A Pattern Classification Approach to Aorta Calcium Scoring in Radiographs

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Abstract. A method for automated detection of calcifications in the abdominal aorta from standard X-ray images is presented. Pixel classification based on local image structure is combined with a spatially varying prior that is derived from a statistical model of the combined shape variation in aorta and spine.

Leave-one-out experiments were performed on 87 standard lateral lumbar spine X-rays, resulting in on average 93.7% of the pixels within the aorta being correctly classified.

1 Introduction

Calcifications in the abdominal aorta were shown to correlate with the presence — or future development — of calcifications at other sites such as the coronary arteries, and are an important predictor for future cardiovascular morbidity and mortality [7,12,13]. Accurate and reproducible measurement of the amount of calcified deposit in the aorta is therefore of great value in diagnosis, treatment planning, and the study of drug effects. Several automatic and semi-automatic calcium scoring methods have been proposed for CT [2,9].

This paper aims at automatically detecting calcified plaques in the lumbar aorta from standard radiographs. Although CT is better suited for identifying and quantifying atherosclerosis, standard X-rays have the advantage that they are cheap and fast. Several approaches to manually quantifying the severity of aortic calcification in radiographs have been proposed, of which the antero-posterior severity score by Kauppila et al. [10] is the most popular. For this score, the lumbar part of the aorta is divided in four segments adjacent to the four vertebra L1-L4, and the severity of the anterior and posterior aortic calcification are graded individually for each segment on a 0-3 scale. The results are summed in a composite severity score ranging from 0 to 24. Such manual scoring systems have been successfully applied in epidemiological studies, but can not describe subtle changes in disease progression and are labor-intensive and prone to inter- and intra-observer variations.

An automated calcification detection scheme would allow for automatic scoring according to the current semi-quantitative standards as well as for continuous and likely more precise quantification by for instance counting the number of calcified pixels or assessing the density of separate calcifications [3]. To our knowledge, no method currently exists for automatic detection of calcified plaques from standard radiographs.

Calcifications show up in X-ray images as small and usually elongated bright structures. One of the main problems in automatic detection of calcification is that many

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other structures in the image, e.g. bone and image artifacts, have a similar appearance. If the location of the aorta is known in the image the detection becomes easier, but aorta segmentation is a difficult problem as well since the non-calcified parts of the aorta are not visible in X-ray. However, the shape and position of the aorta are strongly correlated to the shape and position of the spine, which is much easier detected in the image. In this work we use knowledge of the shape of the spine to aid appearance-based calcification detection.

We combine pixel classification on the basis of local intensity features with a spatially varying calcium prior that is dependent on the position of a pixel with respect to the spine. The spatially varying prior is derived from a statistical model of combined spine and aorta shape variation, together with a model of how the calcium is distributed within the aorta. The method requires the localization of the corner and midpoints of the first four lumbar vertebra. Currently manual input is used here — obtained from a vertebral morphometry study on the same dataset — but these point positions could also be derived from an automatic spine segmentation, see e.g. [6,11].

Section 2 of this paper deals with modelling the distribution of calcium inside the aorta as well as modelling the distribution of calcium in relation to the vertebrae. Our approach to calcium detection, combining appearance-based pixel classification and the models of calcium distribution, is described in Section 3. Section 4 presents experiments on 87 digitized X-ray images, and a discussion and conclusion are given in Section 5.

2 Estimating Calcium Prior Probability

It is well known that the distribution of calcification in the aorta is not uniform. The number of plaques increases towards the aortic bifurcation, and due to the projection imaging the majority of the plaques is visible along the anterior and posterior aortic walls and not in between.

If a large training set of example images with annotated aorta and calcifications was available, the probability of presence of calcium in each pixel could be estimated by labelling calcified pixels as 1 and non-calcified as 0, warping all aortas on top of each other, and computing the average labelled aorta image.

If the training set is limited the above procedure will lead to incorrect results; pixels inside the aorta may coincidentally have a very high or low probability of being calcified. As a trade-off between generalizability and specificity, in this work we model the cross-sectional and longitudinal presence of calcium separately.

In a set of labelled training images, the part of the aorta adjacent to the first four lumbar vertebrae is selected and intensity profiles are sampled perpendicular to the vessel axis, reaching from the anterior to the posterior wall. All profiles are normalized to equal length and averaged to form a cross-sectional calcium prior distribution. For each image, one longitudinal profile is formed by summing the values in the individual profiles. An average longitudinal profile is computed by length normalizing and averaging the longitudinal profiles of all images.

