A validation study of automated mammographic breast positioning metrics

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Authors: K. Wang, E. Ross, N. Khan, C. Tromans, L. Johnston, A. Chan, R. Highnam; Wellington/NZ
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Aims and objectives

The aim of screening mammography is the early detection of breast cancer, and to achieve this goal, optimal image acquisition with maximum breast tissue visualization are essential. Mammography has been described as the science of imaging, and the art of positioning [1]. Advances in hardware and software have largely addressed the technical factors of exposure, sharpness, noise and contrast that can affect image quality. Good positioning of the breast is a key factor affecting interpretive capability and numerous studies indicate that accepting even borderline positioning reduces visualization and, subsequently, mammographic sensitivity [2, 3]. Inclusion of maximal breast tissue through correct positioning is monitored and controlled by the technologist and is vulnerable to variation.

Furthermore, the assessment of image adequacy is also plagued with variation due to the subjective nature of visual assessment of breast positioning. The current method of peers judging peers is less than optimal with the process heavily relying on labour-intensive manual assessment. Adding to the difficulty of monitoring breast positioning and image quality, is the fact that current standards and guidelines are subjective and vary globally. The American College of Radiology (ACR) [4], The Royal Australian and New Zealand College of Radiologists (RANZCR) [5] and the NHS in the United Kingdom [6] all publish quality assurance guidelines for mammography, but differ in the frequency that assessments should be made, as well as the exact definition of good positioning.

Although optimal positioning is integral to screening mammography, and its assessment is such a time consuming subjective task, automated tools to assess breast positioning 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 them;
- The opportunity for incorporating automated positioning metrics into quality assurance guidelines; and
- 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 four breast positioning metrics from digital mammograms was assessed by comparison to an internal ground truth analysis.
Methods and materials

Evaluation of the breast-positioning algorithm utilized 715 "For Processing" digital mammographic images, comprising of a mix of the standard four-view screening images (i.e. left craniocaudal (LCC), right craniocaudal (RCC), left mediolateral oblique (LMLO) and right mediolateral oblique (RMLO)). The algorithm determined the following four measurements, which are described in more detail below:

- The location of the nipple
- Whether or not the nipple was in profile
- Whether the nipple was pointing medially or laterally (craniocaudal (CC) views only)
- Whether or not the inframammary fold (IMF) was visible (mediolateral oblique (MLO) views only).

Automated nipple detection

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

1. For processing digital mammography images (Fig. 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 Fig. 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 Fig. 1C).
4. The breast edge was determined (see Fig. 1D).
5. Scanning the edge strip downwards, the pixel values were analyzed to find the nipple coordinate (see Fig. 1E).

Nipple profile detection

Followed by the nipple detection, the nipple profile was determined based on the procedures below:
1. Combing texture feature and adaptive thresholding methods (Fig. 2A), the pixels belonging to the entire nipple object were determined in the vicinity of the pre-located nipple projection position (see the red object in Fig. 2B).
2. Based on the margin of the nipple object and the curvature of the breast boundary, the areola boundary was therefore estimated (see the blue line in Fig. 2B).
3. Nipple profile was reported as a binary score based on the sufficient percentage area of the nipple that was located anterior to the areola boundary.

Refined nipple location

Once the entire nipple object was found, a more precise nipple location can be extracted by averaging the coordinates of the pixels for the nipple object.

Nipple pointing direction

The angle subtended by the line from the midpoint posterior breast edge perpendicular to the posterior image edge and the line from the midpoint of the posterior breast edge to the nipple was first determined (see Fig. 3). For a negative angle, the nipple was considered to be pointing medially. For a positive angle, the nipple was considered to be pointing laterally.

IMF visibility detection

The IMF region was searched for in the lower posterior quadrant of MLO images, with the determined nipple location being the origin. Then, a morphological filter was applied on this restricted posterior quadrant to highlight the corner pixels as IMF candidates (see red corner in Fig. 4). The IMF visibility is determined based on the area of the candidature pixels reaching a particular threshold.
Fig. 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 Pixel values at the breast edge strip.

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Fig. 2: Nipple profile detection. A Morphological filter processed density map highlighting the nipple object; B Extracted nipple object (red) and areola boundary (blue line).

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**Fig. 3:** Demonstrations for nipple pointing A medially or B laterally.

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Fig. 4: Highlighted IMF corner (red) superimposed on a density map being morphological filter processed. The image is divided into four quadrants with the nipple as the origin. The IMF corner is searched for in the lower left quadrant.

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Results

The nipple XY co-ordinate was marked on every image and nipple location error was computed between the algorithm and ground truth. The median nipple location error was very low at 1.5 mm (IQR 0.9 - 2.7 mm; see Fig. 5) and the algorithm correctly identified the nipple location (i.e. within 10 mm) in 99.4% of images.

Whether the nipple was in profile was assessed visually and reported as "Yes" or "No". The algorithm computed the correct result 84.6% of the time (Table 1) and the incorrect results were similar for when the nipple was and was not in profile.

The algorithm outputs a positive or negative angle if the nipple is pointing laterally or medially, respectively. Using a threshold of ±10°, the algorithm correctly identified which direction the nipple was pointing in 72.7% of CC images (Table 2). There was only 1 case where the algorithm computed the opposite direction to the ground truth and the most disagreements occurred around the threshold of horizontal and medial/lateral.

