Automating Quality Assurance Metrics to Assess Adequate Breast Positioning in Mammography

Gerald R. Kolb, JD, The Breast Group, Sunriver, OR; Kaier Wang, PhD, VolparaSolutions, Wellington, NZ; Ariane Chan, PhD, VolparaSolutions, Wellington, NZ; and Ralph Highnam, PhD, VolparaSolutions, Wellington, NZ

Abstract

Introduction
Breast positioning is one of the key factors that can affect the performance of mammographic screening and is a leading cause of mammography units failing to earn accreditation in the United States [1]. Optimal positioning can reduce unwanted artifacts and ensure that the maximum amount of breast tissue is being included in the image. As manual quality review of mammographic images can be both subjective and time-consuming, research is underway to automate image quality assessment. Fundamental to such automated methods, is correctly identifying both the nipple and the pectoral muscle on mammographic images.

Objectives
The purpose of this study was to preliminarily assess whether breast positioning for mammography might be objectively analyzed. The first objective of this study was to assess the performance of a novel algorithm for automated nipple detection. The second objective was to assess two additional breast positioning metrics that rely on correct identification of the nipple (i.e. the relative lengths of the posterior nipple line on the CC and MLO views and the extension of the pectoral muscle relative to the position of the nipple on the MLO) and how these metric compare to a visual clinical image review and automated breast volume estimates.

Materials & Methods
The dataset used to evaluate the breast-positioning algorithm comprised of standard four–view mammographic studies [i.e. left craniocaudal (LCC), right CC (RCC), left mediolateral oblique (LMLO) and right MLO (RMLO)] from 23 women. The algorithm was run over the raw images to automatically assess the following:
- correct identification of the nipple that the length of the posterior nipple line (PNL) on the CC views was within 1 cm of that on the MLO views
- that the inferior edge of the pectoral muscle on the MLO views extends to or below the level of the nipple.

The results of the algorithm were visually assessed to determine its accuracy. Comparisons of the breast volume estimates between CC and MLO views and left and right breasts were used as a surrogate measure of the consistency in breast positioning.

Conclusion
Automated methods for assessing adequate breast positioning in mammography have the potential to improve the quality of mammographic images and, therefore, clinical performance.

Automating Quality Assurance Metrics to Assess Adequate Breast Positioning in Mammography
The mortality benefits of mammographic screening are largely dependent on the ability to detect cancers at as early stage as possible. Therefore, it is critical that mammograms are acquired and interpreted to the highest possible standards of quality. Efforts to ensure and improve the quality of screening mammography (including breast tomosynthesis) should focus on aspects of the acquisition process that are known to affect the sensitivity of the final interpretation. Breast positioning is one of the most important of these factors and is a leading cause of accreditation failure in the United States. More importantly, poor positioning can lead directly to delayed diagnosis of breast cancer, potentially impacting patient mortality and morbidity. With delayed diagnosis of breast cancer also retaining its position as the number one source of medical legal risk, the impact of poor positioning goes far beyond its importance as an accreditation standard.

Although positioning plays a critically important role in image quality, automated tools to assess breast positioning in real-time are currently lacking. There are numerous clinical benefits to presenting a set of easily understandable, objective metrics of breast positioning, including:
- The potential for technologists to retake inadequately positioned images immediately, while the patient is still in the clinic, rather than having to re-schedule or recall her.
- The opportunity for incorporating automated positioning metrics into quality assurance guidelines.
The ability to perform system-wide and population-wide analyses comparing breast positioning. In this study, the performance of a novel algorithm for the automatic assessment of two breast positioning metrics from digital mammograms was assessed by comparison to a visual clinical review and automated, volumetric, breast density measurements.

**Materials & Methods**

Evaluation of the breast-positioning algorithm utilized a set of “For Processing” digital images comprising the standard four-view screening image sets (i.e. left craniocaudal (LCC), right craniocaudal (RCC), left mediolateral oblique (LMLO) and right mediolateral oblique (RMLO)) from 23 women. The algorithm determined the following three measurements, which are described in more detail below:

- The location of the nipple
- The length of the posterior nipple line (PNL) (distance from edge of image to the nipple) on the CC views and on the MLO views
- The relationship of the lower edge of the pectoral muscle on the MLO view and the level of the nipple

**Automated nipple detection**

The nipple was automatically detected and its location defined using the following process:

1. For processing digital mammography images (Figure 1A) were processed by the Volpara algorithm to obtain a breast density map containing the thickness of dense tissue between each pixel in the image and the x-ray source.
2. As the anterior breast edge is comprised of skin, the nipple and a thin subcutaneous layer of fat, and contains little fibroglandular (dense) tissue, the image was processed to accentuate this breast edge (see Figure 1B, the breast edge is indicated by the dark pixels).
3. The density map was then filtered by a morphological operation to highlight only the likely positions of the nipple (see Figure 1C).
4. The breast edge was determined (see Figure 1D).
5. Scanning the edge strip downwards, its average pixel intensity evolution was analyzed for a global maximum value, the y-coordinate of which corresponds to the nipple projection position on the breast edge (see Figure 1E).

