Model Based Non-Rigid Registration Framework For High Dynamic Range Mammography

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Abstract: - Mammography screening is the most prominent method for finding breast cancer at an early stage. The acquired mammograms are High Dynamic Range images having a 12 bit gray scale resolution. When viewed by a radiologist, a single image must be examined several times, each time focusing on a different intensity range. So this paper proposes the Computer aided approach for enhancing standard lesions in digital mammograms, where we have developed a Model based Non-rigid Registration Framework (MBNRF) for High Dynamic Range mammogram image enhancement in a fully automatic way. The proposed system considers two views of mammogram images such as MLO (Mediolateral Oblique View) and CC (Craniocaudal) for processing and consists of two parts: 1) Preliminary processing operations involves in use of Contrast limited Adaptive Histogram Equalization technique to remove noise and intensity in homogeneities and 2) Registering the CC (Craniocaudal) model with MLO (Mediolateral Oblique View) mammogram view image by entropy based registration. The algorithm's performance has been tested on few mammography images in collaboration with radiologists.

Key-Words: - Image Registration, High Dynamic Range Images, Model based Image registration, Mammogram

1 Introduction

Breast cancer is one of the leading causes of mortality among women in the world today. Mammography is currently the most common procedure available for early detection of breast cancer, which is done through x-ray examination of the breast. It enables to determine the different types of abnormalities [1]. These HDR mammograms are acquired with a 12-14 bit gray scale resolution. The common display devices that have a low dynamic range of 8 bit gray scale resolution cause the mammography images to have low contrast. This might lead to the missed detection of valuable information. An efficient registration, therefore, of the dynamic range is required that would bring the images from different exposure into a suitable, displayable range, while presenting all of the image details. The reliable diagnosis of abnormalities from a single mammogram is an extremely difficult task even for a skilled radiologist, and so it is increasingly the case that pairs of mammograms are compared. These may be, for example, the left and right mammograms taken at the same session or two views of the same session such as MLO and CC. Equally, when mammograms from an earlier time are available, the radiologist will routinely compare the older and more recent images. For this reason alone, the development of mammogram registration is increasingly important for the early detection of pathology[2]. Registration of mammograms is not only important in displaying mammograms but it can also be used to develop computer-aided diagnosis (CAD) methods that use information from previous mammograms. Most current CAD techniques for mammography are based on the analysis of single views and detection. However, interest in CAD for classification into benign and malignant has grown, and for this purpose temporal analysis is usually required. In addition to improving classification, detection might also be improved by using information from previous mammograms.

The mammographic appearance of breast tissue in previous and current mammograms of the same patient may vary considerably, because of differences in breast compression and positioning, differences in imaging techniques, and changes in the breast itself. As mentioned earlier, after menopause the dense glandular tissue starts disappearing. Together with the fact that there are no clear landmarks in a mammogram, except for the nipple, this makes mammogram registration a challenging task.

2 Related Work

In addition to the noise present in mammograms, some artifacts further complicate the diagnosis and introduce uncertainty into the image interpretation. These artifacts are related to the variability in tissue density and the inhomogeneous nature of tissue in some anatomical structures. These artifacts imply that designing algorithms for mammography enhancement by registration is a significantly more demanding task than for, say, medical images of homogeneous structures. The main goal is to decrease the in homogeneities leading to increased accuracy in the subsequent mass segmentation algorithm. In literature, some approaches have been described for mammogram registration and techniques to find corresponding lesions in pairs of mammograms. Most work has been done on the registration of temporal pairs of mammograms.

Many of the earliest approaches to mammogram registration assumed some form of rigid or affine deformations and performed registration in a similar manner. In terms of non-rigid models for mammogram registration various algorithms have been proposed including point-based models [2-4], a simple physical model of the breast [5], and a pyramid-based multiresolution techniques [6,7]. Work by Kostelec et al. [6] offered one of the earliest approaches to mammogram registration which incorporated the use of similarity measures. They use a non-rigid pyramid-based multi resolution technique which incorporates a rigid similarity-measure (least-squares difference) based model and a Thin-Plate Spline spatial transformation to match bilateral mammograms. First a global rigid transformation incorporating image correlation is performed to remove gross deformations. The mammogram is then divided into four sub-images of equal size and each sub-image is rigidly aligned with the corresponding sub-image in the reference image. This coarse-to-fine registration is continued, matching smaller and smaller regions at finer and finer scales until the final, predetermined minimum sub-image size is achieved. At each stage the registration parameters of the sub-images "parent "image is used as the initial guess. After n stages the floating image has been subdivided into 4^{n-1} sub-images, and for each sub-image determined a rotation angle and translation vector. The individual sub-images are then interpolated using a Thin-Plate Spine to obtain a smooth moulding of the image to fit the reference image.

