COMBINING ADAPTIVE SEGMENTATION APPROACH FOR IMPROVING MULTI-RESOLUTION IMAGE REGISTRATION ON X-RAY MAMMOGRAMS ACQUIRED USING FISCHER’S FUSED FULL FIELD DIGITAL MAMMOGRAPHY AND ULTRASOUND SYSTEM (FFDMUS)

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ABSTRACT: Mammogram registration can help avoid biopsies and help follow-up analysis. Mammogram registration is a challenge because of the compressibility of the breast tissue.

We used the CIRS breast phantom image to study the registration methodology. The phantom images were acquired in Fused Full Field Digital Mammogram and Ultrasound (FFDMUS) framework. The acquired images were registered using our proposed three-stage registration system. The registration results were measured and evaluated, and the comparison was made for the registration procedure with and without mask operation.

It is demonstrated that the mask operation can help improve the performance of the intensity based registration. The mean error from the polyline distance measurement is improved by 19.6%, and the standard deviation of the error is improved by 13.7%.

KEY WORDS: Fused system, image registration, adaptive segmentation, mutual information, polyline distance

1. Introduction

Medical Image registration has been an active topic of research for over a decade. This is particularly useful in image fusion of mono- and multi- modality, such as MR with CT, MR with PET, etc. (Maintz et al. [1]). The registration techniques are usually divided into two groups, feature-based and intensity-based. Feature-based technique uses features extracted from image, such as points and curves, for image matching. Intensity-based technique uses image gray level intensities directly, and no pre-processing of the feature extraction is required. Most of the past research in medical image registration has been focused on brain imaging [2-8].

The research on mammogram registration is a challenging problem. In the mammographic study, the 3-D positioning of the breast, the amount of pressure applied to it through compression, and the imaging conditions may vary considerably. This is in addition to the inhomogeneous, anisotropic nature of the soft-tissue within the breast, and its inherent non-rigid body behavior. These factors result in various spatial differences between breast images, including nonrigid deformations. Such variations make the registration of mammogram pairs difficult. In literature, some approaches have been described for mammogram registration. Martí et al. [9] proposed a two-stage strategy that utilized a combination of segmentation and registration. The segmentation stage was developed to extract control points, which were the input for the thin-plate spline (TPS) registration process. Sanjay-Gopal et al. [10] described a regional registration technique for identifying masses on temporal pairs of mammograms, and Hadjiiski et al. [11] improved lesion registration by including a local alignment step. In their methods the breast region was segmented from the background first, and the breast border and nipple located were used for initial global alignment. Then the search region was refined by warping and alignment, and the optimal region was located. Yin et al. [12] described a three-stage automated technique for the alignment of right and left breast images. In the segmentation stage, the breast region was segmented using gray-level thresholding and morphological filtering operation. In the image feature extraction stage, breast borders and nipple positions were extracted as landmarks to establish the correspondence between two breast images. In the registration stage, one of the two images was translated and rotated to match spatially with the other breast image. Richard et al. [13] described a method that combined feature and intensity-based registration constraints in the same mathematical model. But his method focused on the region of interest (ROI) instead of the whole image. It had two stages. In the segmentation stage, the breast regions were isolated from the background, and the breast contours were extracted. Then in the second stage, breast regions, breast contours, and the initial transformation after matching the breast contours were all combined into the numerical iterations to find the optimal parameters for the energy term being defined. All of the above methods used the combination of segmentation and registration, and the registration result depends on the features...
extracted from the segmentation stage. Wirth et al. [14] proposed a non-rigid registration algorithm. First a normalized mutual information (NMI)-based global registration was performed to find the approximate rigid alignment. Then the mammograms were partitioned into smaller sub-images, and each pair of the corresponding sub-images was matched independently using NMI. The control point pairs constructed from the aligned sub-images were associated with TPS registration to generate a smooth global non-rigid transformation. No pre-processing is required in this method, but the control point extraction is still important for the registration accuracy.