**Calculation of the PNL**

The detected nipple serves as a reference point for PNL length measurement. Calculation of the PNL is depicted in 2, and was determined as follows:

1. Volpara Algorithm™ was used to first identify the edge of the pectoral muscle (see Figure 2, red lines).
2. The PNL was then measured as the perpendicular distance (in cm) between the detected nipple and the pectoral edge on the MLO view, and the distance between the detected nipple and the edge of the image on the CC view.

![Diagram of nipple detection and PNL calculation](image)

1: Procedure for Nipple detection. A Raw mammogram image; B Volpara Algorithm processed density map indicating dense tissue height; C Morphological filter processed density map highlighting the nipple object; D Extraction of breast edge strip; E Average pixel intensity change at the breast edge strip.
2: Illustration of how the breast-positioning algorithm calculates the Pectoral Nipple Line (PNL) for CC and MLO views.

3: A) Example CC image showing automated algorithm correctly identifying the location of the nipple (green circle). B) Example MLO image where the algorithm detected that the pectoral muscle (red line) did not extend to or below the level of the nipple (green circle).

4: Example case where the PNL distances for the right MLO and right CC views were not within 1 cm, and the corresponding breast volumes for the right MLO and right CC is large. In contrast, the PNL distances for the left MLO and left CC views are within 1 cm, and the breast volumes for the left MLO and left CC is much smaller.
Assessing adequate extension of the pectoral muscle

To assess optimal positioning of the MLO view, the positioning algorithm automatically identified the pixel coordinates of the nipple relative to the lower edge of the pectoral muscle.

All cases were visually reviewed to determine that the algorithm correctly identified the location of the nipple (see example in Figure 3A). Well-positioned images were considered to be ones where: (1) the PNL on corresponding CC and MLO views were within 1 cm; and (2) the lower edge of the pectoral muscle extended to at least the level of the nipple on MLO views. To further assess the clinical relevance of the automated PNL estimates, differences in the PNL between corresponding CC and MLO views were compared to breast volume estimates.

Results

The positioning algorithm correctly detected the location of the nipple in all images from the 23 cases. The PNL distances for corresponding CC and MLO views were within the 1 cm criteria for 50% (23/46) of the image pairs. The pectoral muscle on the MLO view was determined to be adequately positioned (i.e. at or below the level of the nipple) in 70% (32/46) of images. In only those MLO images where the pectoral muscle was considered to be well-positioned relative to the nipple, the PNL distances were within the 1 cm criteria for 53% (17/32) of image pairs. 3B is an example where the location of the pectoral muscle reflects suboptimal positioning according to the algorithm.

Overall, Pearson Correlation Coefficients (PCC) indicated the breast volume estimates from Volpara algorithm were highly correlated for the LCC versus RCC (0.908), LMLO versus RMLO (0.953), CC versus MLO (0.954) and left versus right breasts (0.954). The results from the automated positioning metrics were significantly correlated to the breast volume estimates (see 4 for an example case). For example, for corresponding CC and MLO images where the PNL distances were within the acceptable range (i.e. 1 cm), smaller differences between the CC and MLO breast volumes were observed compared to images that had PNL differences greater than 1 cm (median differences in breast volumes were 89.4 cm³ and 165.7 cm³, respectively; p = 0.03). This suggests that the automated positioning metrics can predict the risk of posterior tissue being excluded from the image.

Discussion

Optimal breast positioning in mammography is fundamental for obtaining high quality images. However, previous attempts at real-time, automated quality control appear to have floundered, largely due the sheer number of factors that need to be considered and the fact that they can vary depending on the underlying patient population. This paper outlines promising preliminary work to automate key factors used in the assessment of patient positioning, with applicability to both digital mammography and breast tomosynthesis. Such positioning metrics can be easily integrated into real-time alerts or presented in survey-form with no disruption to the clinical workflow.

Recently, systems have started to become commercially available that can relay both positioning and image quality information in survey-form, in the context of the underlying population. Thus, technologists can be told, for example, that their MLO versus CC PNL distances meet the criteria for good positioning more so for women with smaller breasts, or that a large proportion of images are blurry when they have not used sufficient mammographic compression. These types of metrics can be utilized to identify training opportunities, as well as allow technologists to measure how their performance compares to their colleagues both within their center and nationally.

Post Script

The research on this topic has continued with good results and we will be submitting another abstract to NCBC this year that outlines that process and the improvements as the algorithm has evolved.

References