For a given aorta shape, a calcium prior probability map can then be constructed by sweeping the cross-sectional prior profile along the axis, modulated with the longitudi-

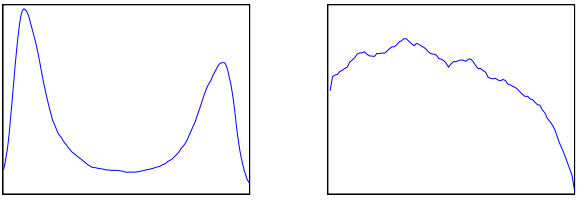

Fig. 1. Cross-sectional profile (left) and longitudinal profile (right) of calcium distribution inside the aorta. Prevalence of calcium is higher at the aortic walls and near the aortic bifurcation.

nal profile. The two profiles and an example of a calcium probability map are given in Figures 1 and 2.

2.1 Estimating the Location of Aortic Walls

In general, the shape and location of the aorta will not be known a priori, and since the aortic walls are only visible if calcium is present, automatic aorta segmentation can not be used as a first step to guide calcium detection. However, the shape and location of the aorta are strongly correlated with the shape and location of the spine [4]. In the following we will use a set of training images in which the aorta and the vertebrae have been annotated to model the probability density function of aorta shape and location conditional on the spine shape.

To constrain the shapes of possible aortas, any kind of shape model from which samples can be drawn can be inserted here. We will use the popular linear point distribution models (PDM) as proposed by Cootes and Taylor [5] to model the object shape variations observed in the training set.

In PDMs, shapes are defined by the coordinates of a set of landmark points which correspond between different shape instances. A collection of training shapes are aligned using for instance Procrustes analysis [8] and a principal component analysis (PCA) of the aligned shapes yields the so-called *modes of shape variation* which describe a joint displacement of all landmarks. Each shape can then be approximated by a linear combination of the mean shape and these modes of variation. Usually only a small number of modes is needed to capture most of the variation in the training set.

To construct a conditional shape model of the aorta given the spine, the spine and aorta landmarks are combined into one shape vector. The Procrustes alignment must be done only on the spine part of the combined shapes. The distribution $P(S_1|S_2)$, the probability distribution of the expected aorta shape and pose S_1 for a given spine S_2, can be then modelled as the Gaussian conditional density

$$P(S_1|S_2) = \mathcal{N}(\mu, K)$$

with

$$\mu = \Sigma_{12}\Sigma_{22}^{-1}S_2$$
$$K = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21}$$

and Σ_{ij} are obtained from the covariance matrix of the combined model

$$\Sigma = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}$$

as

$$\Sigma_{ij} = \frac{1}{n-1} \sum_{n} (S_{in} - \bar{S}_i)(S_{jn} - \bar{S}_j)^T.$$

An example of the modes of variation of such a conditional model is given in Figure 3.

2.2 Spatially Varying Prior

To derive a spatial calcium prior, the aorta shape distribution is represented by a random sample of N shapes drawn from the Gaussian conditional shape model. The final calcium probability map is then constructed by averaging the N individual prior maps. Note, that to get a true probability the 'prior' would need to be normalized so that the probabilities of the two classes sum to 1. We here omit this normalization.

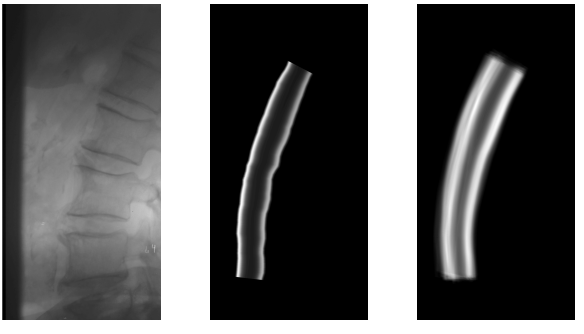

Fig. 2. From left to right: Original image, inverted for better visibility of calcium (left); annotated aorta with constructed calcium probability map; calcium probability map from 50 random samples of the aorta conditional shape model

3 Calcification Detection

A pixel classifier is trained to distinguish between calcium and background pixels on the basis of local image descriptors. We have chosen a general scheme in which pixels are described by the outputs of a set of Gaussian derivative filters at multiple scales, and a k-NN classifier is used for probability estimation. The probability that a pixel with feature vector $\mathbf{x}$ belongs to class ω is thus given by

$$P(\omega|\mathbf{x}) = \frac{k_\omega}{k}, \tag{1}$$

where k_ω among the k nearest neighbors belong to class ω.