Weaver and colleagues [7,8] formulate a similar algorithm with three notable differences. Firstly, they use Fourier-based correlation to determine the rotational/translational parameters. Secondly, they mould between stages, and not only at the end of the algorithm. Thirdly, they use overlapping sub-images, as opposed to the non-overlapping sub-images of Kostelec. An alternate approach was proposed by Marti et al. [9,10]. Their non-rigid registration algorithm uses mutual information in combination with joint histograms derived from gray-level co-occurrence matrices (GLCM) to match bilateral mammograms. Their approach incorporates spatial information that is not provided by traditional joint histograms.

Kok-Wileset al.[12] developed a method for matching salient regions (iso-contours) between mammograms. The main problem with this method is the large number of salient regions (iso-contours that fulfil the saliency constraints) and heuristics necessary for the matching, though Hong and Brady [13] have recently reported developments that address this issue. Wirth et al. [14] use mutual information (MI) to define similar sub images in a mammogram pair before registering them using radial-basis functions. However, mutual information strongly depends on the size of the selected image window (the smaller the window the weaker the statistics) and it is difficult to overcome non-rigid changes of a region’s intensity profile over time. Finally, Richard and Cohen [15] present an interesting registration method that minimizes the energy of the linear elasticity without any boundary constraints. Here again, the method is highly dependent on the degree of preservation of the intensity profiles and tissue architecture of the mammogram pair. In our paper, we have observed that for most temporal pairs of mammograms it is possible to identify a set of corresponding “landmarks”—points or regions—that can be used to refine and improve the registration. This observation stems from the preserved “architectural similarity” of temporal pairs of mammograms. Based on this, we also developed a novel method for defining internal landmarks in mammogram sequences. To the best of our knowledge, designing a MBNRF to enhance the original mammographic image, while preserving its natural intensity variations, has not been reported previously. In this work we enhance the original mammograms while maximizing their inherent characteristics.

3 Proposed Method

3.1 Overview of the proposed System

We suggest a MBNRF technique which is based on entropy based registration for the preservation all features. To preserve all the features of Mammogram images effectively, we first require to remove all noises occurred during image capture. Then, the mammogram model is constructed from the CC view mammogram image. The feature points in the model are hierarchically registered with the MLO view of mammogram image. The Non-Rigid registration process of mammogram is adjusted using entropy information feature with respect to the model created.

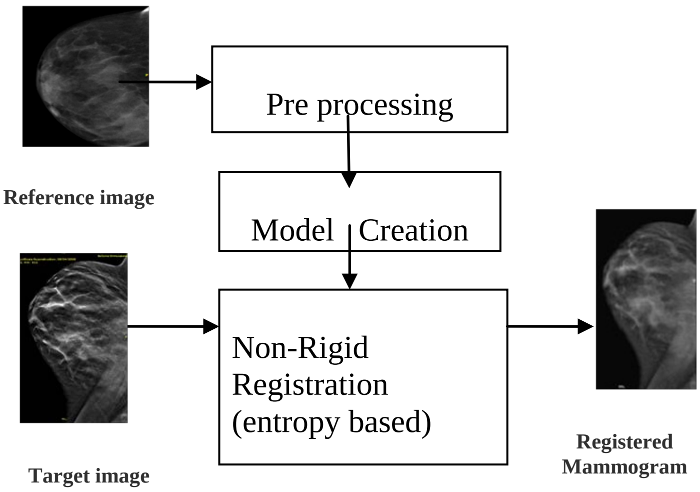


Figure 1.Steps involved in Image Registration

3.2 Image Preparation

The original HDR images were acquired by General Electric (GE) machine. The images were stored in DICOM format with spatial resolution of 94 µm/pixel and matrix size of 2294 x 1914. The LDR resultant images were stored in GIF format.

3.3 Mammogram Image Processing

In order to extract the local and global image features for the registration process, several image pre processing techniques are sequentially implemented on the mammogram images. First, a contrast-limited adaptive histogram equalization approach [20] is used to enhance image contrast, and then the anisotropic diffusion smoothing filter [21] is employed to remove image noises.

3.4 Model based Mammogram Registration

The Mammogram model used to preserve the local and global features of mammograms plays a pivotal role in the proposed MBNRF Technique. Since, Breast abnormalities are defined with wide range of features and may be easily missed or misinterpreted by radiologists while reading large amount of mammographic images provided in screening programs, we hence assign the model a relationship that specifies or includes feature point information.

A non-rigid registration typically follows a rigid registration that corrects for the misalignment and change of coordinate systems between the two images. In this work we employ a model-based alignment based on an algorithm that was used in [19] for a bone posture segmentation.

