Published in final edited form as:

Acad Radiol. 2009 April ; 16(4): 456–463. doi:10.1016/j.acra.2008.09.013.

Towards Optimized Acquisition Scheme for Multi-projection Correlation Imaging of Breast Cancer

Amarpreet S. Chawla, M.S.,

Duke Advanced Imaging Laboratories, Departments of Radiology and Biomedical Engineering,
Duke University, Durham, North Carolina 27705

Robert S. Saunders, Ph.D.,

Duke Advanced Imaging Laboratories, Department of Radiology, Duke University, Durham, North
Carolina 27705

Swatee Singh, M.S.,

Duke Advanced Imaging Laboratories, Departments of Radiology and Biomedical Engineering,
Duke University, Durham, North Carolina 27705

Joseph Y. Lo, Ph.D., and

Duke Advanced Imaging Laboratories, Departments of Radiology, Medical Physics, and
Biomedical Engineering, Duke University Durham, North Carolina 27705

Ehsan Samei, Ph.D.

Duke Advanced Imaging Laboratories, Departments of Radiology, Physics, Medical Physics, and
Biomedical Engineering, Duke University Durham, North Carolina 27705

Abstract

Rationale and Objectives—Correlation Imaging (CI) is a form of multi-projection imaging technique in which multiple images of a patient are acquired from slightly different angles. Information from these images is combined to make the final diagnosis. A critical factor affecting the performance of CI is its data acquisition scheme since a non-optimized acquisition may quickly distort the pathological indicators. In this article, we are presenting a Computer Aided Detection (CADE)-based methodology to optimize the acquisition scheme of CI towards superior diagnostic accuracy.

Materials and Methods—Images from 106 subjects were employed. For each subject, 25 angular projections of a single breast were acquired. Projection images were supplemented with a simulated 3 mm 3D lesion. Each projection was then processed by a traditional CADE algorithm at high sensitivity, followed by reduction of false positives by combining geometrical correlation information available from the multiple images. Performance of the CI system was determined in terms of free-response receiver operating characteristic (FROC) curves and the area under the ROC curves. For optimization, the components of acquisition such as the number of projections, and their angular span were systematically changed to investigate which one of the many possible combinations maximized the obtainable CADE sensitivity and specificity.

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Tel. 919-684-1466, FAX 919-684-1492, asc14@duke.edu.

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Results—Performance of the CI system improved by increasing the angular span. Increasing the number of angular projections beyond a certain number does not improve performance. Maximum performance was obtained between 7–10 projections spanning our maximum angular arc of 45°.

Conclusion—Findings suggested the existence of an optimum acquisition for CI of the breast. CAdE-based results confirmed earlier predictions based on observer models. Optimized CI system may potentially be an important diagnostic tool for improved breast cancer detection.

Keywords

Multi-projection Imaging; Correlation Imaging; Breast Tomosynthesis; FROC; CAdE

INTRODUCTION

The field of diagnostic imaging is fast adopting the use of multiple images of the same patient for clinical workup. These images may be acquired by one or a combination of different imaging modalities. The information from these images is combined by either a clinician or a computer algorithm to extract knowledge about the presence as well as the morphology of a potential pathology within the patient.

In the context of digital radiographic imaging, the multi-image scheme takes the form of multi-projection imaging in which different projection images of a patient may be obtained by a single modality from different positions around the patient along a limited angular arc. This imaging scheme can take the form of tomosynthesis (1), stereoscopic imaging (2), or correlation imaging (CI) (3). In CI, projection images are directly analyzed, thereby avoiding reconstruction artifacts inherent to tomosynthesis. CI thus builds on the advantages of standard projection techniques and combines it with the proven benefits of fusing information from multiple images to potentially improve the accuracy of cancer detection (4). In practice, CI can take different forms including scrolling the images manually or in cine mode, stereoscopic display of projections images, computer-aided analysis of the multiple images, and may also possibly be used as an adjunct application to tomosynthesis.

While CI is a promising imaging technique, the diagnostic outcome of CI, like that of any other multi-projection imaging technique, is a function of its data acquisition scheme, i.e., the number of images acquired, the total angular span of those acquisitions, and the clinical dose at which those images are acquired. The inherent flexibility built into its image acquisition process enables CI to have multiple possible combinations of these acquisition parameters. Of course, not all combinations are optimal – some of the configurations may in fact obscure or distort the pathological indicators. An optimum image acquisition scheme of an imaging system is a specific combination of those various components of acquisition that maximizes the available diagnostic information.

