the radiologist.

In cases where the arterial wall is poorly defined, the topology of the automated contour in these regions is entirely defined by a circular region of interest imposition, which inserts variability in the algorithm and also interferes in the lumen contour found by the algorithm. A new methodology of automatic segmentation of the lumen in transversal ultrasound images of the carotid artery is discussed here. The methodology consists of three main stages. The first stage consists on the implementation of pre-processing and processing image techniques on a transversal ultrasound image to extract the coordinates of the contours of the carotid artery. The second stage has the objective of applying a smoothing algorithm to the coordinates of the contours using the Bezier curves to generate the geometric model. The third stage feeds the neural network classifier which determines if the region contains a blood vessel or not.

The first stage is composed by two main steps. Firstly, the region of interest in the image is binarized and structures smaller than 1% of the total number of image pixels are discarded since they are most likely assigned as noisy artifacts. The process of identifying the lumen consists in maximizing a function composed by three parameters: circularity index, irregularity index and center index. This methodology has been suggested by Jodas et al. (2018). Circularity indexes are commonly used to quantify the roundness of regions in images and can be used to find the region with the maximum roundness, the larger the mean roundness, the more circular the region is. The irregularity index is used to avoid regions with irregular contours: comparing the shortest diameter and the greatest diameter of the same contour if the difference is equal to 0 (zero) or close to it, the irregularity index decreases, thus, the boundary is due to be more regular. Since the medical team, images vessels located close to the center of image, a center index is used to avoid regions distant from the center of the input image. The distance between the center coordinates of the image and the center coordinates of each segmented region is calculated and used as a term to maximize the likelihood of finding the lumen of the carotid artery under study. Maximizing roundness and the inverse of irregularity plus center index has been considered as suggested previously:

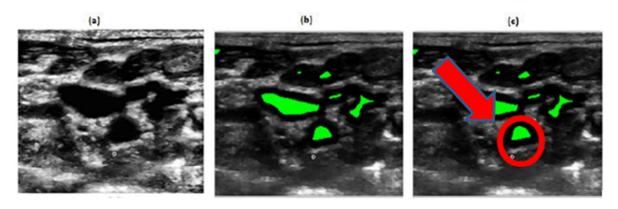


Fig. 2 - Identification of the carotid lumen by maximizing three parameters: circularity index, irregularity index and center index: (a) Selection of the region of interest; (b) Lumen identification; (c) Carotid lumen assignment.

Secondly, each pixel is labeled by associating a value of gray level (between 1 and 255), differentiating lumen and vessel contour. This way, regions of the image that are not associated with the carotid arteries will be discarded. Subsequently, the contour extractor uses a control variable to identify whether a pixel belongs to the contour or not and the coordinates of the pixels identified as contour are stored.

The second stage considers the geometric modeling of the vessel wall using Bezier curves. For each contour, pixels are classified in two subsets: Sup and Inf based on the y-direction, as the Bezier curves are not capable of generating closed trajectories. Therefore, a Bezier curve is achieved for Sup and another curve for Inf and at the end, both curves are joined keeping the continuity in a single curve that represents the vessel contour.

The next step of the proposed method is to send each vessel candidate image through a deep convolutional neural network classifier to determine if the image belongs to a blood vessel. Vessel candidate images of blood vessels and other non-vessel structures were used for training the neural network.

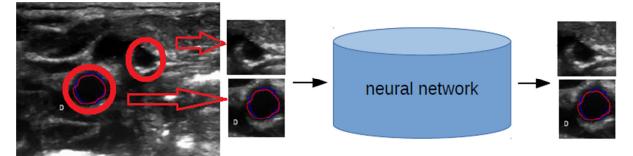


Fig. 3 - Overview of the proposed developed artificial neural network: sub-images are then passed on to a neural network which identifies the sub images belonging to vessels, and discards those that are not of vessels

An underlying framework both for training and testing of the classifier were acquired by scanning different subjects with varying image quality and different ultrasound acquisition settings. Every frame was run through the vessel candidate search step and the resulting images were stored on disk. There is no theoretically sound way of choosing the optimal architecture for each separate model. The considered network has one hidden layer with N

neurons. Synapses send data on to a hidden layer, which in turn sends to the output layer representing the dependent variables. Input and hidden layer biases need to be adjusted in all learning algorithms of neural networks and thus there exists dependency between different layers of parameters (weights and biases). The activation functions (hyperbolic tangent functions), the weights of the synapses and the bias applied to the neurons at the hidden and output layers are to be controlled during the supervised learning process. In this particular classification problem, generalization is a central issue, because severe clinical consequences can result from the To increase the amount of training data, all vessel candidate images were flipped horizontally, effectively doubling the amount of training data.

DISCUSSION

The vessel model used in the proposed method assumes elliptical shapes, what often holds true for arteries. Since vessels usually are compressed in the vertical direction, due to pressure from the ultrasound probe applied by the user, including rotation in the vessel candidate search reduces runtime performance and training data set. With ultrasound imaging, a large amount of unlabeled data can easily be acquired from the target body regions. Thus, unsupervised pre-training will be a useful technique within ultrasound imaging. The implemented methodology allows the user to load images and process and extract features enabling plaque detection and discrimination. Limitations similar to other technologies are expected to be resolved with further studies and technical improvements. The present research contributes to the analysis of hemodynamic conditions of the carotid bifurcation stenosis and occlusion.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the funding by FCT, Portugal, of the Research Unit of LAETA-INEGI.

REFERENCES

[1] Castro CF, Sousa LC, Henriques HAM, António CC, Santos RM, Castro PMAC, Azevedo E. Hemodynamic Abnormalities in a Carotid Bifurcation Based on Doppler Ultrasound Imaging. Medical Engineering: June, 2017; 02(05): 085-095 men/17/1720/gmj.

[2] Jodas DS, Pereira AS, Tavares JMRS. Automatic Segmentation of the Lumen in Magnetic Resonance Images of the Carotid Artery. In: Tavares J., Natal Jorge R. (eds) VipIMAGE 2017. ECCOMAS 2017. Lecture Notes in Computational Vision and Biomechanics, vol 27. Springer, Cham(2018).

[3] Pinho N, Bento M, Sousa LC, Pinto S, Castro CF, António CC, Azevedo E. Patient-Specific Study of a Stenosed Carotid Artery Bifurcation Using Fluid-Structure Interactive Simulation. Proceedings of the VI ECCOMAS Thematic Conference on Computational Vision and Medical Image Processing, VipIMAGE 2017, Porto, Portugal, October 18-20, 2017.

[4] Sousa LC, Castro CF, António CC, Santos AMF, Santos RM, Castro PMAC, Azevedo E, Tavares JMRS. Toward hemodynamic diagnosis of carotid artery stenosis based on ultrasound image data and computational modelling. Med. Biol. Eng. Comput., 52 (11) 971-983, 2014.