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An ellipse-fitting based method for efficient registration of breast masses on two mammographic views

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Abstract

When reading mammograms, radiologists routinely search for and compare suspicious breast lesions identified on two corresponding craniocaudal (CC) and mediolateral oblique (MLO) views. Automatically identifying and matching the same true-positive breast lesions depicted on two views is an important step for developing successful multiview based computer-aided detection (CAD) schemes. The authors developed a method to automatically register breast areas and detect matching strips of interest used to identify the matched mass regions depicted on CC and MLO views. The method uses an ellipse based model to fit the breast boundary contour (skin line) and set a local Cartesian coordinate system for each view. One intersection point between the major/minor axis and the fitted ellipse perimeter passed through breast boundary is selected as the origin and the majoraxis and the minoraxis of the ellipse are used as the two axis of the Cartesian coordinate system. When a mass is identified on one view, the scheme computes its position in the local coordinate system. Then, the distance is mapped onto the local coordinate of the other view. At the end of the mapped distance a registered centerline of the matching strip is created. The authors established an image database that includes 200 test examinations each depicting one verified mass visible on the two views. They tested whether the registered centerline identified on another view can be used to locate the matched mass region. The experiments show that the average distance between the mass region centers and the registered centerlines was ± 8.3 mm and in 91% of testing cases the registered centerline actually passes through the matched mass regions. A matching strip width of 47 mm was required to achieve 100% sensitivity for the test database. The results demonstrate the feasibility of the proposed method to automatically identify masses depicted on CC and MLO views, which may improve future development of multiview based CAD schemes.

Keywords

ellipse-fitting; computer-aided detection; mammography; breast mass; image registration; region matching

I. INTRODUCTION

In screening mammography both craniocaudal (CC) and mediolateral oblique (MLO) views are routinely acquired on each breast. Hence, during mammogram reading and interpretation radiologists routinely compare (among other comparisons) the suspicious regions depicted on the CC and MLO views to identify and confirm true-positive lesions while eliminating as many false-positive findings as possible. A number of clinical studies have demonstrated that radiologists' performance in breast lesion (or cancer) detection is higher with two-view mammograms as compared with single views.^{1,2} Although development of computer-aided

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detection (CAD) schemes has been attracting extensive research interest during the past 20 years and significant progress has been accomplished in term of CAD performance,³ most CAD schemes (including those used in the commercially available systems) are primarily single-view based with the exception of a limiting maximum number of CAD-cued regions allowed in a single case (e.g., four views).⁴ No other comparison information from multiple views is incorporated into the decision making process of these schemes. Current CAD schemes still generate more false-positive detections as compared to radiologists.

To decrease the number of false positives, researchers have attempted to develop multi-image based CAD schemes since the early stage of CAD development.^{5,6} Previous studies have demonstrated that incorporating information extracted from matched mass regions depicted on two views (CC and MLO) of the same breast could improve CAD performance.⁷⁻¹⁰ All previous multiview based CAD schemes basically apply two steps to identify matched mass regions on two views: geometry-based image registration and feature-based region matching. In the first step research effort has been largely focused on (1) detecting geometric landmarks depicted on mammograms (e.g., nipple, pectoral muscle, and skin line of the breast), (2) building a local polar coordinate system, and (3) identifying a region of interest, which can be a straight¹¹ or curved (fan-shaped)^{12,13} region that is superimposed onto the corresponding CC or MLO view when a mass is detected. The matching strip serves as the search area for detecting the mass in the CC or MLO view. In the second step, schemes analyze and compare feature similarity between a depicted mass region on one view and each of detected suspicious mass regions depicted inside the matching strip of another corresponding view. Two most “similar” matched regions are identified as one mass depicted on two views (CC and MLO). The underlying assumptions for finding correct matches through a comparison of a large number of candidates are that (1) a true-positive (TP) mass has a higher chance of being detected by CAD on both views than a false-positive (FP) region does, and (2) the same TP mass detected on two views (a TP-TP pair) has features that are measurably more similar than either TP-FP or FP-FP pairs.⁸

