Published in final edited form as:
Proc SPIE Int Soc Opt Eng. 2011 March 4; 7963: . doi:10.1117/12.878207.

Probabilistic method for context-sensitive detection of polyps in CT colonography

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Abstract

Radiologists can outperform computer-aided detection (CAD) systems for CT colonography, because they consider not only local characteristics but also the context of findings. In particular, isolated findings are considered as more suspicious than clustered ones. We developed a computational method to model this problem-solving technique for reducing false-positive (FP) CAD detections in CT colonography. Lesion likelihood was estimated from shape and texture features of each candidate detection by use of a Bayesian neural network. Context features were calculated to characterize the distribution of candidate detections in a local neighborhood. A belief network was applied to detect isolated candidates at a higher sensitivity than clustered ones. The detection performances of the context-sensitive CAD and a conventional CAD were compared by use of leave-one-patient-out evaluation on 73 patients. Conventional CAD detected 82% of the lesions 6 – 9 mm in size with a median of 6 false positives per CT scan, whereas context-sensitive CAD detected the lesions at a median of 4 false positives with significant increment in overall detection performance. For lesions ≥10 mm in size, the detection sensitivity was 98% with a median of 7 false positives per patient, but the improvement in detection performance was not significant.

Keywords

CT colonography; polyp detection; context-sensitive detection; virtual colonoscopy; computer-aided detection; CAD

1. INTRODUCTION

Computer-aided detection (CAD) systems for CT colonography are usually designed to detect colorectal polyps as round luminal protrusions on colon surface.[1] After detecting a large number of candidate locations, the number of false-positive (FP) detections is reduced by use of a statistical classifier that calculates a lesion likelihood for each candidate detection based upon shape and texture features of the detected region. The candidates that have highest lesion likelihood are displayed as the output of the CAD system.[2]

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Although such conventional CAD schemes have been shown to detect polyps in high sensitivity, they display large numbers of FP detections. The FP CAD detections reduce the benefit of CAD in clinical practice by increasing radiologists' interpretation time and by reducing detection specificity.[3] They may also reduce detection sensitivity.[3]

In prospective observer studies where CAD was used by trained radiologists in a realistic clinical setting, CAD has generally not been able to provide meaningful positive influence on the performance of CT colonography.[4, 5] Trained radiologists not only can detect polyps with similar or higher sensitivity than CAD systems, but they also report a much smaller number of FP detections than do CAD systems. Although CAD may occasionally be useful in helping radiologists to find an overlooked polyp, this benefit tends to be overcome by a corresponding reduction in detection specificity due to FP CAD detections that radiologists can occasionally confuse with true lesions.

One reason for the superior performance of radiologists over CAD is that they consider not only local features of findings but also the characteristics of the surrounding region, i.e., the context of the findings, for problem solving.[6, 7] In particular, radiologists are more likely to dismiss multiple findings that appear within a small region of the colon as normal pathology or untagged feces (Fig. 1a), whereas a single isolated finding is considered as more suspicious (Fig. 1b).[8]

The purpose of this study was to develop a computerized detection method for modeling this context-based problem-solving technique used by radiologists by considering the distribution and characteristics of candidate detections in the vicinity of each CAD detection. Candidate detections that appear isolated in the colon are detected at a high sensitivity, whereas those that appear clustered in a local region of the colon are detected at a low sensitivity. We hypothesized that such an approach would reduce the number of those FP CAD detections that are caused by uncommon image patterns of normal anatomy in a local colon segment.

2. METHODS

We compared the detection performance of two CAD systems. A conventional CAD system determined the final output by use of a global lesion-likelihood threshold, whereas the new context-sensitive CAD system used a local lesion-likelihood threshold that varied based upon the values of context features.

The details of the fully automated conventional CAD system have been described elsewhere.[9] First, a lumen-tracking (LUTR) algorithm is used to extract a thick region encompassing the colonic wall in CT colonography data. Lesion candidates are detected from the extracted region by use of volumetric shape features. Volumetric shape or texture features are calculated from each detected candidate region. A Bayesian neural network calculates a lesion likelihood p that indicates how likely it is that a candidate detection represents a true lesion. The candidate detections with lesion-likelihood values $p \geq P_0$ are considered as the final detections displayed by the CAD system, where the value of the global threshold P_0 is determined from training data.

