Applied Soft Computing xxx (2016) xxx-xxx

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc



Early-stage atherosclerosis detection using deep learning over carotid ultrasound images

Rosa-María Menchón-Lara a,*, José-Luis Sancho-Gómez A, Andrés Bueno-Crespo b

- a Departamento de Tecnologías de la Información y las Comunicaciones, Universidad Politécnica de Cartagena, Murcia, Spain
- ^b Departamento de Informática de Sistemas, Universidad Católica San Antonio, Murcia, Spain

ARTICLE INFO

Article history:

10

14

22 Q2

23

24

25

26

27

28

29

30

31

32

- Received 11 March 2016
- Received in revised form 24 June 2016 11
- 12 Accepted 31 August 2016
- Available online xxx

Kevwords:

- 15 16 Deep learning
- Auto-encoders
- Extreme learning machine
- Intima-media thickness 19
- 20 Image segmentation

ABSTRACT

This paper proposes a computer-aided diagnosis tool for the early detection of atherosclerosis. This pathology is responsible for major cardiovascular diseases, which are the main cause of death worldwide. Among preventive measures, the intima-media thickness (IMT) of the common carotid artery stands out as early indicator of atherosclerosis and cardiovascular risk. In particular, IMT is evaluated by means of ultrasound scans. Usually, during the radiological examination, the specialist detects the optimal measurement area, identifies the layers of the arterial wall and manually marks pairs of points on the image to estimate the thickness of the artery. Therefore, this manual procedure entails subjectivity and variability in the IMT evaluation. Instead, this article suggests a fully automatic segmentation technique for ultrasound images of the common carotid artery. The proposed methodology is based on machine learning and artificial neural networks for the recognition of IMT intensity patterns in the images. For this purpose, a deep learning strategy has been developed to obtain abstract and efficient data representations by means of auto-encoders with multiple hidden layers. In particular, the considered deep architecture has been designed under the concept of extreme learning machine (ELM). The correct identification of the arterial layers is achieved in a totally user-independent and repeatable manner, which not only improves the IMT measurement in daily clinical practice but also facilitates the clinical research. A database consisting of 67 ultrasound images has been used in the validation of the suggested system, in which the resulting automatic contours for each image have been compared with the average of four manual segmentations performed by two different observers (ground-truth). Specifically, the IMT measured by the proposed algorithm is 0.625 ± 0.167 mm (mean \pm standard deviation), whereas the corresponding ground-truth value is 0.619 ± 0.176 mm. Thus, our method shows a difference between automatic and manual measures of only $5.79 \pm 34.42 \,\mu m$. Furthermore, different quantitative evaluations reported in this paper indicate that this procedure outperforms other methods presented in the literature.

© 2016 Elsevier B.V. All rights reserved.

41

42

43

44

45

46

47

1. Introduction

Cardiovascular diseases (CVD) remain the major cause of death in the world [1]. A large proportion of CVD are caused by an underlying pathological process known as atherosclerosis. Thus, its early diagnosis is critical for preventive purposes. Atherosclerosis involves a progressive thickening of the arterial walls by fat accumulation, which hinders blood flow and reduces the elasticity of the affected vessels.

The intima-media thickness (IMT) of the common carotid artery (CCA) is considered as an early and reliable indicator of atherosclerosis [2] and it is extracted from ultrasound scans [3], i.e. by

Corresponding author. E-mail address: rmml@alu.upct.es (R.-M. Menchón-Lara).

http://dx.doi.org/10.1016/i.asoc.2016.08.055

1568-4946/© 2016 Elsevier B.V. All rights reserved.

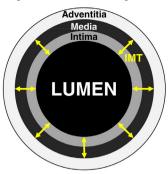
means of a non-invasive technique. As can be seen in Fig. 1 (left), blood vessels present three different layers, from innermost to outermost: intima, media and adventitia. The IMT is defined as the distance from the lumen-intima interface (LII) to the media-adventitia interface (MAI). The use of different protocols and the variability between observers are recurrent problems in the IMT measurement procedure. To ensure the repeatability and reproducibility of the process, according to the Mannheim consensus [2], the IMT should be measured preferably on the far wall of the CCA within a region free of atherosclerotic lesions (plaques), where a double-line pattern corresponding to the intima-media-adventitia layers can be clearly observed (see Fig. 1, right).

Usually, the IMT is manually measured by the specialist, who marks pairs of points corresponding to the LII and MAI on the ultrasound. It is possible to reduce the subjectivity and variability of

Please cite this article in press as: R.-M. Menchón-Lara, et al., Early-stage atherosclerosis detection using deep learning over carotid ultrasound images, Appl. Soft Comput. J. (2016), http://dx.doi.org/10.1016/j.asoc.2016.08.055

R.-M. Menchón-Lara et al. / Applied Soft Computing xxx (2016) xxx-xxx

Layers of the Artery Wall:



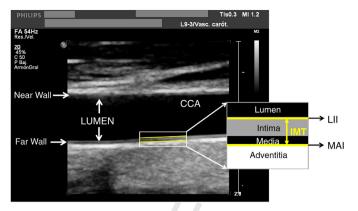


Fig. 1. Diagram of the arterial layers in a transverse section (left) and longitudinal view of the CCA in an ultrasound image (right).

manual approaches and detecting the IMT throughout the artery length by means of image segmentation algorithms.