Due to the elastic and deformable nature of breast tissue, the shapes and projected (overlapped) tissue patterns of the same breast often appear different on CC and MLO views. Therefore, it is difficult and often impossible to identify invariant landmarks or highly correlated features depicted on both views. As a result, two major technical challenges remain in developing multiview based CAD schemes. First, due to the difficulty and/or errors in geometrical image registration, the corresponding TP mass regions are often missed in the attempt to register the CC and MLO views. In order to avoid a reduction of sensitivity, the width of matching strip needs to be substantially increased¹³ thereby substantially increasing the number of matching candidates inside the matching strip (e.g., >5).¹²⁻¹⁴ Second, the correlation between image features of subtle TP masses depicted on two views is often low. Consequently, lowering the accepted level of correlation to increase detection of the TP-TP matched pairs substantially increases the number of incorrect TP-FP or FP-FP pairs detected by the CAD schemes. Hence, although multiview based CAD schemes aim to detect more TP lesions on two views resulting in higher lesion region based sensitivity, in the clinical applications CAD performance is commonly evaluated using case-based sensitivity in which a mass is counted as detected if it is detected in either one or two views. Studies have shown that in order to achieve a comparable case-based sensitivity, the most previously developed multiview based CAD schemes typically generate much higher false-positive detection cueing rates than the commercial single-image based CAD schemes (e.g., ≥ 1 FP per image⁸ versus ≤ 0.25 FP per image¹⁵ at approximately 75% case-based sensitivity). Our previous study demonstrates that in order to maintain comparable or achieve improved performance to the single-image based CAD schemes (both case-based sensitivity and false-positive rate), one has to limit the width of the matching strip and thereby reduce the number of possible matching candidate pairs for a given mass.¹¹

In this study, we describe an ellipse-fitting based method to adaptively fit the breast areas depicted on breast images and build a local Cartesian coordinate system for both the CC and the MLO view images. Using this coordinate system, the registered centerline of the matching strip can be automatically determined on a corresponding CC and MLO view. To test the feasibility and performance of this method, we assembled a relatively large and diverse image database. We describe here the concept of the ellipse-fitting based scheme, the selection of the testing image database, and the preliminary experimental results.

II. MATERIALS AND METHODS

The primary idea implemented in our method is the use of an ellipse to fit the breast boundary in the MLO and CC views of the breast and then establish local Cartesian coordinate systems on the two views under examination. Our underlying assumption is that despite the shape deformation of the breast the shapes of the breast regions depicted on the two views are essentially elliptical. We note that the ellipses are not used to model the breasts itself but to approximate a reference coordinate system that can be used to identify the correspondences between the CC and MLO views. The basic procedure of this method is depicted in Fig. 1. The involved steps are explained in detail in the following sections.

II.A. Breast contour extraction

The first step in the approach investigated here is to extract the breast skin line contour. The procedures of the breast skin contour extraction are shown by an example in Fig. 2. It is based on the fact that the breast area generally forms the largest concave region in the threshold (binary) image. Given a digitized mammogram [Fig. 2(a)], there are three steps in extracting the breast skin contour. First, a threshold is automatically selected as the minimal pixel value located between the two largest peaks of the pixel value histogram and applied to the image to create a binary image where one represents breast area and the other represents all background areas (or air) [Fig. 2(b)]. Second, the scheme traces the contour of the “air” or “background” region using an inner border tracing algorithm.¹⁶ The result [Fig. 2(c)] is a sequence of points that form a set of directed closed contours, in which the contour with the largest area is selected for further processing. All other smaller areas (if any) are eliminated. Third, the scheme computes the convex hull of the selected contour [Fig. 2(d)] using the QuickHull algorithm.¹⁷ By comparing the contour and its convex hull, the local region with the largest convexity is obtained. The extracted breast contour is represented by a sequence of points of this convex boundary [Fig. 2(d)]. The extracted contour points may include portion of chest, in particular in MLO view [Fig. 2]. In order to eliminate the possible impact of the chest wall pixels on the fitted ellipse, we shorten the obtained boundary contour curve by moving the closing line of the breast contour forward a small distance Δp (e.g., $\Delta p=2$ mm) in a parallel manner [Fig. 2 (d)].

II.B. Ellipse fitting

Considering the general shape of the imaged breast, we use an ellipse model to fit the breast contour in this study. As a basic task in pattern recognition and computer vision, a number of primitive models of fitting circles and ellipses are widely used in image processing that can simplify the representation of the original data and thus allow a higher level of analysis.^{18, 19} Unlike many other ellipse fittings, our task has several requirements specific to this application: (1) the breast contour represents only a fraction of an ellipse (roughly half of an ellipse). This necessitates that the fitting routine robustly manage the occlusion (varying curve length of the detected breast boundary contour); (2) since in digitized images (film-based mammograms) breast boundaries (skin-air interfaces) are often fuzzy or noisy, the fitting methods should be insensitive to noise; (3) the fitted ellipse should have low eccentricity bias and affine invariance because the breast region depicted on the image could be in varying

positions and orientations; and (4) the fitted result cannot represent other quadratic curves such as a hyperbola or a parabola. If it does, one cannot define a unique and consistent reference coordinate system. These incorrect fittings are frequently unavoidable in other ellipse-fitting methods because the fitting process is generally regarded as a minimization process.

