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Automatic multiscale vascular image segmentation algorithm for coronary angiography

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ABSTRACT

Cardiovascular diseases, particularly severe stenosis, are the main cause of death in the western world. The primary method of diagnosis, considered to be the standard in the detection and quantification of stenotic lesions, is a coronary angiography. This article proposes a new automatic multiscale segmentation algorithm for the study of coronary trees that offers results comparable to the best existing semi-automatic method. According to the state-of-the-art, a representative number of coronary angiography images that ensures the generalisation capacity of the algorithm has been used. All these images were selected by clinics from an Haemodynamics Unit. An exhaustive statistical analysis was performed in terms of sensitivity, specificity and Jaccard. Algorithm improvements imply that the clinician can perform tests on the patient and, bypassing the images through the system, can verify, in that moment, the intervention of existing differences in a coronary tree from a previous test, in such a way that it could change its clinical intra-intervention criteria.

1. Introduction

Cardiovascular diseases (CVD) are the number one cause of death globally. An estimated 17.9 million people died from CVDs in 2015, representing 31% of all global deaths. Of these deaths, an estimated 7.4 million were due to coronary heart disease and 6.7 million were due to stroke. Over three quarters of CVD deaths take place in low- and middle-income countries. Out of the 16 million deaths under the age of 70 due to non-communicable diseases, 82% are in low and middle income countries and 35% are caused by CVD [1].

The most used diagnostic technique at present, and that which is used for evident symptoms of cardiovascular problems, is an angiography obtained through catheterisation [2,3]. This procedure is recommended in patients with a high probability of coronary heart disease. In these cases, cardiologists analyse the angiography images, establish a diagnosis for the disease and even anticipate its prognosis, depending on the severity and extent of the coronary disease.

Due to the importance of this type of test and its implications on public health, researchers such as O'Brian and Ezquerra [4] have been working on the automatic segmentation of the coronary tree since the mid 1990s. Since then, a large number of processing techniques have increased to efficiently segment the coronary tree, as can be verified in the comparative studies of Kirbas and Quek [5], published in 2004, and the studies of Novoa et al. [6], published in 2011. In this last study, it was concluded that the algorithm with the best results was that of Poon et al. [7]. However, this technique has the downside of a very long execution time, to the order of several minutes for an average sized image, and its semi-automatic nature requires human intervention. What is more, semi-automatic arterial segmentation has the issue of the existence of an inter- and intra-observer variable. Even though it is a value that can be minimised, as has been documented in several studies and publications, it is not possible to completely eliminate it [8]. Lastly, the efficiency of these semi-automatic algorithms is completely dependent on the experience of a clinical expert, and largely eliminates the generalisation capacity of this algorithm.

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This article presents a new coronary tree segmentation technique that is completely automatic and efficient, in terms of execution time. Its results surpass those obtained by Poon et al. [7] in precision, a state of the art technique that was previously mentioned, and, according to several state of the art reviews, which currently offer the best results for this type of medical image.

2. Background

In the field of processing coronary angiographies, segmentation algorithms have to solve very complex problems, such as the noise that angiography capture devices register, the spontaneous movements of the patient and of his/her internal organs, bifurcations, different level blood-vessel crossings, stenotic lesions, etc. Due to all of this, it is very difficult to develop a technique that behaves appropriately in all of these situations.

Over the years, may studies have come into existence that present algorithms whose aim is to offer the user a reliable segmentation based on the data entry set within a reasonable period of time. However, many methods offer only one of these two characteristics. An example of this fact are Random Walk methods [9], which are one of the fastest, in general terms, of all the developments at present. However, they suffer from problems of false positives and are unable to completely ignore the noise of the input image. On the other hand, the active contour methods [10] are less sensitive to random noise, but the required execution time is much longer than that of the multiscale methods. Algorithms based on artificial neuron networks [11,12] have experienced a significant gap in terms of new publications, given their low precision in coronary angiographies, whose quality is generally far from optimal.

In the state of the art review, approximately 50 articles were analysed, based on different focuses and methodologies. Based on these reviews performed by different research groups, we concluded that, among all the algorithms published up until now, Poon's multiscale method [7] provides the highest sensitivity and specificity values for the segmentations performed using it. Furthermore, this algorithm has been used to carry out arterial segmentation in different medical imaging modalities related to angiographies, such as in the case of angiographies of vessels in the retina or in the recording of cerebral vessels [13]. Therefore, it will be used as a reference point to explain our automatic multiscale algorithm proposal for the segmentation of vessels (vascular) in coronary angiography imaging. Its greatest deficiency is relative to the processing times, since it is a semi-automatic method.

