An Improved Algorithm Based on SIFT and Graph Transformation for Mammogram Registration

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Abstract

Mammogram registration is an important step in the processing of automatic detection of breast cancer. It provides aid to better visualization correspondence on temporal pairs of mammograms. This paper presents an improved algorithm based on SIFT feature and Graph Transformation methods for mammogram registration. First, features are extracted from the mammogram images by scale invariant feature transform (SIFT) method. Second, we use graph transformation matching (GTM) approach to obtain more accurate image information. At last, we registered a pair of mammograms using Thin-Plate spline (TPS) interpolation based on corresponding points on the two breasts, and acquire the mammogram registration image. Performance of the proposed algorithm is evaluated by three criterions. The experimental results show that our method is accurate and closely to the source images.

Keywords: SIFT, Thin-Plate Spline, Graph Transformation Matching, Mammogram Registration

1. Introduction

Image registration is the process of overlaying two or more images of the same scene taken at different times, from different viewpoints, and/or by different sensors [1].

Research in the area of image registration has been receiving considerable attention, and a number of algorithms have been proposed over the last ten years. These algorithms of registration are applied to remote sensing images [2], natural scenes images [3], and some forensic science images [4], etc. In recent years, many researchers have worked on medical image registration, such as CT, MRI, and PET. However, the study of breast registration is rare. Mammography is one of the most the most effective and popular screening technology for the early detection of breast cancer. Radiologists use the temporal pairs of mammograms to provide reliable diagnosis, but it’s an extremely difficult task to obtain reliable diagnosis of abnormalities from a single mammogram even for a skilled radiologist. So, the development of mammogram registration plays an important role in the early detection of pathology.

In general, registration algorithms can be roughly divided into two main categories: intensity-based and feature-based registration methods [1]. Rueckert et al. employed a free-form deformation model based on B-splines to describe the local deformation of 3D breast MR images [5]. Jianzhe et al. proposed the free-form deformation based on non-uniform rational B-splines (NURBS) to acquire non-rigid transformation [6]. Although the intensity-based approaches are getting more attention by research community, they suffer from large computation effort. Furthermore, for small structure features in mammogram images, these approaches often tend to produce mis-registration results. In contrast, the feature-based methods are more accurate and faster to compute as long as the algorithms of feature extraction are reliable. Urschler et al. presented a feature-based non-linear registration method consist of 3D corner detection, local SIFT feature descriptor and global shape context feature descriptor, robust feature matching and calculation of a dense displacement field [7]. The quantitative and qualitative evaluations showed that their method produces superior results to some other methods. However, because breasts are elastic bodies, the two images differ significantly, it is not an easy task to extract features from some mammogram images and to compare mammogram images acquired at different screenings automatically. The primary sources of difference are variations in positioning, compression and changes normally encountered in breast. So, precise mammogram registration is much difficult and intractable [8].

In this paper, the reference mammograms are obtained from the MIAS digital mammogram database [9], and the sensed images are three simulated transformation images of the reference images.
Firstly, some preprocessing is applied on the mammogram images. Secondly, we employ SIFT algorithm to extract and match image features. Thirdly, we use GTM to eliminate outliers. So a more accurate and robust point-matching result can be obtained. At last, we use the correct point pairs to estimate the TPS model parameters and acquire the mammogram registration image after image resampling and transformation.

The rest of this paper is organized as follows: Section 2 acquires accurate control point pairs from the reference image and the sensed image. Section 3 obtains TPS transformation model using control point pairs acquired in Section 2. Experimental results are given in Section 4. Finally, in Section 5 we outline our conclusion.

![Figure 1](image1)  
(a) Original image mdb008; (b) binary representation; (c) extracting breast region;

### 2. Extracting control points pairs

Medical images present in the mammogram database often contain deliberately inserted identifiable labels, which need to be eliminated to avoid mismatching of features caused by labels.

In this section, we remove the labels and extract breast region from the mammogram using threshold segmenting and morphology methods [10]. The resultant image is shown in Figure 1.