In this paper, we propose a mask based registration strategy. The mask generation is the segmentation method based on adaptive thresholding. Compared to previous mammogram registration techniques, our strategy here is to first use breast boundary as mask for region of interest (ROI) extraction, then use ROI for image registration. The registration error is evaluated using a polyline distance measurement.

The layout of the paper is as following. Section 2 describes the combined segmentation and registration system. Section 3 presents the experimental protocol and results, and the conclusion is given in section 4.

2. Brief Overlay of the System

The algorithm proposed is illustrated in Figure #1. This combined registration system has three stages: segmentation stage, registration stage and performance evaluation stage.

In the segmentation stage, breast images were thresholded using adaptive thresholding techniques similar to the method by Ojala et al [15]. Then morphological operations were implemented to smooth the boundary. The binary image obtained was taken as the mask to operate on the original breast images, and masked images were used in the following registration stage.

The registration process is a multi-resolution NMI-based registration procedure. The transformation parameters are first optimized at the coarsest level, and then these parameters are used as the initial parameters for the next level, until the finest level is reached.

In the performance evaluation stage, the registered results were segmented again. The breast boundaries of the registered source image and the target image were extracted, and the polyline distance between two boundaries were computed. The calculated distance was used as the performance evaluation for the registration.

2.1 Theory of Registration

2.1.1 Definition

Image registration can be defined as a mapping between two images both spatially and with respect to intensity. Given two images denoted by \( I_1 \) and \( I_2 \), the mapping between images can be expressed as:

\[
I_2 = g(T(I_1))
\]

where \( T \) is the spatial transformation, and \( g \) is the intensity transformation function.

The registration problem is to find the optimal spatial and intensity transformations such that the images are matched either for determining the parameters of the matching transformation or for exposing the differences of interest between the images. Most of the time, the intensity transformation is not necessary, and often a simple lookup table will be sufficient. In the medical image registration, when multi-modality images are treated, the intensity mapping will be redundant since the complementary properties of the images are to be preserved for image fusion. So when the image registration is mentioned, we are talking about spatial transformation.

2.1.2 Normalized Mutual Information (NMI)

Mutual information (MI) is a similarity criteria derived from an information-theoretic approach to measure the dependence of one variable on another. It has been applied to medical image registration independently by Collignon et al. [2] and Wells et al. [3]. MI is based on the shared information between the overlapping regions in the two images, which should be maximized at registration. It was demonstrated that mutual information based registration technique performed better for mammograms (Engeland et al. [16]).
The definition of the mutual information $I$ of two images $A$ and $B$ combines the marginal and joint entropies of the images in the following manner

$$I(A,B) = H(A) + H(B) - H(A,B)$$

where

$$H(A) = - \sum_a p_a(a) \log p_a(a)$$

$$H(B) = - \sum_b p_b(b) \log p_b(b)$$

and

$$H(A,B) = - \sum_{a,b} p_{ab}(a,b) \log p_{ab}(a,b)$$

$P_A(a)$ and $P_B(b)$ denote the marginal distributions of the image intensities of $A$ and $B$, respectively, and $P_{AB}(a; b)$ is their joint probability. $H(A)$ and $H(B)$ are the entropies of $A$ and $B$, and $H(A,B)$ is their joint entropy, i.e., the entropy of the joint probability distribution of the image intensities.

Studholme et al. [4] have shown that the mutual information measure is sensitive to the amount of overlap between the images. Normalized mutual information (NMI) was introduced to overcome this problem.

$$NMI(A,B) = \frac{H(A) + H(B)}{H(A,B)}$$

where $NMI(A,B)$ is the normalized mutual information between image $A$ and $B$. NMI was adapted as the similarity measure in this paper.

### 2.1.3 Multiresolution Registration Framework

In the general registration framework, the transformation parameters are updated until the optimal solution, that maximizes the similarity measurements, is reached. Downhill simplex method is selected as the optimization strategy here.

Multi-resolution approach [5-8] is widely used in medical image registration. The idea of multi-resolution hierarchical approach is to register the coarse (low resolution) image first and then to use the result as the starting point for finer (high resolution) image registration, and so on. In practice, the multi-resolution approach proves to be helpful. It can improve the optimization speed, improve the capture range and the algorithm is relatively robust.