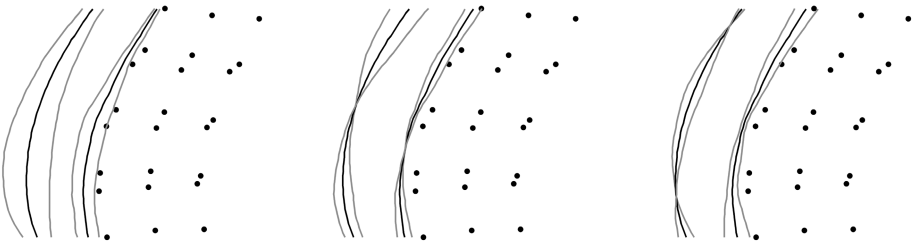

Fig. 3. Modes of variation of the aorta (gray and black lines) given the known positions of vertebrae corner- and mid-points (black points). The mean aorta shape is given in black, the mean shape $\pm$ 3 standard deviations in gray. From left to right the first three modes of variation are shown.

The spatial prior can be applied simply as a multiplication of the soft classification from Equation 1 with the calcium prior map as computed in Section 2.

For classification with as well as without spatial prior, a threshold defining the desired sensitivity/specificity tradeoff should be selected in order to make a final binary decision of whether calcium is present or not in each pixel.

4 Experiments

Leave-one-out experiments are performed on 87 lateral spine radiographs taken from a combined osteoporosis-atherosclerosis screening program. The dataset is diverse, ranging from uncalcified to severely calcified aortas. The original radiographs have been scanned at a resolution of 0.1 mm per pixel and were inverted for better visibility of calcific deposits. A medical expert outlined all calcifications adjacent to vertebrae L1 through L4 manually and also placed 6 points on each vertebra as is routinely done in vertebral morphology studies.

4.1 Parameter Settings

Before further analysis the images were normalized to zero mean and unit variance. The appearance features used include the original image and the derivatives up to and including the third order computed at three different scales. Training pixels were selected randomly from a region of interest including the aorta and its surroundings. The set of samples is normalized to unit variance for each feature, and k-NN classification is performed with an approximate k-NN classifier [1] with k=25. In all cases, results reported are accuracies of hard classification with the overall optimal threshold that is kept constant for all 87 images.

In the conditional shape model, 6 manually placed landmarks on each of the vertebrae are used and 50 aorta landmarks are selected on each aortic wall by equidistant sampling along the manual outlines. The first 5 modes of shape variation are selected for the conditional shape model, and $N = 100$ aorta shapes are sampled randomly from the model to form the calcium prior probability map.