### 3. Extracting potential points

SIFT algorithm [11] has been proved to be a very powerful approach in computer vision application. SIFT descriptor is robust to deformations such as translation, rotation and affine [12, 13]. SIFT extract potential landmarks from the two images by constructing a Gaussian pyramid and searching for local extreme over location and scale in a series of difference-of-Gaussian (DoG) images. Then, each landmark is described by a feature vector, which contains location, scale, and orientation. The scale space of an image is defined as a function $L(x, y, \sigma)$:

$$L(x, y, \sigma) = G(x, y, \sigma) \ast I(x, y)$$  \hspace{1cm} (1)

where $G(x, y, \sigma)$ is two-dimensional Gaussian kernel as follows:

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$  \hspace{1cm} (2)

$I(x, y)$ is an input image, and $\ast$ denotes the convolution operation. Difference-of-Gaussian function is $D(x, y, \sigma)$

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)) \ast I(x, y) = L(x, y, k\sigma) - L(x, y, \sigma)$$  \hspace{1cm} (3)
After the locations of control points are obtained, the orientation of every point is created by computing the gradient magnitude \( m(x, y) \) and orientation \( \theta(x, y) \) in a region around this point location.

\[
m(x, y) \sqrt{(L(x+1, y) - L(x-1, y))^2 + (L(x, y+1) - L(x, y-1))^2}
\]  

(4)

\[
\theta(x, y) = \tan^{-1}\left(\frac{(L(x, y+1) - L(x, y-1))}{(L(x+1, y) - L(x-1, y))}\right)
\]  

(5)

The next step is to match these control points. The best candidate match for each control point in the reference image is found by identifying its nearest neighbor from the sensed image. The nearest neighbor is formulated as the control point with minimum Euclidean distance of the eigenvector. Fig. 2 displays the results of potential points extraction (the green-colored crosses in two mammogram images) and alignment of these control points in two mammogram images by SIFT.

4. Removing incorrect matching pairs

In some cases, SIFT algorithm can’t obtain accurate matching result. For example, it can be seen that there are many mis-matching exist in Fig. 2 (c). In this section, we adopt a feature-graph point-matching algorithm named GTM [14] to remove incorrect matches using the local structure information. Its principle is to enforce coherent spatial relationships of corresponding points between both images [15]. GTM relies on the hypothesis that the transformation occurs between both images is reasonably smooth, so that neighbor points in the reference image correspond to neighbor points in second image, for example \( Q \{ q_i \} \) and \( Q' \{ q'_i \} \) of size \( N \) (where \( q_i \) matches \( q'_i \) ) are two sets of corresponding points (SIFT initial matching points). If the matches are all correct, graph \( G(Q) \) and \( G(Q') \) are isomorphic, otherwise, the structure of \( G(Q) \) is different from that of \( G(Q') \). The main steps of the GTM algorithm are as follows:

- Construct median K-nearest-neighborhood \( (K-NN) \) graph \( G_0 = (V_0, E_0) \) in the reference image and \( G'_0 = (V'_0, E'_0) \) in the sensed image.

- Construct the adjacency matrix \( A_0 \) and \( A'_0 \) based on the \( G_0 = (V_0, E_0) \) and \( G'_0 = (V'_0, E'_0) \). (where \( A_0 = 1 \) when \((i, j) \in E_0 \) and \( A_0 = 0 \) otherwise).

- Compute the residual adjacency matrix \( R = |A_0 - A'_0| \), and selecting column \( j^{\text{inc}} \) that yields the maximal number of different edges in both graphs. That is, if the column \( j^{\text{inc}} \) is consistent with the following formula: \( j^{\text{inc}} = \arg\max_{j} \sum_{i=1}^{N} R(i, j) \). The pair \( (V_{j^{\text{inc}}}, V'_{j^{\text{inc}}}) \) is viewed as an incorrect match.
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- Remove the pair \((V_j, V'_j)\), as well as all correspondence to them.
- Decrease \(N\), and repeat the above steps from the surviving vertices until \(R(i, j) = 0, \forall i, j\).

Now, consensus graphs have been found, and the vertices of the graphs also have been returned. Finally, we obtain accurate matching.

Figure 3 is an example of the graph transformation process for two mammogram images, from iteration 0 (initial graphs) to iteration 114 (final resultant graphs), with \(K = 12\). Parameter \(K\) is adjustable, and we can choose \(K = 11, 12, 15, 20\) based on the number of the initial matches. In our study, we find that the GTM algorithm is not sensitive to the change of \(K\) values.

5. Obtaining TPS transformation

TPS [16] transformation is a popular method for surface interpolation over scattered data, obtained by minimizing the bending energy \(\iint \left( \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \right)dx\,dy\) of the warping function \(f(x, y)\). The solution for the warping function \(f(x, y)\) which is the desired displacement at a point \((x, y)\) has the following form:

\[
f(x, y) = a_0 + a_1 x + a_2 y + \sum_{i=1}^{n} w_i U(r) \left( \| (x, y) - (x_i, y_i) \| \right)
\]  

where \(U(r) = r^3 \log r^2\) is called the kernel function and \((x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\) are control points.