The Poon et al. method [7], used as a starting algorithm, is based on multiscale filters to obtain the cost associated with each pixel of the image. The user must indicate the starting and end point of a vascular segment, and the algorithm automatically selects the required intermediate points between both points to outline the vessel. To do so, it uses an exhaustive graphical search based on Dijkstra's algorithm [8]. This method also offers the added control of manual segmentation, allowing the user to only segment the area of the angiography that he/she desires. This is particularly useful when the doctor wishes to focus his/her analysis on a specific area of the image.

The first step of the method is to create the cost matrix of the angiography. Optimization in Poon's et al. is achieved by minimizing the cumulative cost function at each (x, y, z) node. Thus, in this approach the cost associated from a node of a vascular segment $q = (x, y, z)$ to a neighboring node $p = (x', y', z')$ is calculated as:

$$Cost(q, p) = w_1 C_v(p) + w_2 C_{Ev}(q, p) + w_3 C_{Ie}(p)$$
$$+ w_4 C_R(q, p) + w_5 C_S(q, p)$$

This will be used retrospectively to choose the minimum cost path between the two points that the user selects as the start and end points of a vascular segment. The justification for selecting the minimum cost path is simple: the filters are designed to offer the minimum response inside the vessels and a greater response on what is considered the background. The filters that are used in this phase are the multiscale vessel enhancement filters described by Frangi et al. [14], Koller et al. [15] and several structural filters.

In the case of the former, developed by Frangi et al., the noise and background of the image are suppressed while the vessels are enhanced, in accordance with the following function:

$$C_v(q) = v(\lambda_1, \lambda_2) = \begin{cases} 1 & \text{if } \lambda_2 > 0 \\ 1 - \exp\left(-\dfrac{R_\beta^2}{2\beta^2}\right)\left(1 - \exp\left(-\dfrac{T^2}{2c^2}\right)\right) & \text{if } \lambda_2 \le 0 \end{cases}$$

with λ_1 and λ_2 being the eigenvalues of the Hessian matrix, $\lambda_1 < \lambda_2$, $R_b = \lambda_1/\lambda_2$, $T = \sqrt{\lambda_1^2 + \lambda_2^2}$, β and c affect the sensitivity of the filter and have values of 0.5 and 0.3, respectively.

The second filter is that of the direction, work of Koller et al. [15]. This algorithm is based on a non-linear combination of linear filters. It searches for elongated, symmetrical and linear structures, such as the minimisation of response at the edges of these structures. This filter creates highly intense coloured lines in the middle of these structures, along their entire length. Its value is calculated according to the following mathematical expression:

$$C_{Ev}(q, p) = \frac{2}{\pi} \arccos \frac{E_v(p) \cdot E_v(q)}{|E_v(p)||E_v(q)|}$$

with $E_v(i)$ being the eigenvector with the kth smallest magnitude of the Hessian matrix in point i.

Lastly, the structural filtering must be mentioned, which tends to favour the pixels that are found in the middle of the vessels. To do so, it uses different operators, such as the Canny edge detector [16], the gradient of the image [17] and the Laplacian of Gaussian Matrix [18]. The average response of these three operators is called $R(x, y)$. Representing r as the scale, for each $q = (x, y, r)$ analysed, its $E_v(x, y, r)$ and $R(x, y)$ are combined to thus define a marker of how centred the point in question is inside of a vessel. This filter then calculates the $R(x, y)$ value at N points, including these points and all the adjacent and normal $(P_R = (x_i, y_i); i = 1, 2, \ldots, N)$ to the node q. The final cost of the structural filter is defined this way, in order to minimise a response to noise, such as:

$$C_{Ie}(q) = 1 - \left(\frac{1}{N}\right) \sum_{i=1}^{N} R(P_R)$$

In addition to these three filters, the algorithm uses two restrictions to detect the best path between the two points. The first is the spatial restriction, which sums a small constant value to the cost of the path for each additional pixel added to it. This way, the distance between the points on the path tends to be smaller, thus avoiding the see-saw effect on the edges of the vessels. For example, the cost that this restriction applies to a path that starts at point $q = (x, y, r)$ and that ends at point $p = (x', y', r')$ is:

$$C_S(q, p) = \sqrt{(x - x')^2 - (y - y')^2}$$

The algorithm also applies a radius restriction, which penalises the paths on which sudden radius changes appear. This occurs for two reasons. The first of these is that the vessel enhancement filter is sensitive to noise and that it is not reliable to base the radius calculation of the arteries on only the output of this filter. The second is that the radius of the vessels does not tend to suddenly change, unless there is a strong stenosis. Therefore, adding this restriction