LETTER

An Automatic Detection Method for Carotid Artery Calcifications Using Top-Hat Filter on Dental Panoramic Radiographs

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SUMMARY The purpose of this study is to develop an automated scheme of carotid artery calcification (CAC) detection on dental panoramic radiographs (DPRs). The CAC is one of the indices for predicting the risk of arteriosclerosis. First, regions of interest (ROIs) that include carotid arteries are determined on the basis of inflection points of the mandibular contour. Initial CAC candidates are detected by using a grayscale top-hat filter and a simple grayscale thresholding technique. Finally, a rule-based approach and a support vector machine to reduce the number of false positive (FP) findings are applied using features such as area, location, and circularity. A hundred DPRs were used to evaluate the proposed scheme. The sensitivity for the detection of CACs was 90% with 4.3 FPs (80% with 1.9 FPs) per image. Experiments show that our computer-aided detection scheme may be useful to detect CACs.

key words: carotid artery, calcification, top-hat transform, dental panoramic radiograph, computer-aided detection

1. Introduction

Surveys conducted by the Ministry of Health, Labour, and Welfare in 2009 revealed that heart diseases and cerebrovascular diseases were 15.8% and 10.7%, respectively, of all mortalities in Japan [1]. These diseases are called “arteriosclerosis diseases.” Carotid artery calcifications (CACs) are one of the indices useful in predicting the risk of arteriosclerosis [2], [3]. Recent studies on dental panoramic radiographs (DPRs) include the clinical indication on radiographic signs of CACs [4], [5]. It is likely that some patients with arteriosclerosis diseases do not visit medical clinics at an early stage due to its asymptomatic nature. If the risk of arteriosclerotic diseases is explained to patients when dentists detect CACs on DPRs, these patients could be motivated to visit medical clinics in a timely manner. Such supplemental screening through dentists has the potential to play an important role in preventive medicine. However, general dentists are apt to focus only on dental diseases on DPRs. In addition, CACs are not easily visible on DPRs given the window level common in dental examinations. For those reasons, it is likely that radiographic signs of CACs are overlooked. A framework that suggests the presence of CACs to dentists may be helpful to solve this problem. Therefore, we have proposed a new screening pathway that involves the cooperation of dentists and a CAD system [6].

The purpose of this study is to develop a computer-aided detection (CADE) scheme for CACs on DPRs as a part of such CAD system.

To our knowledge, the only computerized scheme for detecting CACs on panoramic images was reported by Izumi et al. [7]. Their method is based on the grayscale gradient on images. The positions that had the local maximum grayscale values were estimated as CAC regions. However, the direct and quantitative evaluation and the comparison with this study are not possible because different databases were used.

In this study, we adjust parameters such as the threshold of the initial candidate detection as an improvement over our previous preliminary study [6]. In addition, we expanded our database from 34 cases to 100 cases in this study.

2. Materials

Our database consists of 100 panoramic images with 34 cases including CACs and 66 control cases that were obtained at Asahi University Dental Hospital in Japan. The DPRs were taken with the standard positioning of the head such that the Frankfort horizontal plane was used as a reference line. The automatic mode was used to control the x-ray exposure. A panoramic x-ray unit (Veraview Epocs, Morita, Japan) and a computed radiography (CR) system (CR 75.0, Agfa, Germany) were utilized for the acquisition of patients' DPRs. The matrix size of the DPRs was 2920 × 1420, with a spatial resolution of 0.1 mm/pixel. All calcifications were confirmed by a dental radiologist using the modalities such as CT. This study was approved by the Institutional Review Board of Gifu University and Asahi University.

3. Methods

3.1 Overall Scheme for the Detection of CACs

The process flow of our scheme is shown with example images in Fig. 1. As the first step, to exclude regions not related to carotid arteries, regions of interest (ROIs) were extracted. CACs are visualized below and lateral to the mandible on
Fig. 1  The process flow of our scheme. The CAC indicated by the arrow was detected in our scheme. FP indicated by the dotted arrow was also detected on the hyoid bone.