### 2.2 Segmentation

The thresholding method developed by Ojala et al [15] is fully automated and gives correct results for digitized mammograms, including low-quality images.

#### 2.2.1 Histogram Analysis

The selection of the threshold is based on the analysis of the histogram of a mammogram. Figure #2 shows a mammogram and its histograms. $P_{bg}$ indicates the background bump, and $P_{br}$ is the second bump corresponding to the breast area. The threshold being selected is denoted as $t_0$. The selection of $t_0$ will be described later in the next section.

The intensity value $p_t$ corresponding to the peak within the bump $P_{bg}$ is first located. For the calculation of $p_t$, the bin range of the peak is first determined, and the position $t_0$ is the bin corresponding to the maximal value within the bin range.

The upper bound of the bin range $[p_c, p_{max}]$, $p_{max}$ is the rightmost bin of the histogram. The lower bound $p_c$ is determined as the first large change in histogram values occurs when examined from $p_{max}$ toward bin 0.

![Figure #2: Histogram analysis](image)

The “discontinuity” is measured by the local discontinuity measure $ldm(q)$, which is defined for the current bin $q$ as:

$$ldm(q) = \sum_{j=0}^{K} [H(q-K/2+j) - H(q-K/2+1+j)]$$

where $K$ is the size of the local window. We modified $K$ value to 11, which is determined experimentally in [15].

Let $p_{var}$ be the position of the maximum $ldm(q)$ within the background bump $P_{bg}$.

$$p_{var} = \{ q : \arg \max_{q \in P_{bg}} ldm(q) \}$$

The threshold $t_0$ is selected within the bin range $[p_{var}, p_b]$. Therefore, the threshold $t_0$ is the position of the maximal increase in $ldm(q)$ within this range. The original mammogram is thus thresholded using $t_0$.

### 2.2.3 Morphological Filtering

The approximate breast area is obtained by histogram thresholding. Due to uneven contrast from the
compression tapering along the breast boundary (skin-line) and noises along the boundary, the morphological closing and opening are used to smooth the boundary. Morphological opening and closing are the combination of the basic morphological operations: dilation and erosion. Dilation joins (fills) the pieces of a segmented area along the boundary of the region, while erosion removes (breaks) small pieces of a segmented area at the edge.

In order to fill join small pieces and remove jaggedness, the binary image is first processed by the closing operation with a disk-shaped SE, \( S_{d_1} \), where \( d_1 \) is the diameter of the element. Then, the binary image is processed by an opening operation with a disk-shaped SE, \( S_{d_2} \) of the diameter \( d_2 \). The parameters \( d_1 \) and \( d_2 \) are modified from the experimental number in [15]. We used \( d_1 = 5 \) pixels and \( d_1 = 21 \) pixels.

2.3 Polyline Distance Measure (PDM)

In order to evaluate the performance of the registration technique, a quantitative error evaluation method is developed. The quantitative measure is based on the average polyline distance [17-19] of each boundary points. Polyline distance is defined as the closest distance from the estimated boundary/skin-line points on the boundary detected from the registered source image to the boundary detected from the target image. The closest distance of each estimated boundary point can be the perpendicular distance (shortest Euclidean distance) to one of the intervals made from the successive boundary points of the target image, or can be one of the end boundary points joining the points of the closest interval.

Let \( B_f \) be the first boundary, and \( B_2 \) be the second boundary. Let the Cartesian coordinate of a point \( A \) on \( B_1 \) be \((x_0, y_0)\). Let there be two successive boundary points \( B \) and \( C \) given by coordinates \((x_1, y_1)\) and \((x_2, y_2)\) on \( B_2 \). The two distance measures \( d_1 \) and \( d_2 \) between \( A \) on \( B_1 \) and \( B/C \) on \( B_2 \) are defined as Euclidean distances:

\[
\begin{align*}
  d_1 &= \sqrt{(x_0 - x_1)^2 + (y_0 - y_1)^2} \\
  d_2 &= \sqrt{(x_0 - x_2)^2 + (y_0 - y_2)^2}
\end{align*}
\]