We adopted the direct least-square ellipse-fitting approach proposed by Fitzgibbon *et al.*²⁰ in this study. Unlike other fitting algorithms that either fit general conics or are computationally inefficient, this method not only meets our specific requirements mentioned above and at the same time is also computationally efficient. The algorithm can be briefly explained as follows. It is well known that the equation describing an ellipse can be written as

$$F(x, y) = ax^2 + bxy + cy^2 + dx + ey + f = 0, \quad (1)$$

with the constraint $b^2 - 4ac < 0$, where a, b, c, d, e , and f are the ellipse coefficients and (x, y) are the coordinates of the points on the ellipse. The best fitted ellipse may be approached by minimizing the sum of square algebraic distance

$$D(a, b, c, d, e, f) = \sum_{i=1}^N F(x_i, y_i), \quad (2)$$

where N is the number of the scattered points. As recommended by Fitzgibbon *et al.*,²⁰ the minimization of the least-squares algebraic distances is achieved by solving a generalized eigenvalue system

$$\mathbf{A}^T \mathbf{A} \boldsymbol{\alpha} = \lambda \mathbf{C} \boldsymbol{\alpha}, \quad (3)$$

where $\mathbf{A} = [\mathbf{x}_1 \mathbf{x}_2 \dots \mathbf{x}_n]^T$, $\mathbf{x} = [x^2 \ xy \ y^2 \ xy \ 1]$, $\boldsymbol{\alpha} = [abcde f]$, and $\mathbf{C}$ is the matrix that express the constraint $4ab - b^2 = 1$. One of the properties of this method is that it always finds a unique solution and the solution $[F(x, y)]$ is always an ellipse. The complete description of the characteristics of this method and its detailed theoretic proof as well as a comparison with other ellipse fitting methods can be found elsewhere.²⁰ Solving the generalized eigenvalue system [Eq. (3)] will give us the ellipse coefficients. The scheme then computes (1) the major axis and the minor axis of the ellipse and (2) the four intersection points between the two axes and the ellipse curve.

These computed parameters of the ellipse will be used to set up a local Cartesian coordinate system for registration purpose. For example, one of the four intersection points will be selected as the origin and the two ellipse axes will be selected as the axes of its local Cartesian coordinate system. The detailed description of the registration coordinate system will be presented in the next section. These parameters are computed as follows. Given an ellipse in the general quadratic equation form as Eq. (2), its center is the solution of the equations²¹

$$\begin{aligned} 2ax + by + d &= 0, \\ bx + 2cy + e &= 0. \end{aligned} \quad (4)$$

Since the major axis and the minor axis are perpendicular to each other, the major axis and the minor axis have slope k and $-1/k$, respectively,

$$k = \sqrt{\frac{(c-a)^2}{b^*(b+1)}} + \frac{c-a}{b}. \quad (5)$$

The lines representing the major axis and the minor axis can be determined from Eqs. (4) and (5). Next, the scheme computes four intersection points between these two axes and the ellipse.

Several examples in Fig. 3 are used to show the results of applying this ellipse-fitting method to the digitized mammograms with different breast shapes and sizes. From these examples, it can be seen that given an estimated breast contour, this method can always fits an ellipse that represents the breast contours despite varying shapes and sizes of the fitted breasts.

We note that the ellipse fitting described above is not intended to fit exactly the whole breast. Rather, it is intended to serve as the basis for building a local reference coordinate system of the depicted area on either MLO or CC view considering the shape of the breast contour. The procedure to build such a reference system is explained in next section.

II.C. Registration of matching strips

Given a fitted ellipse, a local Cartesian coordinate system is determined by a reference point (an origin of the coordinate system) and two directions (X and Y axes of the coordinate system). The origin in our approach (e.g., the point O_1 or O_2 as shown in Fig. 4) is one of the four intersection points between the major or minor axes and the ellipse which is located on the fitted breast skin boundary but is not necessarily represented by the nipple. Rather, it is identified as the most protruding point on the ellipse fitting to the breast contour. The majoraxis and the minoraxis of the fitted ellipse are used as the two axes of the local Cartesian coordinate system. Using this approach the scheme can identify the registered centerline of the matching strip on corresponding CC or MLO view.