In image registration, we actually need two warping functions, \(f_2(x, y)\) and \(f_1(x, y)\), to define displacements in \(x\) and \(y\) directions. The control point \((x_i, y_i)\) are points in the reference image and their corresponding points are denoted as \((x'_i, y'_i)\).

Using the set of control points in the reference image, a \(n \times 3\) matrix \(p\) is defined as

\[
p = \begin{bmatrix}
1 & x_1 & y_1 \\
& \vdots & \vdots \\
1 & x_n & y_n
\end{bmatrix}
\]  

\[(6)\]
Using the kernel function, we define $K$ as:

$$K_{ij} = U\left(U\left(x_i, y_i\right) - U\left(x, y\right)\right)$$

Finally, we define $L$ as a combination of $K$ and $P$:

$$L = K \begin{bmatrix} P \\ P^T \\ 0 \end{bmatrix}$$

where $0$ is a $3 \times 3$ matrix of zeros.

The solution of Eq. (6), i.e. the vector $W = (w_1, w_2, ..., w_n)$ and the coefficients $a_i, a_x, a_y$ is obtained from

$$L^T Y = [w | a_i, a_x, a_y]$$

where $Y = (V | 0 \ 0 \ 0)$, $V$ is an $n$-vector consisting of coordinates of the target points, i.e. $V = (x'_1, x'_2, ..., x'_n)$ to solve for $f_x(x, y)$ function of $X$-direction displacements and $V = (y'_1, y'_2, ..., y'_n)$ to solve for $f_y(x, y)$ function of $Y$-direction displacements.

In this process, we use 30 points, which are well-distributed in mammogram image to obtain TPS transformation and deformation.

### 6. Experimental results

In this paper, data derived from the MIAS digital mammograms database are used as the reference images and the reference images subject to two sinusoidal (sinusoidal-1, sinusoidal-2) transformations and an unknown local distort transformation, three of which are used as sensed images. We use the reference images and these three transformation images to assess the performance of the proposed algorithm.

The number of reference images is 10, five of which are non-label, others exist artificial label. The sinusoidal transformation function is described as follows:

$$X = x + a \left(\frac{y}{T}\right)$$

$$Y = y + a \left(\frac{x}{T}\right)$$

where $a = 8$ and $T = 128$ for Sinusoidal-1 and $a = 12$ and $T = 64$ for Sinusoidal-2 transformation respectively. The unknown local distort transformation is obtained by image processing software. In Fig. 4 a typical mammogram image (mdb001) of the breast along with its corresponding images transformed by the aforementioned three transformations are displayed.

The registration performance is evaluated in terms of the CC (correlation coefficient), SSD (sum of squared differences) and visual effect. Fig. 5, Fig. 6, Fig. 7 show the registration results of the reference image and one of transformation images using the proposed registration algorithm. It is clearly that most of the simulated deformations have been effectively recovered.

Figure 4. (a) Mammogram reference image with a superimposed square grid and the three corresponding images generated using; (b) Sinusoidal-1 transformation; (c) Sinusoidal-2 transformation; (d) Local distort transformation.
As shown in Table 1. In our experiments, the CC values of the pre-registered mammogram images are from 0.9692 to 0.9225. In registered images, the CC values are from 0.9988 to 0.9924, they are obviously increased. The SSD values also reduce.

<table>
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<tr>
<th>Mammogram</th>
<th>Pre-registered</th>
<th>Registered</th>
</tr>
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<td></td>
<td>CC</td>
<td>SSD</td>
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<td>mdb001-Sinusoidal-1 transformation</td>
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<td><strong>Mean</strong></td>
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7. Summary

Strictly speaking, due to the deformable, inhomogeneous, and anisotropic natures of the breast as well as the variation in the acquisition conditions, accurate mammogram registration is an intractable problem. In this paper, we have introduced a novel efficient approach for mammogram registration based on SIFT feature and Graph Transformation methods. Firstly, we use SIFT algorithm obtain potential points pairs. Secondly, GTM method is used to remove outliers. At last, we use the control point pairs to estimate TPS transformation parameters, and acquire the transform model. The experimental results have demonstrated that the proposed method is novel and effective.

In future work, we will expand our approach apply to actual temporal mammogram images. So as to assist the radiologists make accurate diagnosis.

8. References