The context-sensitive CAD system establishes a neighborhood region for each candidate detection *C* by use of a modified volumetric distance transform. The calculation of the distance transform is initiated from the boundary of the extracted region of *C*. The calculation is limited to the region of colon surface that was extracted by the LUTR algorithm. The context of *C* is defined by concentric regions R_i that have distance transform values of $< d_i$ mm ($i = 1, ..,N$) (Fig. 2). For each R_i, context features are calculated to characterize the number and lesion likelihood of the candidate detections that appear within the region.

The lesion likelihood and the values of context features are provided as nodes to a belief network that determines the final detection sensitivity. A belief network is a directed acyclic graph with a set of nodes that correspond to random variables.[10] Connections between the nodes of the graph represent direct causal relationship between the variables. The local detection sensitivity that is calculated by the network is high for isolated candidate detections that do not have nearby detections and low for candidate detections that are surrounded by several candidate detections (Fig. 3).

To evaluate the polyp detection performance, 73 patients with 107 clinically significant colonoscopy-confirmed lesions were sampled randomly from a large clinical multi-center trial that was designed to evaluate the performance of CT colonography in daily clinical practice.[11] The patients were prepared with cathartic bowel cleansing. No specific colon cleansing directions were given to the 11 participating institutions, except that internationally recognized quality standards had to be met.[12] Orally administered positive-contrast tagging was performed on 1/3 of the patients by hydrosoluble iodine agent without or with barium sulfate. The CT colonography was performed in supine and prone positions with 120 kVp, 50 effective mA per second, and section thickness of 2.5 mm. After a same-day optical colonoscopy, polyp matching was performed according to the clinically adopted segmental checking procedure.[13]

To assess the CAD detection performance, a lesion was considered as detected correctly by CAD, if the mass center of a candidate detection was located within the pre-determined center location and radius of a colonoscopy-confirmed lesion in the CT colonography data. Other CAD detections were considered as FP candidate detections. The detection sensitivity was characterized in terms of per-lesion sensitivity, where a lesion is considered detected correctly by CAD if it is detected correctly in at least one CT scan of the patient. The overall detection performance was characterized by use of a non-parametric method for estimating the area under free-response operating characteristic (FROC) curve.[14]

To minimize evaluation bias, the detection performance was estimated by use of leave-one-patient-out (LOPO) evaluation.[15] In a LOPO evaluation with *n* patients, the CAD system is trained with the data of $n - 1$ patients and tested with the data of the remaining unseen *n*th patient. After recording the testing result for the *n*th patient, the process is repeated for new training and testing sets until all patients have been tested in this manner.

3. RESULTS

There were 107 colonoscopy-confirmed lesions. Forty-five lesions measured 6 – 9 mm in maximum diameter, and 62 lesions were ≥10 mm in size. Fig. 4 illustrates the detection sensitivity of the context-sensitive CAD for lesions ≥6 mm.

For lesions 6 – 9 mm in size, the conventional CAD system detected 82% of the lesions with a median of 6 false positives per CT scan. The context-sensitive CAD system detected these lesions with a median of 4 false positives per scan. Thus, the application of context-sensitive CAD reduced the number of FP detections by 33%. At a median of 10 false positives per patient, the detection sensitivity was 87%. The improvement in overall detection performance (area under FROC curves) was significant ($p = 0.04$).

For lesions ≥10 mm in size, the conventional CAD system and the context-sensitive CAD system detected 98% of the lesions at a median of 7 FP candidate detections per patient. In this case, the overall detection performance between the CAD systems did not vary significantly.

4. DISCUSSION

Most CAD systems have been designed to detect lesions based upon atypical shape or texture patterns in image data.[16] To reduce FP detections, a statistical classifier is used to perform an analysis of the appearance of detected candidate regions based upon the values of a large number of shape and texture features of the extracted regions. However, such a classifier tends to consider each candidate detection independently from the other detections within a patient. Although most CAD systems are able to exclude a majority of FP detections based upon their local appearance in this manner, many FP detections remain.

Context features have been used recently to improve CAD performance in mammography. By characterizing the local anatomy surrounding CAD detections, the detection sensitivity of standalone breast CAD has been observed to improve significantly.[17, 18] Also, the application of radiologists' eye dwelling and reporting data to establish location-specific CAD performance has been found to improve radiologists' sensitivity more effectively than with conventional CAD.[19]

Our study considered the application of context information in terms of the spatial clustering of initial CAD detections in CT colonography. When the detection sensitivity of CAD is maximized for subtle image patterns, artifacts and uncommon image patterns of normal anatomy are expected to generate increasing numbers of initial CAD detections that are often clustered together in a local region of colon.