DPRs. Therefore, ROIs for CAC detection were determined on the basis of the mandible [8]. The grayscale values of CACs are higher than those of backgrounds in the ROI; therefore, the morphological grayscale top-hat filter [9] that corrects for trends in background values was used to detect CAC candidates as the second step. However, some parts of cervical vertebrae and hyoid bone that are included in the ROI were also detected as CAC candidates because they have locally high grayscale values. Therefore, cervical vertebrae and hyoid bone were identified and removed from CAC candidates in the third step. False-positive (FP) reduction process was applied based on the features of CAC candidates in the last step.

3.2 Regions of Interest (ROIs)

For determining the ROI positions, mandibular contour was automatically detected. The details of the contour determination method have been described elsewhere [8], [10]. Subsequently, the angle of the contour was calculated from the center to outward, and the right and left positions that meet the following requirements were assumed to be right and left gonions, respectively, as shown in Fig. 2: the first time the angle between a vertical line and the line tangent to the contour becomes smaller than 15°. If gonions could not be decided, the threshold of the angle was increased and the process was repeated. Then the ROIs were decided based on the right and left gonions.

3.3 Determination of Initial Candidates for CACs

A moving-average smoothing with $5 \times 5$ pixels was applied to reduce noise of original images. After that, the top-hat filter was applied so that the CAC regions were emphasized. The structure element of the top-hat filter was set as a circle with 15-pixel radius to enhance the CACs because the target CACs are generally smaller than 30 pixels. By applying a thresholding technique to the image after the top-hat transform, the initial candidates for CACs were determined. The threshold value was determined empirically.

3.4 Elimination of Cervical Vertebrae and Hyoid Bone

The endplates that are parts of cervical vertebrae can appear as horizontal edges. Therefore, a $3 \times 3$ sobel filter was applied to the images for emphasizing horizontal edges, and the edges were detected by the thresholding technique. The length of each candidate edge region was calculated in the binarized image. Next, the edge with the width from 70 to 150 pixels was assumed to be a short edge, and the edge with 150 pixels or longer was considered to be a long edge. The long edges were considered to have a higher probability to be true endplates. The vertebrae were assumed to be located within a quarter length of the image width from each of the right and left ends of the images. In each of these right and left regions, the number of candidate edges was counted in each column starting from the medial side of the image. The location where more than 6 long edges or 8 combined edges exist was considered to be a boundary of the cervical vertebra, and the region outside of the boundary was excluded from the subsequent process for calcification detection. During this process, the edges corresponding to the hyoid bones were also detected; these locations were also excluded from the search for CACs.

3.5 Elimination of FPs

Using the techniques described in the previous section, most of the CACs were detected accurately. However, the candidates selected initially also included many FPs. For eliminating these FPs, 11 features in each initial candidate for a CAC were determined. These features include the area, average grayscale value, variance of grayscale values, difference of grayscale values between the candidate region and...
the surrounding region, height, width, ratio of the width and the height, circularity, irregularity, and $x$ and $y$ locations. The circularity is defined as a fraction of the overlapped area of a candidate with a circle that has the same area as the candidate and is centered at the candidate’s center. The irregularity, $I$, is defined as,

$$I = 1 - \frac{2\sqrt{\pi A}}{P}$$  

(1)

where $A$ and $P$ are the area and perimeter, respectively, of a candidate. The rule based scheme with 11 features was employed as the first step in the elimination of FPs. In this scheme, we first calculated the maximum and minimum feature values of all CACs detected in the initial step for identifying the CACs. The total of 22 cutoff thresholds was used for eliminating FPs (see Appendix). For further elimination of FPs, a SVM [11] with 11 features was employed. The SVM is a novel generation learning system based on recent advances in statistical learning machine. In this study, a polynomial kernel was used. For evaluating our CAC scheme, our database was divided into the training and test sets by randomly selecting a half of CAC and control cases. We built the SVM using the training set and then evaluate it on the test set. After repeating ten times of this procedure independently, the average performance was calculated.