Lastly, when determining whether the IMF was visible, the algorithm agreed with the reader on 87.7% of MLO images (Table 3). The algorithm did not correctly identify the IMF (compared to ground truth assessments) 9.8% of the time.
**Fig. 5:** Range and frequency of nipple location error (mm) between ground truth visual assessment and algorithm.

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<table>
<thead>
<tr>
<th>Nipple in Profile – Ground Truth</th>
<th>Nipple in Profile – Algorithm</th>
<th>No</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>No</td>
<td>86 (12.0%)</td>
<td>58 (8.1%)</td>
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<tr>
<td>Yes</td>
<td>Yes</td>
<td>52 (7.3%)</td>
<td>520 (72.6%)</td>
</tr>
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<td></td>
<td></td>
<td>138 (19.3%)</td>
<td>578 (80.7%)</td>
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**Table 1: Nipple in Profile Agreement**

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Table 2: Nipple direction on CC view

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<table>
<thead>
<tr>
<th>Nipple Direction - Ground Truth</th>
<th>Horizontal</th>
<th>Lateral</th>
<th>Medial</th>
</tr>
</thead>
<tbody>
<tr>
<td>Horizontal</td>
<td>172 (59.3%)</td>
<td>6 (2.1%)</td>
<td>21 (7.3%)</td>
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<tr>
<td>Lateral</td>
<td>25 (8.6%)</td>
<td>13 (4.5%)</td>
<td>1 (0.3%)</td>
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<tr>
<td>Medial</td>
<td>26 (8.9%)</td>
<td>0</td>
<td>26 (8.9%)</td>
</tr>
<tr>
<td>Total</td>
<td>223 (76.9%)</td>
<td>19 (6.6%)</td>
<td>48 (16.6%)</td>
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Table 3: IMF visible on MLO view

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<thead>
<tr>
<th>IMF visible – Ground Truth</th>
<th>No</th>
<th>Yes</th>
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<tbody>
<tr>
<td>No</td>
<td>115 (31.3%)</td>
<td>9 (2.5%)</td>
</tr>
<tr>
<td>Yes</td>
<td>36 (9.8%)</td>
<td>207 (56.4%)</td>
</tr>
<tr>
<td>Total</td>
<td>151 (41.1%)</td>
<td>216 (58.9%)</td>
</tr>
</tbody>
</table>
Conclusion

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 to 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. Such positioning metrics can be easily integrated into real-time alerts or presented in survey-form with no disruption to the clinical workflow.

As shown in our methods, a precise nipple detection is essential in deriving other positioning metrics. The result of our nipple detection was compared with other methods in the literature and found to outperform many previous attempts. van Engeland et al. reported a 75.15% accuracy (detecting nipple within 10 mm error) out of 566 images from two public databases (mini-MIAS and DDSM) [7]. Using the same databases, the method of Paola, despite having an accuracy of 79.3% and mean error of around 6 mm, which is the most promising result quoted in the literature, has a maximal error over 50 mm (nearly three times as large as our 17 mm maximal error) [8]. Finally, Chandrasekhar and Attikiouzel declared a 96% accuracy within 1 mm error, but their methods were tested on only 24 images [9]. Also it is worthwhile to mention that our positioning methods were developed based on the Volpara density map, a normalised description of the mammogram independent of the image contrast or noise, resulting in a robust method independent of image condition.

Having the ability to access automated, objective positioning results may help improve with training of technologists and performance throughout their career. A recent study by Miglioretti et al., among CT technologists determined that providing them with audit feedback on patient radiation dose in CT imaging could lower patient dose [10]. Although this is a different radiologic examination, their study shows that personalised feedback on performance can change the technologists’ attitudes and behavior. A recent Cochrane Collaboration review [11] found that audits on professional performance are most effective when the professionals are not performing well. Therefore, using these positioning metrics in countries where peer-review is not systematic or accreditation is done infrequently, could improve image quality substantially and potentially affect screening programs. A study from The Netherlands has also highlighted the importance of ongoing review of technologist performance throughout their career [12] as they found overall positioning technique was lower in the more experienced technologists compared to the newer recently trained technologists.
In addition to individual metrics being reported, future work will focus on the incorporation of these metrics into an overall score. This will allow people to use an automated system that is more aligned with current guidelines which recommends assessing multiple components of an image. However, for an overall score to work, every individual component must have high accuracy and reproducibility. Compared to visual ground truth assessment, our automated algorithm for breast positioning is highly robust and has the potential to improve the efficiency of assessing mammographic breast positioning.
Personal information

Kaier Wang, PhD, Volpara Solutions Ltd
Kyle.Wang@volparasolutions.com

Emma Ross, MSc, Volpara Solutions Ltd
Emma.Ross@volparasolutions.com

Nabeel Khan, PhD, Volpara Solutions Ltd
Nabeel.Khan@volparasolutions.com

Chris Tromans, PhD, Volpara Solutions Ltd
Chris.Tromans@volparasolutions.com

Lisa Johnston, PhD, Volpara Solutions Ltd
Lisa.Johnston@volparasolutions.com

Ariane Chan, PhD, Volpara Solutions Ltd
Ariane.Chan@volparasolutions.com

Ralph Highnam, PhD, Volpara Solutions Ltd
Ralph.Highnam@volparasolutions.com
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