The results of this pilot study are promising in that the use of context information improved the detection performance of CAD for polyps 6 – 9 mm in size. However, the observed improvement did not seem highly significant. This suggests that further optimization of the method may be desirable, or it is possible that the benefit of contextual information may be muted in cathartically prepared CT colonography cases where most polyps are easy to

detect. The benefit of using context information may be greater in non-cathartic CT colonography.

There was no meaningful benefit in the detection of large lesions. This can be explained by the observation that large lesions are usually represented accurately by CT colonography image data, whereas the detection of small polyps and subtle lesions tends to be affected by image artifacts such as partial-volume effect.

5. CONCLUSIONS

The proposed context-sensitive method presents a potentially useful approach for improving CAD performance in CT colonography. Current CAD systems identify polyps based upon local features that are calculated from detected regions only, whereas context-sensitive detection considers also the characteristics of the surrounding region. The results indicate that context-sensitive CAD may be able to reduce FP detections significantly in the detection of lesions 6 – 9 mm in size, whereas for larger lesions any benefit is likely to be small.

ACKNOWLEDGMENTS

This work was supported in part by Prevent Cancer Foundation and by NIH R21CA140934, CA095279, CA139600, and CA131718 grants. We also thank Partners Research Computing for high-performance computing services.

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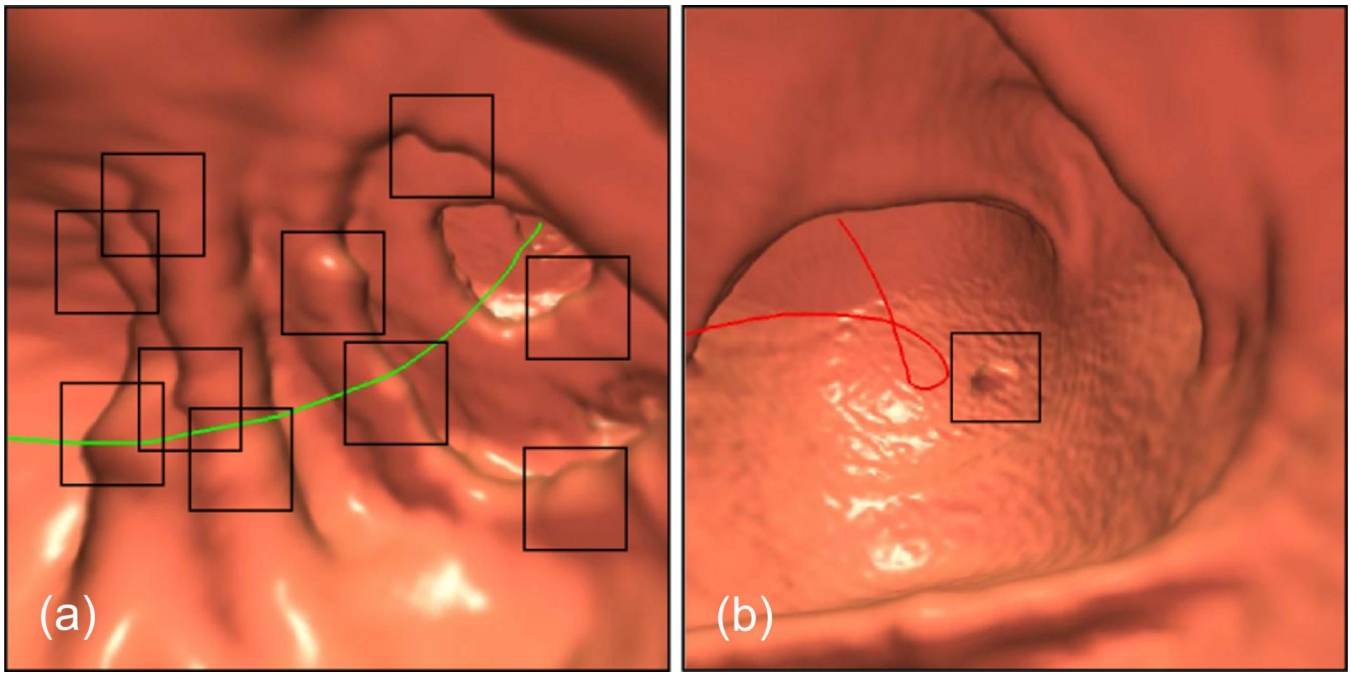

Figure 1.

An example of the use of context information in differentiating between normal anatomy and abnormalities. (a) Polypoid shapes (indicated by black boxes) that appear clustered in a local region tend to represent normal anatomy rather than true lesions. (b) An isolated polypoid shape (indicated by black box) is more likely to represent a true lesion than normal anatomy.