In an earlier study based on mathematical model observer, we found that CI's performance may potentially be optimized with 11–17 angular projections spanning an angular arc of 45° (5). The purpose of this study was to optimize the geometry of CI data acquisition using a CAdE-based technique and to substantiate the earlier results from the mathematical observer model. As a key step towards that goal, a CAdE processor developed earlier (6) for standard projection technique was extended to take advantage of the CI configuration. To optimize the geometry of acquisitions, the acquisition parameters were systematically changed and the CAdE-based performance measured for different settings of those parameters. These results were compared to the observer model-based performance to confirm the optimality of our CI scheme.

MATERIALS AND METHODS

A. Image Database

The study employed a database of image sets from 106 subjects recruited for our ongoing tomosynthesis clinical trial (7). Each image set consisted of 25 images of a single breast acquired about the CC or MLO orientation from 25 different but fixed angular positions uniformly spaced in steps of 1.8° over a $\sim 45^\circ$ arc. A prototype clinical multi-projection system, Siemens' Mammomat Novation TOMO (Fig. 1) was used (8). The images were acquired at kVps ranging between 28 and 30, with a total glandular dose less than that delivered in a standard two-view screening procedure. All cases were interpreted by one of five dedicated breast imaging radiologists to be normal (without any lesions).

Next, a database of lesion present images was generated. Toward that end, 53 out of the available 106 cases in the database of normal clinical images were supplemented with projections from a simulated 3D 3 mm lesion (5). The lesion was simulated to be located at the center of the breast a distance of 3 cm above the detector plane. The projections of this lesion on the detector were simulated for all the 25 different tube positions and embedded into corresponding angular projections of the subject images. Thus there were two datasets each of 53 subjects, one with lesion absent and the other with lesion present. The contrast of the lesion was set assuming a heterogeneous breast (50% glandular/50% adipose tissue, representing an average breast composition) and accounting for the acquisition kVp, target/filter combination, breast thickness, anode type, and appropriate scatter fractions (9).

B. CADe processor

A previously reported computer-aided detection (CADe) processor developed for standard projection (single-view) technique (6) was used to evaluate each of the 25 angular projections/case available in CI. Specifically, the projection images were first filtered using a modified adaptive elliptical gradient convergence filter creating a blurry estimate of the anatomical background and highlighting suspicious abnormalities in the images. Following filtration, the suspicious regions were segmented with a grayscale duration technique (10). The segmentation was optimized to highlight structures with sizes similar to the expected 3 mm embedded lesion. The segmented suspicious regions were analyzed for nine morphological features. These features were combined using a Bayesian decision fusion scheme to reduce false-positives (11). The false-positive reduction program was trained using a genetic algorithm to find optimum feature thresholds that eliminated the greatest number of false positives while maintaining high sensitivity. The result was a set of 25 binary images per case, each showing potential locations of the embedded mass.

Next, the binary images per case obtained by the single-view CADe routine were processed to incorporate the CI configuration. Specifically, a shift and add reconstruction technique was applied to generate a stack of 20 image slices resulting in a CADe-enhanced volume of image slices within which the potential lesion was segmented. The stack of slices was then collapsed (summed) into a single 2D image comparable with the central (CC) projection and containing information from all the processed projections. The collapsed 2D image brought into focus the most suspicious regions, while the regions with a less likelihood of a presence of lesion were blurred out. Finally, a thresholding mechanism was applied to pick the region with the suspected pathology, thus providing a 2D contour map of the possible locations of the lesion.

To evaluate the performance of CI, the 2D contour map was compared to a truth file. The truth file was defined as a binary mask of area that encompasses the known locations of the embedded lesion taking into account its spatial displacement across all the 25 projections. If a region on the 2D contour map overlapped the true lesion area, a true-positive finding was

registered. All other regions that did not overlap were counted as false-positive findings. Using this rule, free-response receiver operating characteristics (FROC) curves were generated.

C. Optimization of Data Acquisition

To optimize the acquisition scheme, the components of acquisition, namely, the number of projections and their angular span were systematically changed within 2 – 25 and 3.6° – 44.8° range, respectively, to investigate which one of the many possible combinations yielded the highest diagnostic performance.

The diagnostic performance was measured in terms of two performance indices, first as the ratio: True Positives/(True Positives + False Positives). This ratio, termed Positive Predictive Index (PPI), is a measure of the true positive locations as a fraction of the total number of identified locations *per image set* and is easily derivable from the FROC curves. These values were then averaged across all the cases for each possible combination of the number of projections and angular range.

