Robust Automatic Calcium Scoring for CT Coronary Angiography

Matthias Teßmann[1,2], Fernando Vega-Higuera[2], Bernhard Bischoff[3], Jörg Hausleiter[3], Günther Greiner[1]

[1]Computer Graphics Group, University of Erlangen-Nürnberg, Germany
[2]Siemens AG, Sector Healthcare, Computed Tomography, Forchheim, Germany
[3]Klinik für Herz- und Kreislauferkrankungen, Deutsches Herzzentrum München
matthias.tessmann@informatik.uni-erlangen.de

Abstract. Currently, an increased number of studies are being performed in order to evaluate the clinical value of calcium scoring on contrast enhanced computed tomography coronary angiography images. One major finding is the increased diagnosis time and manual effort required to accurately segment calcified lesions in the contrast enhanced data. In this paper, a novel approach for the fully automatic segmentation and quantification of calcified lesions in coronary computed tomography angiography is presented. The algorithm includes a robust segmentation threshold determination based on an automatically generated vessel-tree histogram. Thereby, lesions can be accurately segmented and scores can be determined without user interaction. Validation against manual scores obtained by a radiologist yielded a very high correlation, which indicates the clinical value of the presented method.

1 Introduction

Cardiovascular events are currently the leading cause of death in developed countries. It is thus essential to identify high-risk patients for the prevention of secondary effects [1]. Since contrast enhanced CT coronary angiography (CTCA) has proven to allow a reliable diagnosis of cardiovascular stenoses [2], more and more clinical studies are published on the topic of establishing an equivalence between traditional coronary calcium (CAC) scoring and scoring methods on CTCA data [1, 3]. However, working with contrast enhanced data is a complex task requiring more time and manual effort than traditional methods [1]. In order to reduce the complexity and duration of the diagnosis process on CTCA data, there exist several algorithms that do provide semi-automatic detection of calcified lesions on this data, e.g. from Wesarg et al. [4]. However, these methods also require manual intervention to some degree. In this paper, a novel approach for fully automatic detection and quantification of calcified lesions on CT coronary angiograms is presented. Its major contributions are a robust estimation of a Hounsfield-Unit (HU) threshold for calcium detection and segmentation in contrast enhanced CT data as well as an accurate detection of lesions within

the vascular tree. The resulting algorithm has been validated against diagnostic data provided by radiological experts and showed to yield equivalent clinical results.

2 Materials and Methods

In order to examine a CTCA dataset for calcified coronary lesions, the entire vascular tree is extracted with the method presented in [5]. Having this tree is a prerequisite for the remaining two steps of the algorithm: HU threshold determination and lesion segmentation, as explained in the following sections.

2.1 HU-Threshold Determination

A major problem for the detection of an adequate calcium segmentation threshold is that image contrast in CTCA data has a high variability. This is due to varying contrast agent absorption rates over time and patient physiology. As a consequence, HU values for vessel lumen vary from patient to patient and from study to study. Therefore, a threshold has to be computed individually for each data set. For this purpose, the previously generated vascular tree can be exploited. In order to determine a threshold τ, a histogram $H(x)$ based on the intensity values of the voxels along the automatically segmented vessel centerlines is generated. It is assumed that by only taking into account the voxel values that are covered by the segmented vascular tree, the HU values for which the histogram function reaches its maximum are equivalent to the mean value of healthy vessel lumen. Moreover, it can be assumed that the number of voxels belonging to calcified plaques is not significant in comparison to the number of voxels belonging to contrast agent. Subsequently, the histogram function is scanned for the maximum number of hits. The width of the histogram area around this peak covers the distribution of vascular lumen within the histogram function. The ideal HU threshold for calcified plaque segmentation corresponds to the lowest intensity value that belongs to calcium but does not fall into the range of contrast agent. Hence, in order to find the optimal value for separation of vessel lumen and coronary calcium, it is required to find the point where the descent of the function starting at the peak position flattens. This can be done by computing the derivative of the histogram function $H'(x)$ and examining its values starting at the peak position until it drops below a certain threshold ϵ. Based on the ground truth database we found $\epsilon = -10^{-2}$ to be the optimal value. Selecting this point yields the desired threshold value τ (Fig. 1).