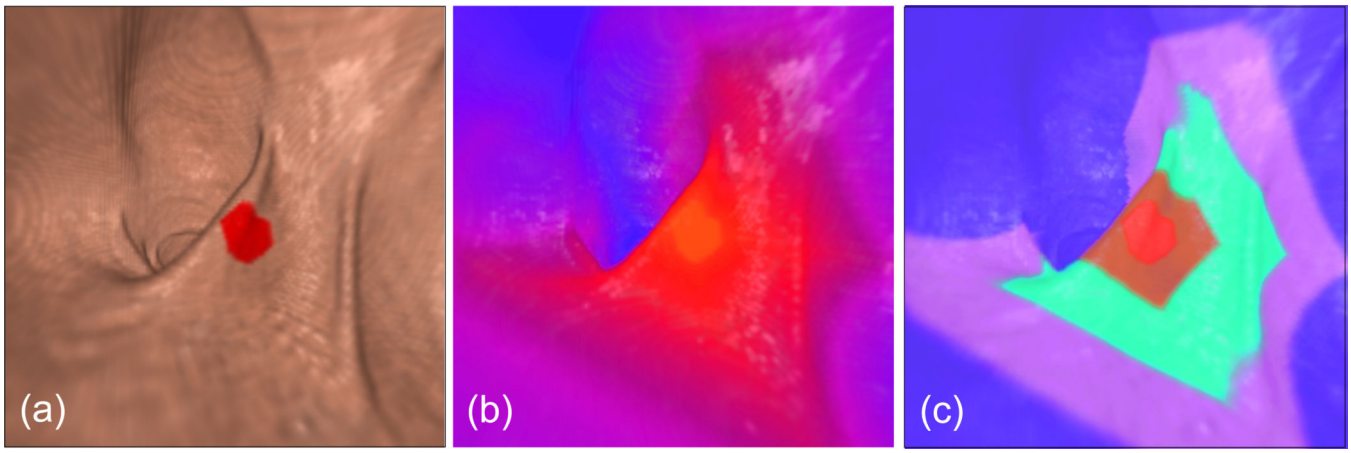

Figure 2.

An illustration of the context calculation for a candidate detection. (a) Red color indicates the region of candidate detection in colon. (b) The colormap represents surface distance from the region of the candidate. Red color indicates points that are located close to the candidate, whereas blue color indicates points that are located far away from the candidate. (c) The different colors show how different context regions can be obtained by thresholding of the calculated distance values.

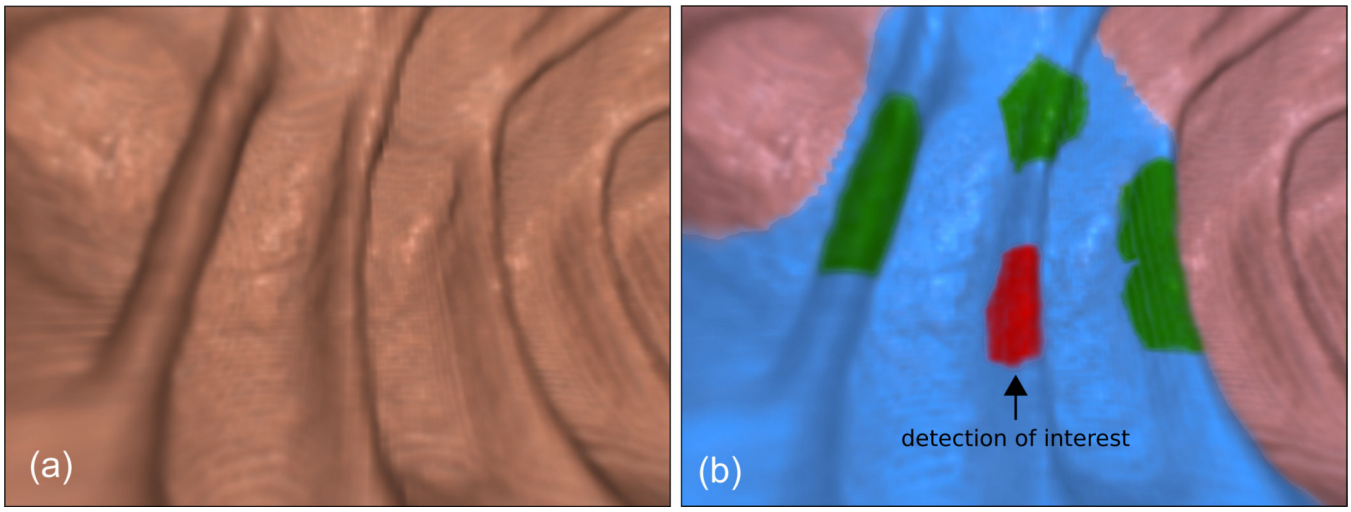

Figure 3.