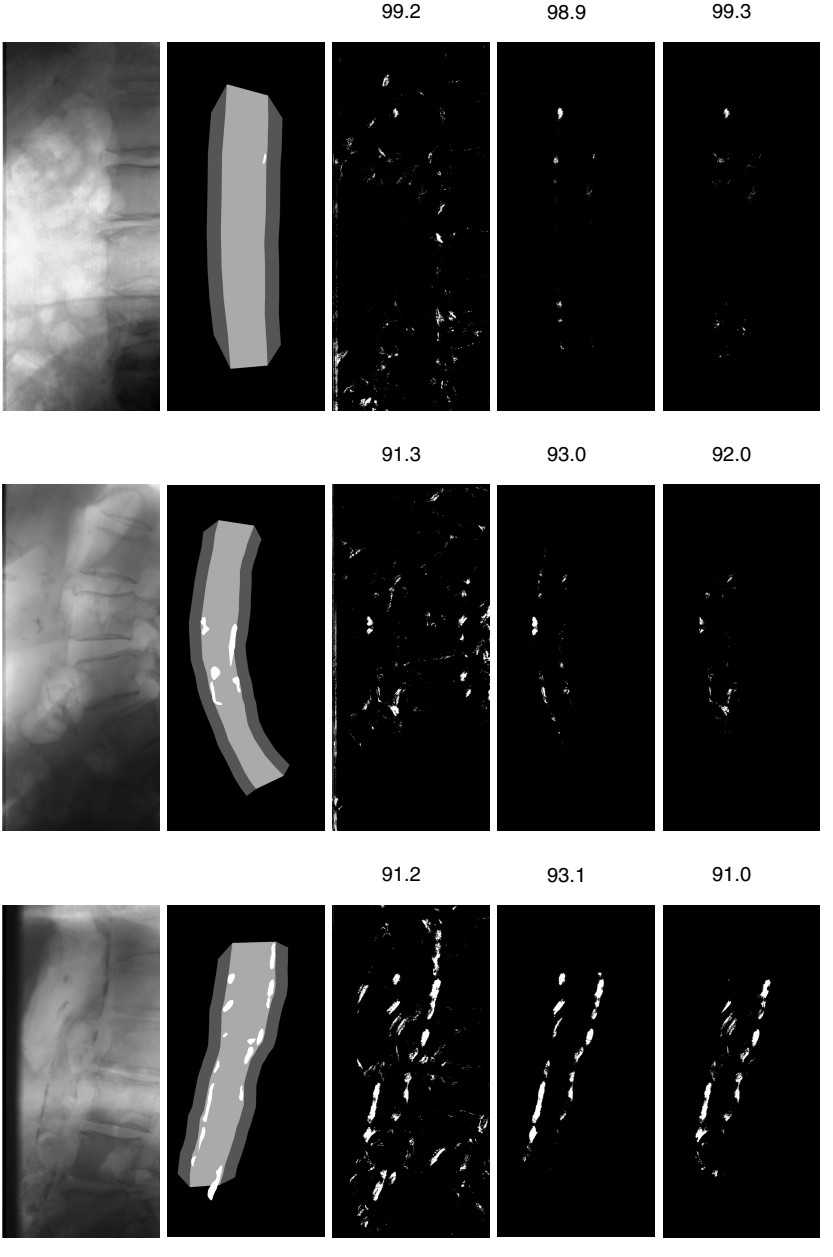

Fig. 4. Examples of classifications obtained for images of varying degree of calcification. Each row gives the different results for one image, from left to right: Original image (inverted for improved visibility of calcium); Manual segmentation; Pixel classification alone; Pixel classification combined with calcium prior for manually segmented aorta; Pixel classification and calcium prior from conditional shape model. The numbers above each image denote the classification accuracy.

4.2 Results

To assess the performance of separate parts of the proposed method, we measure the accuracy in three different experiments:

1. Pixel classification on the basis of appearance features alone
2. Pixel classification on the basis of appearance features combined with calcium prior for a known aorta
3. The complete scheme; pixel classification on the basis of appearance features combined with calcium prior from the conditional model

The pixel classification alone yields an average accuracy, defined as the percentage of correctly classified pixels *inside the aorta*, of 93.8%. Combining this with the spatially varying prior based on the manually drawn aorta shape results in a small, but significant ($p = 0.0004$ in a paired t-test) improvement to 94%.

The classification obtained by pixel classification combined with the fuzzy calcium prior for the aorta estimates is of course less good, but the average accuracy is still 93.7%.

Figure 4 shows examples of the classification results by the three different schemes.

5 Discussion and Conclusion

We propose an automated method for detection of calcified deposits in radiographs of the lumbar aorta, which may be used as an inexpensive screening tool for quantifying atherosclerosis and cardiovascular risk.

The results of a standard pixel classification were improved by combination with a spatially varying prior. The assumption underlying the proposed combination by multiplication is that the two individual probabilities, based on appearance and on position with respect to the spine, are independent. If this is not the case, modelling appearance and position features together in one k-NN classification, with appropriate scaling of features, may be more appropriate. On the other hand, combination by multiplication is much faster.

The current approach, in which the calcification detection task is guided by samples of an aorta shape model, can be extended to a joint optimization of aorta shape distribution and calcification detection. A likelihood weight for each of the aorta shape samples can be defined on basis of how well the expected calcium distribution coincides with the measured calcifications, and subsequently a new shape set — with smaller variance — can be constructed through weighted resampling from the current set. In such an iterative optimization in which the spatial prior is updated in each iteration, the advantage of combination by multiplication instead of using one large k-NN classifier becomes obvious. We are currently investigating the feasibility of such methods.

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