In the last two decades, several solutions have been developed to perform the carotid wall segmentation in ultrasound images [4,5] for the IMT measurement. Most of the proposed methods require user interaction [6-10]. However, some fully automatic approaches have already been published [11-17].

It is possible to make a classification of techniques according to the used methodology. In this sense, we can find algorithms based on edge detection and gradient-based techniques [6,8,9,18], and other proposals based on dynamic programming [19–24], active contours [7,14,25–27,13], neural networks [11,12] or in a combination of techniques [10,16]. There are also techniques based in statistical modelling [28,17] or in Hough transform [15,29].

This work addresses a fully automated segmentation technique completely based on machine learning to recognize IMT intensity patterns in the carotid ultrasound images. In particular, the developed system intends to emulate the procedure followed by the specialist in the manual protocol. That is, firstly, the detection of the optimal measurement area and, then, the identification of the arterial wall layers. With this purpose, a deep learning strategy has been designed to obtain abstract and efficient feature representations by means of auto-encoders based on extreme learning machine (ELM). The proposed method jointly extracts the LII and MAI from ultrasound CCA images in a totally user-independent and repeatable manner. Therefore, it improves the reproducibility and objectivity of the IMT evaluation to assist in the early diagnosis of atherosclerosis.

The remainder of this paper is structured as follows: Section 2.1 describes the dataset of ultrasound CCA images and the manual segmentations, while Section 2.2 introduces the machine learning concepts used in this work. In Section 2.3, the proposed segmentation method is explained in detail. The obtained results are shown in Section 3. Finally, the main extracted conclusions close the paper.

2. Material and methods

2.1. Image database and manual segmentations

The set of images used in this work consists of 67 ultrasounds of the CCA taken with a Philips iU22 Ultrasound System using three different ultrasound transducers or probes, with frequency ranges of 9–3 MHz, 12–5 MHz and 17–5 MHz. All of them were provided by the Radiology Department of Hospital Universitario Virgen de la Arrixaca (Murcia, Spain). The parameters of the scanner were adjusted in each case by the radiologist. The spatial resolution of the images ranges from 0.029 to 0.081 mm/pixel, with mean and standard deviation equal to 0.051 and 0.015 mm/pixel,

respectively. Some blurred and noisy images, affected by intraluminal artifacts, and some others with partially visible boundaries are included in the studied set.

To assess the performance of the proposed segmentation method, it is necessary to compare the automatic results with some indication of reference values. In our case, the ground-truth corresponds to the average of four manual segmentations for each ultrasound image. In particular, two different observers delineated each image twice, with a mean period of one month between tracings. Each manual segmentation of a given ultrasound image includes tracings for the LII and MAI on the far carotid wall. The delineations were performed by marking at least 10 points over the images for each contour, which were subsequently interpolated. Once the four manual contours have been interpolated, the ground-truth for each IMT interface (LII and MAI, separately) is assessed by averaging these in a column-wise manner, i.e., along the longitudinal axis of the image. Fig. 2 illustrates the process for the manual segmentations and the definition of the groundtruth for each contour. Hereinafter, we will refer to the different segmentations as:

109

110

111

112

113

120

121

122

123

124

125

126

127

128

- MA1: first manual segmentation from observer A.
- MA2: second manual segmentation from observer A.
- MB1: first manual segmentation from observer B.
- MB2: second manual segmentation from observer B.
- GT: ground-truth, average of MA1, MA2, MB1 and MB2.
- AUT: proposed automatic segmentation.

2.2. Machine learning techniques

In the last decade, extreme learning machine (ELM) has emerged as a powerful tool in the learning process of single-layer feed-forward networks (SLFN) by providing good generalization capability at fast learning speed [30]. Given N arbitrary distinct samples $(\mathbf{x}_n, \mathbf{t}_n)$, where $\mathbf{x}_n \in \mathbb{R}^d$ is an input vector and $\mathbf{t}_n \in \mathbb{R}^m$ its corresponding target vector, the output of a SLFN with M hidden neurons and activation function $f(\cdot)$ is given by

$$\mathbf{y}_n = \sum_{j=1}^M \mathbf{\beta}_j f(\mathbf{w}_j \mathbf{x}_n + b_j), \quad n = 1, ..., N;$$
(1)

where $\mathbf{w}_j = [w_{j1}, w_{j2}, \ldots, w_{jd}]$ is the input weight vector connecting the input units and the *j*th hidden neuron, $\mathbf{\beta}_j = [\beta_{j1}, \beta_{j2}, \ldots, \beta_{jm}]$ is the output weight vector connecting the *j*th hidden neuron and the output units, and b_j is the bias of the *j*th hidden neuron. If it

51

63

65

67

75

77

Download English Version:

https://daneshyari.com/en/article/4963588

Download Persian Version:

https://daneshyari.com/article/4963588

<u>Daneshyari.com</u>