An example of the application of context analysis. (a) A region with marginally thickened folds imitating flat lesions. (b) Red color indicates the current CAD detection of interest, green color indicates other CAD detections, and blue color indicate the region that is considered to assess the suspiciousness of the detection of interest.

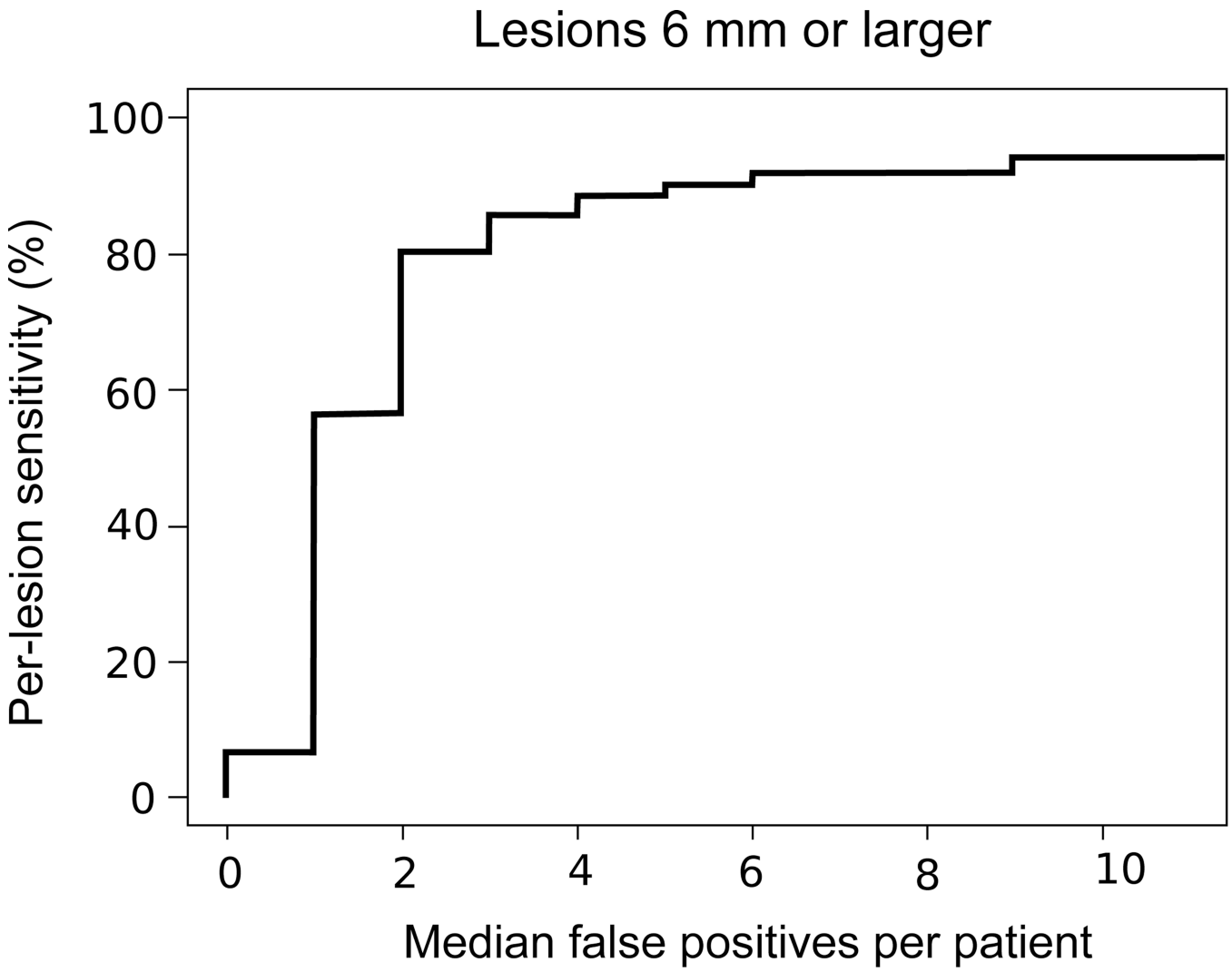

Figure 4.
Per-lesion sensitivity of the context-sensitive CAD for lesions ≥6 mm.