2.2 Detecting Calcifications

In the calcification detection step, the vascular tree is processed in a point-by-point fashion. At each centerline point the voxel neighborhood within a spherical radius of 1.5 mm is examined. If a voxel is found to have a HU value $> \tau$ it is marked as a possible calcium candidate (Fig. 2). The resulting candidate points

together with the threshold τ are then used as input seeds for a standard region growing algorithm as indicated by the clinically established calcium scoring methods [2, 6]. Next, the resulting segmentation mask is used as input to a connected components analysis in order to identify single lesions and remove lesions whose size is below or above a plausible value, e.g. 1-voxel lesions that may be detected due to image noise. Finally, the detected lesions are scored individually by the use of standard scoring algorithms: Agatston score [6], calcium volume and calcium mass on a per-lesion, per-vessel and overall calcium burden basis.

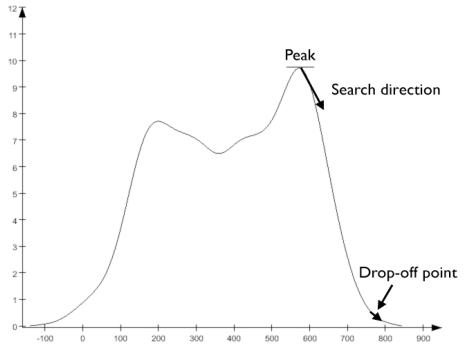


Fig. 1. Histogram of the centerline tree of a dataset from the test database. Marked are the peak value, descending direction and the drop-off point that is finally selected as segmentation threshold.

2.3 Validation Setup

For the validation of the presented algorithm 47 clinically relevant data sets were used. All calcified lesions contained in the data were marked manually by a

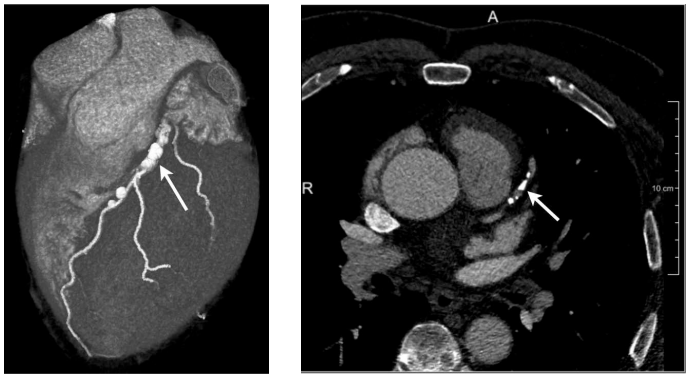


Fig. 2. Candidate selection result on an example dataset. Left: volume rendering of the heart with marked calcium positions (indicated by the arrow); right: corresponding slice image including calcified lesions.

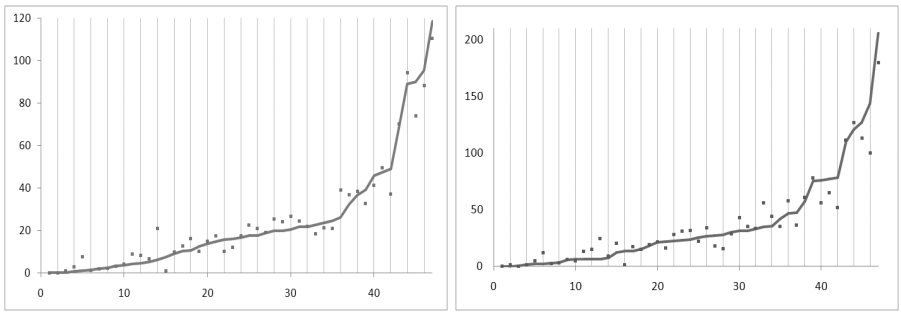
Table 1. Correlation and limits of agreement between manual and automatic scoring.