4. Results

A hundred panoramic images were used to evaluate the proposed scheme. The sensitivity for the detection of CACs was 90% with 4.3 FPs per image. Examples of results are illustrated in Fig. 3. The case 1 in Fig. 3 shows that the CAC indicated by the arrow was detected in our scheme; a FP was also detected on the other side. The case 2 indicates that the CACs were detected without FPs. The case 3 shows an example in which no CAC could be detected in this experiment. This calcification was quite blur, and the difference of the grayscale value against the background value was small. Therefore, the top-hat filter hardly emphasized this calcification.

Figure 4 shows the free-response ROC (FROC) curve for the average performance of our CAD scheme. This curve was obtained by changing the threshold value for the output value of SVM. The result shows that our CAD scheme achieved the sensitivity of 90% with 4.3 FPs (80% with 2.0 FPs) per image.

5. Discussion

DPR has a new potential to be used as a supplemental screening tool for early detection of systemic diseases such as arteriosclerosis. For notifying the suspicious findings to dentists, CAD is expected as the technology for assisting such attempt. Relatively high sensitivity obtained by our CAD scheme is encouraging. Most of the calcifications that were not detected by the proposed scheme had very low contrast, making it difficult to detect them without having too many FPs. On the other hand, in order to further decrease the number of FPs, the sensitivity may become too low as shown in Fig. 4. Some of the FPs on vertebra and hyoid bones can be easily dismissed by dentists. Therefore, sensitivities of 90% with the FPs of about 4 per image may be acceptable. Our future study would include the further reduction of FP without decreasing the sensitivity. Note that the performance reported in this study is a lesion-based sensitivity rather than a case based. It can be considered effective for screening if one or some of the multiple calcifications were detected for a case.

Although we attempted to exclude the area of cervical vertebrae for calcification detection, a good portion of FPs are due to vertebral edges. The number of FPs, therefore, could be affected by patients’ positioning.

This study has some limitations. Although the sensitivity for detection of CACs obtained using our CAD scheme was reported to be 90% in this study, the image database used was relatively small and collected from only one hospital. In the future, we need to expand our database by collecting images obtained by various scanners from several hospitals and to evaluate our method by using independent databases. The presence of CACs in our database was
confirmed by a dental radiologist. However, whether the patients had or would have arteriosclerosis diseases is not known, and is beyond the scope of this study.

In this study, we used all 11 features in FP reduction by SVM, and a feature selection was not carried out. It has been suggested that some features, such as the average grayscale value and the difference in grayscale values, are effective, whereas the area and width are not as effective for reducing FPs. An extensive search on the number and combination of features will be investigated with a larger database in the future.

6. Conclusion

We developed a CADe scheme for CACs that applies a morphological grayscale top-hat filter to panoramic images. The experiments revealed that the sensitivity for the detection of CACs was 90% with 4.3 FPs per image. Therefore, it was suggested that the proposed scheme has the potential to help dentists in the detection of CACs.

Acknowledgments

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References


Appendix

The threshold values employed in the rule based scheme.

<table>
<thead>
<tr>
<th>Features</th>
<th>Min</th>
<th>Max</th>
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</thead>
<tbody>
<tr>
<td>Area (pixels)</td>
<td>64</td>
<td>3591</td>
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<tr>
<td>Average grayscale value</td>
<td>184</td>
<td>3032</td>
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<tr>
<td>Variance of grayscale values</td>
<td>1561</td>
<td>651730</td>
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<tr>
<td>Difference of grayscale values</td>
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<td>718</td>
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<tr>
<td>Height (pixels)</td>
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<td>113</td>
</tr>
<tr>
<td>Width (pixels)</td>
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<td>114</td>
</tr>
<tr>
<td>Ratio of width and height</td>
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<tr>
<td>圆周率</td>
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<td>0.926</td>
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<td>Irregularity</td>
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<td>Relative location x</td>
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<td>79</td>
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<tr>
<td>Relative location y</td>
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<td>88</td>
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