As shown in Fig. 4, computation of the matching strip for a known mass region on the MLO view begins by measuring the perpendicular distance (d_1) between the X_1 axis and the center of the mass region (i.e., the Y coordinate of the center of the mass region). Next, the scheme maps the distance measured on the MLO view onto the corresponding CC view to identify a registered centerline of the matching strip (r_2), which is parallel to the X axis (X_2) of the local Cartesian coordinate system in the CC view. If the registered line (r_2) misses the center of the mass depicted on the CC view as shown in Fig. 4, the scheme can measure the distance between line (r_2) and actual mass center (line s_2) and define this distance as the matching error (Fig. 4). Assuming that the distance between the origin point on the CC view (O_2) and the mass center as projected onto the Y axis in the local Cartesian coordinate system is computed (d_2), the matching error is then computed as $\Delta_{CC} = d_1 - d_2$. Similarly, the error in matching distance on the MLO view is $\Delta_{MLO} = d_2 - d_1$ with a relation of $\Delta_{CC} = -\Delta_{MLO}$ (Fig. 4)

II.D. Testing data set and performance evaluation

Our hypothesis is that applying the ellipse-fitting based method would result in an automated approach to identify the registered centerlines of the matching strips (i.e., r_1 and r_2 as shown in Fig. 4) that should pass through the corresponding masses depicted on the corresponding CC and MLO views with low matching errors (i.e., Δ_{CC} or Δ_{MLO}). To test this hypothesis, we randomly selected a testing data set that includes 200 pairs of CC and MLO view images (a total of 400 images) acquired during examinations of 200 women later verified as having breast cancer. Each examination depicted one mass that was considered to be visible on both the CC and the MLO views by experienced radiologists. The image characteristics of these masses (including size and subjective subtleness rating) have been reported elsewhere.⁴ In brief, the average measured mass size is 1.5 cm^2 (median 1.1 cm^2) with the range of $0.1\text{--}9.5 \text{ cm}^2$. Approximately one-half of the masses were rated subjectively as “somewhat subtle” to “very subtle” by the radiologists. All images (film-based mammograms) had been digitized using a Howtek digitizer (iCAD, Inc., Nashua, NH) with original pixel sizes of $43 \mu\text{m} \times 43 \mu\text{m}$. For the purpose of mass detection, these images were then subsampled using a pixel averaging method

to reduce image size by eightfold in two dimensions (with pixel size of 0.344 mm×0.344 mm). For each verified mass region, a rectangular frame that covers the depicted mass had been visually determined by the radiologists and recorded in the “truth file.” The center of the marked frame is automatically computed and used to represent the mass center in this study.

The new computer scheme using the ellipse-fitting method was applied to the 200 paired MLO and CC view images. For each case, we tested the performance twice by first using the mass region depicted on CC view as a “known” mass and then using the mass region depicted on the MLO view as the known mass. In each test, we recorded the matching error defined as the Euclidean distance from the center of the mass region to the automatically identified registered centerline of the matching strip. We also counted the number of the registered centerlines that passed thorough the mass regions as defined by the covering rectangular frames saved in the truth file. Although absolute values of two matching errors are equal ($|\Delta_{CC}| = |\Delta_{MLO}|$) by definition for each pair, the sizes of the two mass regions depicted on CC and MLO views may not be the same due to the projection of the mass in two different directions. Hence, the number of the identified registered centerlines that pass through the corresponding mass area (the covering rectangular frame) may be different. Finally, the distribution of matching results was plotted. The average matching error and percentage of registered centerlines of the matching strips that pass through the matched mass regions on corresponding CC and MLO views as well as the required width of the matching strips in order to achieve the maximum matching sensitivity were computed and analyzed.

III. RESULTS

The matching results of applying our computer scheme to a set of example images (as shown in Fig. 3) are demonstrated in Fig. 5. In each image (as shown of Fig. 5), the size of mass region (a rectangular frame marked by the radiologists and recorded in the truth file) and the matching error (the distance between the computer-identified registered centerline of the matching strip and the reference line passing through the mass region center) are shown. In these four pairs of CC and MLO view images, the eight identified registered centerlines of the matching strips all pass through the corresponding matched mass regions.