Score Type	ρ	95% limits of agreement
Agatston Score	0.946	0.26 ± 29.78
Calcium Mass	0.951	0.41 ± 10.83
Calcium Volume	0.950	0.91 ± 22.85

radiologist. Each data set was assigned an individual HU threshold for a region-growing based segmentation of the coronary calcium. The resulting segmentation masks were used to generate ground-truth reference calcium scores (Agatston score, calcium mass score and calcium volume score) for evaluation. Finally, our method has been applied in unattended batch-mode on the same database. The resulting automatically detected HU thresholds and calcium scores were then compared to the ground truth data.

3 Results

The generated automatic thresholds are very close to those manually selected. The mean difference between the two values was found to be about 25 HU units. In 62 % of the examined cases, the automatically detected segmentation threshold was lower than the segmentation threshold selected by the radiologist. However, no flooding occurred during region growing, which indicates a better threshold selection in comparison to the manually selected value. The correlation between manually and automatically generated scores expressed as Spearmans ρ and their respective 95 % intervals of agreement [7] for the three scoring types are very high in all cases, as shown in Tab. 1. Plots comparing volume and mass scoring results directly are shown in Figure 3.



(a) Calcium Mass (b) Calcium Volume

Fig. 3. Comparision of manual and automatically generated scores on the test database (Patient number and total score on the x- and y-axis, respectively). The line corresponds to the manual scoring result.

4 Discussion

The presented automatic calcium detection and segmentation method was shown to be adequate for calcium scoring on CTCA data when compared to results obtained by a radiological expert. Considering the broad cluster sizes for risk-grouping of patients in current clinical practice [8], the deviation of values with respect to the expert's ground truth is not significant. Additionally, most of the deviations from the reference scores are caused by the automatically determined segmentation threshold providing a better fit to the data than the manually selected threshold. Therefore, more voxels belonging to a calcified lesion are segmented, yielding an increased score value. It is reasonable to assume that the resulting higher score more accurately resembles the real calcium burden. In the immediate future, we would like to investigate the influence of intra-observer variability for the manual calcium scoring results, in order to determine the correlation of manual and automatic scoring more precisely.

Overall, one of the major burdens when performing studies to the applicability of CTCA scoring for cardiac diagnostics, the increased manual effort, can be avoided by the use of our algorithm. Moreover, should those studies finally verify the clinical value of CTCA calcium scores, the presented method could become a valuable diagnostic tool for clinical practice.

References

1. Glodny B, Helmel B, Trieb T, et al. A method for calcium quantification by means of CT coronary angiography using 64-multidetector CT: very high correlation with agatston and volume scores. Eur Radiol. 2009;19:1661–68.
2. Hoffmann MHK, Shi H, Schmitz BL, et al. Noninvasive coronary angiography with multislice computed tomography. J Am Med Assoc. 2005;293(20):2471–78.
3. Hadamitzky M, Freißmuth B, Meyer T, et al. Prognostic value of coronary computed tomographic angiography for prediction of cardiac events in patients with suspected coronary artery disease. Int J Cardiovasc Imaging. 2009;2(4):404–11.
4. Wesarg S, Khan MF, Firle EA. Localizing calcifications in cardiac CT data sets using a new vessel segmentation approach. J Digit Imaging. 2006;19(3):249–57.
5. Gülsün MA, Tek H. Robust vessel tree modeling. Proc MICCAI. 2008; p. 602–11.
6. Agatston AS, Janowitz WR, Hildner FJ, et al. Quantification of coronary artery calcium using ultrafast computed tomography. J Am Coll Cardiol. 1990;15:827–32.
7. Bland JM, Altmann DG. Measuring agreement in method comparision studies. Stat Methods Med Res. 1999;8:135–60.
8. Budoff MJ, Achenbach S, Blumenthal RS, et al. Assessment of coronary artery disease by cardiac computed tomography: a scientific statement from the american heart association committee on cardiovascular imaging and intervention, council on cardiovascular radiology and intervention, and committee on cardiac imaging, council on clinical cardiology. Circulation. 2006;114:1761–91.