The second index of metric was the area under the ROC curve (AUC) derived from the datasets with and without the embedded lesion. Each case in the two datasets was processed with the CAde processor described earlier to yield a corresponding 2D contour map. The likelihood of the presence of the embedded lesion was examined via a correlation matching of the expected signal with the signal-present and with the signal-absent 2D contour map. The value obtained by this signal-matching step served as decision variables based upon which the probability distribution functions (*pdfs*) of the signal-absent and signal-present decision variables were computed. Finally, non-parametric ROC curves were derived by thresholding the *pdfs*, and the area under the ROC curves subsequently computed by the trapezoidal method.

RESULTS

Fig. 2 shows a representative case with the embedded lesion at angular projections of -22.3° (a), 0° - CC orientation (b), and 23.1° (c). Fig. 2d shows the true positive and false positives findings of the CAde processor projected on the CC image.

Fig. 3 shows the variation in the average positive predictive index (PPI) with the number of projections within 6 angular spans in the 7.5° – 44.8° range. At each angular range, the PPI values first increase and then decrease with an increase in the number of projections, maximizing at a value that is dependent on the angular span. The maximum PPI is obtained for 10 projections spanning an angular arc of 44.8° .

Fig. 4 shows the variation of AUC with the number of projections spanning different angular arcs. At each angular range, the AUC values increase with the increase in the number of angular projections and then appear to approach an asymptote. The number of projections at which the AUC values peak depends on the angular span. The highest AUC is obtained at the maximum angular span of 44.8° with 7 projections.

The trend in the variation of PPI and the AUC values delineate the role of different components of acquisition scheme in the final diagnostic performance of a multi-projection imaging system. These trends indicate that the optimum number of projections for a multi-projection imaging system may be in the 7–10 range for an angular span of 44.8° . Most noteworthy, the observer model results (reported in (5), and reproduced here in Fig. 5 for convenience) show a similar trend in performance where the maximum detectability of an

embedded lesion was found to maximize with between 10–17 angular projections for an angular span of 44.8°.

DISCUSSION

Data acquisition parameters in multi-projection imaging modalities, such as breast tomosynthesis and Correlation Imaging (CI), are currently determined primarily by subjective clinical requirements such as avoiding patient motion and reducing patient discomfort (12). The many possible configurations of data acquisition in such a system such as the number of projections, angular span, and the acquisition dose level can, however, easily lead to a choice of potentially sub-optimal acquisition scheme in a clinical setup. Since the data acquisition plays a pivotal role in the final diagnostic outcome of such a system, it is important to optimize the acquisition parameters to take full advantage of the multi-projection imaging technique.

In this study, the diagnostic performance of CI was assessed using a CADe-based processor. Like mathematical observer-based processors, CAD processor functions like surrogate human observers and thus have been used in the past to evaluate clinical performance of tomosynthesis (13: 14). While the observer model results have been reported earlier (4), the objectives of this study were to extend an existing single-view CADe for CI to confirm the observer model results, and more importantly, to investigate how to best integrate each of the components in the acquisition scheme to maximize the performance of CI under a practical clinical paradigm. Similar to the observer model methodology that computes and incorporates the image background statistics in determining the detectability of the lesion (5: 15), the CADe processor performs a background-dependent image filtration and segmentation, thus taking into account the image background statistics to enable lesion detection. At the same time, the two processors are built on inherently different premises, leading to slightly different results. While the CADe processor revealed 7–10 as the optimum number of projections, the observer model predicted optimization with number of projections in the 10–15 range (5: 15). In spite of those differences both processors show that increasing angular span improves performance, and most importantly, simply increasing the number of angular projections does not improve performance. In that regard, the two processors show similar trends in the performance of a multi-projection system, and are therefore consistent in their findings. The exact number of projections that optimize the system depends on the specific implementation of CI.

The performance of the CADe processor was measured in terms of a positive predictive index (PPI) and the area under the ROC curve (AUC). PPI is a fraction of the true positive findings to the total number of suspicious locations indicated by the CADe processor in an image set. For example, for the particular case shown in Fig. 2, PPI was $1/(1+2) = 0.33$. It may be noted that unlike positive predictive value (PPV) that has a similar definition, PPI is not a population statistics and was computed for each patient case separately. The second figure of merit, AUC, is a measure of the detectability of the embedded lesion following CADe enhanced processing of the images. While PPI was computed based on search process typically used to assess CAD algorithms, AUC was computed using location and signal known exactly (SKE) paradigm similar to the procedure used by mathematical observer model processors. Therefore, although not equivalent, the AUC values obtained by the two processors are comparable. Most importantly, they provide a single platform on which to compare the performance of CI.