The experimental results show that the average matching error (the distance between the mass region centers and the corresponding registered centerline of matching strips identified on CC and MLO view) for the 200 pairs of testing masses is ± 8.33 mm. The distribution of the absolute matching errors ($|\Delta_{CC}|$ or $|\Delta_{MLO}|$) among these 200 mass pairs is shown in Fig. 6. The matching errors range from 0.06 to 23.5 mm [Fig. 6(a)] and more than 83% of the 200 mass pairs have matching errors smaller than 14 mm [Fig. 6(b)]. Since the mass regions located outside of the matching strips cannot be detected and matched, to achieve the maximum matching sensitivity (100%) of this testing data set, two boundaries of the matching strip should be ± 23.5 mm away from the registered centerline of the strip (or the maximum strip width of 47 mm).

In 91% (364/400) of all the matching strip computations (MLO to CC and CC to MLO) the registered centerlines of matching strips passed through the corresponding mass areas depicted on the corresponding CC and MLO view. When the masses depicted on CC view served as the known location, 94% (188/200) of the registered centerlines of the matching strips identified on the corresponding MLO view passed through the corresponding matched mass regions. At the same time, when the 200 masses depicted on MLO view were treated as the known locations, 88% (176/200) of the registered centerlines passed through the mass regions on the corresponding CC view.

IV. DISCUSSION

Automated and correct identification of matched mass regions depicted on CC and the MLO views is an important step in developing multi-view based CAD schemes. For this purpose, one needs to register the two corresponding images based on a reference coordinate system. Previous studies used a “detected” nipple position as the origin and a line starting from the nipple and perpendicular to the pectoral muscle (chest wall) as the axis direction (centerline) of the polar reference coordinate system.^{11–14} Although the nipple is consistently and clearly visible on full-field digital mammograms, it is often much harder to identify on digitized screen-film based mammograms. Nipple detection errors could change the origin and the orientation of the computed reference coordinate system. To manage such errors, previous studies mapped and defined wide matching strips (regions of interest) onto the corresponding CC and MLO views to search for matched mass regions. One study showed that as the widths of the arc-type matching strips increased, the fraction of correctly matched masses increased, but the number of false-positive regions located inside the matching strips also increased. In order to avoid missing matching true-positive mass regions in the tested data set of 412 pairs, the width of matching strips had to be increased to 48 mm.¹⁴ In another study including 24 cases, the matching (searching) area was defined as ± 27 mm from the identified centerline (or a total width of 54 mm).¹³ A third study reported that by setting the width of the matching area to 32 mm, approximately 83% out of 169 paired mass regions could be identified inside the fan-shaped matching strips.⁸ In this study, we tested a totally different concept (approach) to build reference coordinate systems and identify the matching strips. The origin and the (X , Y) axes of the reference coordinate system are adaptively determined by the ellipse-fitting result for the breast areas depicted on one view. The maximum matching distance (error) we found was 23.5 mm, indicating that a 47 mm (± 23.5 mm) matching strip would cover 100% of the tested masses in our data set on the corresponding CC and MLO views. If the width of matching strips was reduced to 28 mm (± 14 mm), the matching strips would cover about 83% of the paired masses. Although it is difficult to directly compare performance of different studies due to the use of different data sets, our preliminary results are quite encouraging as compared to other previous studies.

Unlike other studies that use arc-type (or fan-shaped) matching strips (areas) to search for and identify matched mass regions on a CC or MLO view, our previous study used a straight matching strip. We believe that a rectangular strip better mimics the search pattern of most radiologists when attempting to match mass regions depicted on CC and MLO views.¹¹ To identify the straight matching strips, one needs to detect both the nipple position and the orientation of pectoral muscle. The pectoral muscle is typically not visible on CC view and a small fraction of MLO view images. Hence, estimating the appropriate orientation of the matching strip (that is parallel to the pectoral muscle) is a potential source of errors, in particular for matching mass regions located close to the breast skin boundary (skin-air interface). One advantage of the ellipse-fitting method presented here is that it can build a local Cartesian coordinate system for matching CC and MLO views without the detection of either the nipple or the pectoral muscle. Despite the fact that breast positions and orientations vary widely in the images of our testing data set, the ellipses can always be fitted to cover the depicted breast areas and build the reference coordinate systems for registration of two CC and MLO view images and identification of the matching strips.