The polyline distance \( d_{poly} \) is then defined as:

\[
  d_{poly}(A, B/C) = \begin{cases} 
    \min\{d_1, d_2\}; & \text{if } \lambda < 0, \text{ or } \lambda > 1 \\
    \left| \frac{d_1}{d_2} \right|; & 0 \leq \lambda \leq 1
  \end{cases}
\]

where,

\[
  \left| \frac{d_1}{d_2} \right| = \left| \frac{x_0 - x_1}{x_0 - x_2} + \frac{y_0 - y_1}{y_0 - y_2} \right| \\
  \left| \frac{x_1 - x_2}{x_1 - x_0} + \frac{y_1 - y_2}{y_1 - y_0} \right|
\]

A quantitative error measurement could be defined as the polyline distance described as \( d_{poly} \). It is defined as the average polyline distance of all boundary points of the estimated and ground-truth breast boundaries. We will denote it as \( d_{poly}^{\text{Error}} \). The following equations show the derivation:

\[
  d_{b}(A, B_2) = \min_{S_{\text{diameter}}} d(A, S)
\]

\[
  d_{vb}(B_1, B_2) = \sum_{v_{\text{vertices}}} d_{b}(A, B_2)
\]

The polyline distance between two boundaries is then defined as the average distance errors:

\[
  d_{poly}^{\text{Error}} = \frac{d_{b}(B_1, B_2) + d_{vb}(B_2, B_1)}{\#\text{vertices} \in B_1 + \#\text{vertices} \in B_2}
\]

3. Experimental Protocol and Results

The phantom we used is the CIRS (Norfolk, VA) breast phantom having spherical lesions with diameter of 5 mm. The phantom was scanned by the integrated FFDMUS under development in Fischer Imaging Corp. The acquisition X-ray parameters kVP, mA and ADU were chosen as 35, 100, and 910 respectively. The ideal ADU for a good contrast image is between 700 and 1000.

We rotated the phantom approximately 2° continuously and scanned the phantom to yield a sequence of rotated images. These images were grouped in pairs to test the registration algorithm.

Figure#3 shows an example of phantom image, its corresponding mask image, overlaid image of mask and original image, and the ROI extracted. Two groups of experiments were performed on the same group of phantom image pairs, and the registration results were compared. First group is the registration without segmentation, or without mask. Second group is the registration with mask. Figure #4 gives example of registration results with mask. The first row shows the overlaid image of target and source mask images and their boundaries before registration, while the second row shows the overlaid image of target and registered source mask images and their boundaries after registration. Here the mask images were used instead of gray scale image to better illustrate the registration results.

The registration errors are listed in table #1. Out of the 30 phantom image pairs, we computed the mean error and the standard deviation of the error with and without mask. The table shows that the improvement on the mean is 19.6% after mask operation was applied, and the improvement on the standard deviation is 13.7%.
Figure #3: First row: phantom image (left), binary mask (right); Second row: overlaid image (left), ROI extracted (right).

Table #1: Comparison of mean and standard deviation.

<table>
<thead>
<tr>
<th></th>
<th>Mean (µ)</th>
<th>Standard deviation (σ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>With Mask</td>
<td>2.747 pixels</td>
<td>2.499 pixels</td>
</tr>
<tr>
<td>Without Mask</td>
<td>3.416 pixels</td>
<td>2.896 pixels</td>
</tr>
</tbody>
</table>

Figure #4: Overlaid images. First row: before registration; Second row: after registration.

4. CONCLUSIONS

It is demonstrated that mutual information based registration method has a robust performance on the registration of X-ray phantom images. The mask obtained from the segmentation operation can help improve the performance of the registration procedure after the mask was applied to the original images. We used the polyline distance as a measure to evaluate the performance of the registration techniques with and without mask. Experiments showed an improvement of 19.7% in mean error, and 13.7% in standard deviation of the registration errors, after mask is applied.

References:

11. Hadjiiski, L., Chan, H., Sahiner, B., Petrick, N., Helvie, M. A., Automated registration of breast lesions in temporal pairs of mammograms for interval