The results show that for each of the 12 angular ranges considered, as the number of projections is increased, the PPI values first increase but then decrease. The increase in PPI may be attributed to the increase in true positive findings due to an increase in correlation

information available from multiple projections. With further increase in projections, however, more suspicious regions come into focus, thus increasing the FPs, and hence the decreasing the PPI value. AUC values, on the other hand, appear to reach an asymptote beyond a certain number of projections. This may be because any further increase in the number of projections offers no additional gain in the geometrical information in terms of the relative difference between the lesion and surrounding anatomical structures making detectability only quantum noise limited. However, once the threshold detection signal-to-noise ratio is achieved, any more increase in the number of projections does not improve detectability, thus saturating the AUC values. This saturation of the lesion detectability is also confirmed by the variability in PPI values that decrease with increased angular projections, possibly due to saturation of the TP values and an increase of FPs at the same time. Thus both PPI and AUC analysis showed same trends in the performance of CI.

One limitation of the optimization framework presented here was that it was dependent on the dose level of the acquisitions and thus the total delivered dose to the patient increased with an increase in the number of angular projections considered for optimization. A more clinically realistic optimization would assess system performance at a constant total examination dose. Under this condition, an increase in the number of projections results in lower dose per projection, leading to lower detection rates (15). This inherent difference between dose-variable condition used in this study and dose-constant condition shown in (15) potentially explains the differences in results between the two studies. This difference may be confirmed by constructing a CADe based constant-dose framework. Furthermore, the results of optimization were based on a single representative lesion-type, i.e. on a pre-determined shape and size of a mass, and therefore may vary for other lesion-types, including microcalcifications. However, the framework laid out in this study predicts the inherent performance of a multi-projection imaging system and is thus applicable to other typical detection tasks in a similar setup. Regardless, the results should be implemented only after being confirmed clinically. Notwithstanding, both the CADe and observer model highlighted the relationship between different components of the acquisition scheme and the performance of a multi-projection imaging system to potentially maximize the available diagnostic information in CI.

CONCLUSIONS

A new CADe processor was developed for multi-projection Correlation Imaging (CI) that takes advantage of the geometrical correlation information accrued from the available multiple projections to improve specificity of the CI system. The performance of the CADe system was computed at different data acquisition settings towards optimizing the geometry of image acquisition. Both the CADe and observer model results (reported earlier) show a general trend in the performance of CI as a function of the different acquisition components, and confirm that the maximum performance may be obtained with 7–17 projections for an angular span of $\sim 45^\circ$. The optimization platform presented here is generic in nature and can be used to optimize any multi-acquisition scheme, including tomosynthesis. Most noteworthy, the optimization framework reported here is based on two separate clinically-relevant processors and thus could be used to potentially improve the clinical efficiency of currently-used multi-projection imaging systems.

Acknowledgments

The authors would like to thank Dr. Jay Baker for his valuable inputs. This work was supported in part by DOD - Pre-Doctoral Traineeship grant no. W81XWH-06-1-0449, and grants from Cancer Research Prevention Foundation and the Komen foundation (PDF55806).

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Fig. 1. Schematic of acquisition for multi-projection breast Correlation Imaging (CI). Front view (left); side view (right)

Fig. 2. (a), (b), (c) show projection images of a breast acquired by the multi-projection system at -22.3° , 0° (CC orientation), and 23.1° . The arrows show the locations of the embedded 3D lesion at these projections. (d) shows the CC projection image with suspected locations of lesion marked by the CADe processor in red. The location of the true lesion is encompassed in the green mark. The locations where the red regions intersect the green mark are noted as true-positive findings. (Note: the contrast of the lesions was enhanced manifold for display purposes only.)

Fig. 3.

Average Positive Predictive index $[TP/(TP + FP)]$ as a function of the number of projections spanning different angular ranges (specific values shown in the legends) in a multi-projection Correlation Imaging setup. TP~True Positive findings; FP~ False Positive findings per patient case.

Fig. 4.

Area under ROC curves as a function of the number of projections spanning different angular ranges (specific values shown in the legends) in a multi-projection Correlation Imaging setup. AUCs indicate the detectability of a simulated mass embedded into each projection.

Fig. 5. Variation of AUC for different number of angular projections spanning for representative angular spans in the 7.5°–44.8° range using a mathematical observer model. These results confirm the optimization results obtained from the CADe processor (shown in Fig. 4).