The experimental results of this study also demonstrate the other two important advantages of this ellipse-fitting approach. First, the ellipse can be fitted using only a fraction of breast skin boundary contour pixels and using digitized images where the imaged breast skin boundaries are fuzzy and difficult to determine. Second, we conducted our experiment using a typical personal computer (AMD Athlon™ 64×2 dual 2.11 GHz with 2 GB of RAM). When applying this ellipse-fitting scheme to our testing data set, the complete computation time from reading

image data to build the reference coordinate systems for the two corresponding views (CC and MLO) and identify the matching strips ranges from 0.28 to 0.91 seconds (with an average time of 0.54 s). Hence, this ellipse-fitting scheme is also computationally efficient. These advantages are the critical criteria for the ultimate possible implementation of this approach to the multi-view based CAD schemes and use in the clinical environment.

A number of issues require further investigation in future studies. First, although this new ellipse-fitting model achieves relatively high (or very comparable) performance in automated identification of matching strips depicted on CC and MLO view in this preliminary study, the robustness of the model needs to be further tested using more independent data sets in the future studies. Second, due to the potentially large interobserver variability in identifying mass region boundary,²² the mass region centers recorded in the “truth” file may have errors or inconsistency. This could affect the assessment accuracy of scheme performance.²³ Improving the quality of the truth file is also an important issue in future studies. Third, the algorithm needs to be implemented in a multiview based CAD scheme to assess if and by what magnitude the use of this approach actually improves CAD performance. Fourth, the possible difference in depicted breast sizes due to differences in deformation and breast compression during the imaging of CC and MLO views is not understood very well in particular as to its possible impact on mass locations on corresponding two views. This could be investigated using the size information of the two fitted ellipses resulting in appropriate corrections for nonrigid mapping to improve localization of the matching strips.

V. CONCLUSION

We developed and tested a new computer scheme based on an ellipse-fitting method (algorithm) to build a local Cartesian coordinate system for matching breast masses depicted on two mammographic views (CC and MLO). The scheme was tested using a relatively large and diverse image database involving 200 malignant masses that are actually visible on both the CC and the MLO views. The preliminary experimental results suggest that the performance of this scheme is comparable to other previously reported schemes. Our scheme has several advantages in that it does not require the detection of two invariant landmarks (nipple and pectoral muscle), it can fit an ellipse to breast areas with partial and/or fuzzy skin lines (noisy fitting seeds), and it is computationally efficient.

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References

1. Thurffjell E, Taube A, Tabar L. One-view versus 2-view mammography screening: A prospective population-based study. *Acta Radiol* 1994;35:340–344. [PubMed: 8011382]
2. Warren RM, Duffy SW, Bashir S. The value of the second view in screening mammography. *Br J Radiol* 1996;69:105–108. [PubMed: 8785635]
3. Nishikawa RM. Current status and future directions of computer-aided diagnosis in mammography. *Comput Med Imaging Graph* 2007;31:224–235. [PubMed: 17386998]
4. Zheng B, Leader JK, Abrams G, Shindel B, Catullo V, Good WF, Gur D. Computer-aided detection schemes: The effect of limiting the number of cued regions in each case. *AJR Am J Roentgenol* 2004;182:579–582. [PubMed: 14975949]
5. Hand W, Semmlow JL, Ackerman LV. Computer screening of xero-mammograms: A technique for finding suspicious area of the breast. *Comput Biomed Res* 1979;12:445–460. [PubMed: 498753]

6. Yin FF, Giger ML, Doi K, Metz CE, Vyborny CJ, Schmidt RA. Computerized detection of masses in digital mammograms: Analysis of bilateral subtraction images. *Med Phys* 1991;18:955–963. [PubMed: 1961160]
7. Chang YH, Good WF, Sumkin JH, Zheng B, Gur D. Computerized localization of breast lesions from two views: An experimental comparison of two methods. *Invest Radiol* 1999;34:585–588. [PubMed: 10485074]
8. Paquerault S, Petrick N, Chan HP, Sahiner B, Helvie MA. Improvement of computerized mass detection on mammograms: Fusion of two-view information. *Med Phys* 2002;29:238–247. [PubMed: 11865995]
9. Liu B, Metz CE, Jiang Y. Effect of correlation on combining diagnostic information from two images of the same patient. *Med Phys* 2005;32:3329–3338. [PubMed: 16372412]
10. van Engeland S, Karssemeijer N. Combining two mammographic projections in a computer-aided mass detection method. *Med Phys* 2007;34:898–905. [PubMed: 17441235]
11. Zheng B, Leader JK, Abrams GS, Lu AH, Wallace LP, Maitz GS, Gur D. Multiview-based computer-aided detection scheme for breast masses. *Med Phys* 2006;33:3135–3143. [PubMed: 17022205]
12. Sanjay-Gopal S, Chan H, Wilson T, Helvie M, Petrick N. A regional registration technique for automated interval change analysis of breast lesions on mammograms. *Med Phys* 1999;26:2669–2679. [PubMed: 10619252]
13. Kita Y, Highnam RP, Brady JM. Correspondence between different view breast x rays using curved epipolar lines. *Comput Vis Image Underst* 2001;83:38–56.
14. Engeland S, Timp S, Karssemeijer N. Finding corresponding regions of interest in mediolateral oblique and craniocaudal mammographic views. *Med Phys* 2006;33:3203–3212. [PubMed: 17022213]
15. Gur D, Stalder JS, Hardesty LA, Zheng B, Sumkin JH. Computer-aided detection performance in mammographic examination of masses: An assessment. *Radiology* 2004;233:418–423. [PubMed: 15358846]
16. Cormen, TH.; Leiserson, CE.; Rivest, RL.; Stein, C. *Introduction to Algorithms*. 2nd. MIT Press; Boston, MA: 2001.
17. Barber CB, Dobkin DP, Huhdanpaa H. The QuickHull algorithm for convex hulls. *ACM Trans Math Softw* 1996;22:469–483.
18. Chowdhury TA, Whelan PF, Ghita O. The use of 3D surface fitting for robust polyp detection and classification in CT colonography. *Comput Med Imaging Graph* 2006;30:427–436. [PubMed: 16919911]
19. Kubota T, Okada K. Estimating diameters of pulmonary nodules with competition-diffusion and robust ellipsoid fit. *Lecture Notes in Computer Science* 2005;3765:324–334.
20. Fitzgibbon A, Pilu M, Fisher R. Direct least square fitting of ellipses. *IEEE Trans Pattern Anal Mach Intell* 1999;21:476–480.
21. Abramowitz, M.; Stegun, IA. *Handbook of Mathematical Functions with Formulas, Graphs, and Mathematical Tables*. 9th printing; Dover, New York: 1972.
22. Reeves AP, et al. The lung image database consortium (LIDC): Pulmonary nodule measurements, the variation, and the difference between different size metrics. *Proc SPIE* 2007;6514:65140J–1–8.
23. Kallergi M, Carney GM, Gaviria J. Evaluating the performance of detection algorithms in digital mammography. *Med Phys* 1999;26:267–275. [PubMed: 10076985]

Fig. 1.
Schematic overview of the registration strategy.

Fig. 2.

Breast contour extraction: (a) a MLO image; (b) the threshold (binary) image of (a); and (c) the contour of the binarized region with the largest area is traced. It can be seen that the breast region is located at the largest concave region. To obtain the breast contour, the convex hull of the contour is computed and shown in (d).

Fig. 3.

Examples (a)–(d) of the ellipse fitting performance: the top row shows the MLO views and the bottom row shows the CC views. The thick contours represent the fitted breast contour as described in Sec. II A. The crosses indicate the origins of the reference coordinate system in identifying the matching strip.

Fig. 4.

Illustration of the registration of two mass regions depicted on the MLO view (a) and CC view (b). The reference coordinate systems of the MLO and CC views are specified, respectively, by the local two-dimensional Cartesian coordinate systems (X_1, Y_1) and (X_2, Y_2) with the origins at O_1 and O_2 correspondingly. In addition, r_1 and r_2 are the registered centerlines; s_1 and s_2 indicate the “gold-standard” lines that pass through the centers of two mass regions; and d_1 and d_2 measure the distance between the origin of coordinate system to the registered centerline and gold-standard line, respectively.

Fig. 5.

Examples of matching performance: the top row shows the MLO views and the bottom row shows the CC views of the same cases. In each case, the rectangle box represents the mass location and size, the cross is the origin of the coordinate system, two straight lines are automated identified center line of the matching strip and a reference line that passes through the mass region center and is parallel to the matching strip.

(a)

(b)

FIG. 6. Matching error distribution between the mass region centers and the corresponding registered centerlines: (a) the absolute distance error and (b) the relative distance error distribution.