In the proposed model-based registration, a hierarchical framework is designed to register the HDR Mammogram images of different views. The 3D registration is achieved by using an iterative optimization algorithm. At first, the reference HDR mammogram is pre processed in order to remove noise and intensity in homogeneities. Then, the model is created by doing perspective viewing projection on the reference image. The similarity between the model and Target HDR image is continually evaluated until entropy information converges. The transformation determining the relative motion of the feature points can be estimated and then deformed target is identified according to the reference model.

3.4.1 Generation of Mammogram Model

The Mammogram model, a synthetic X-ray image of a 3-D object, is generated by simulating the X-ray attenuation in the imaging process. Given the initial posture of a bone segment from the knee model, we project the points of the bone segment onto the x–y plane of the reference coordinate system, and the coordinates of the projection points are calculated by Eq.1 as,

$$(x_i', y_i') = (x_i.f/(f-z_i), y_i.f/(f-z_i)), \tag{1}$$

where f is the principal distance and (x_i, y_i, z_i) represents the 3D Coordinate of i^{th} point of the Mammogram with respect to the reference mammogram. Considering the fact X-ray image intensities are determined based on the attenuation degree of X-rays detected by the film, we characterize the distribution of X-ray attenuation based on a 2-D map of summation of projection points. First, the number of bone points on the line from the X-ray source to each pixel of the mammogram model is recorded. Then, by normalizing the histogram values to the interval [0, 255], we can obtain the mammogram model.

(a) Non-Rigid Registration Algorithm

We followed the registration framework described in [16], and provide a model based formulation for the non-rigid registration problem with the corresponding similarity measure and smoother for regularization. Let F, M denote the fixed reference and moving target image respectively, on a 2D domain. Also let 'd' be the

displacement field , such that the deformed target $\widetilde{M}$ according to 'd'(2) is,

$$\widetilde{M}(x; d) = M(x - d(x)) \qquad (2)$$

The general registration problem is finding the suitable transformation or displacement field 'd' such that deformed target is somewhat similar to the reference image. The solution to the above registration problem can be solved by considering the energy function(3) as,

$$\mathrm{E}(d; F, M) = \Im\left[F, \widetilde{M}(x; d)\right] + \mathbb{R}[d] \qquad (3)$$

Where $\Im$ represents the distance measure between the fixed reference and deformed template image and R is the metric that is used for smoothing or for regularization of transformation displacements. Common choices for a distance measure are sum of square differences (SSD), (normalized) cross-correlation, and (normalized) mutual information [17].Work by C. L. Guyader et al.[18] proposed a region-based energy as the distance measure for registration with combined segmentation. They mapped a segmented template image onto the reference image to get the spatial correspondence with the template and segmented reference part also provided, which is used for registration.

One of the assumptions when using established similarity measures such as SSD is that there is a linear relationship between intensity values in the two images. This assumption may not hold true for all mammograms due to variations in intensities between similar structures in differing mammographic studies.

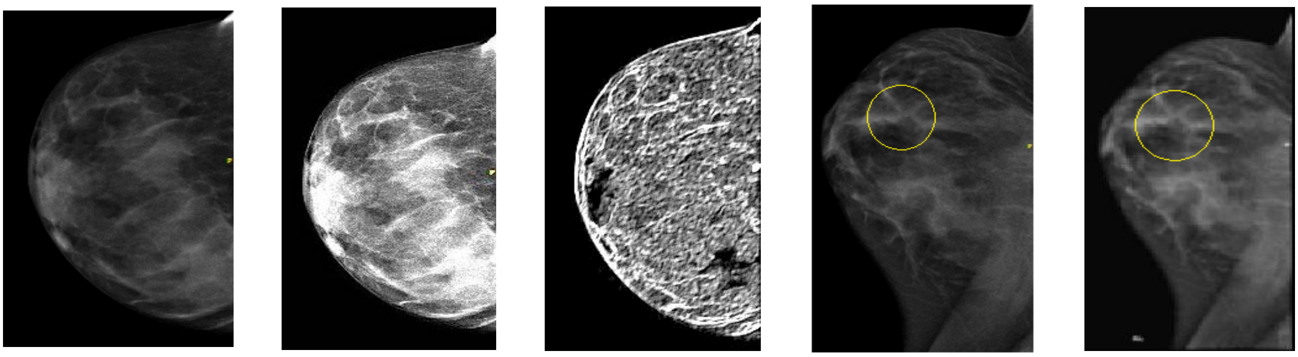
This may be reflective of differences in intensity due to differing imaging parameters, or changes in the composition and distribution of breast tissue between temporal and bilateral mammograms. Similarity measures based on mutual information [24], and normalized mutual information [25] have been used extensively in the registration of Magnetic Resonance images of the breast.

Figure 2. (a) Original Image (b) Contrast improvement (c) Model of the reference image (d) Original target Image (e) Resultant registered image

There has been significant interest in measures of registration based on the information content, or entropy, of images. The basic idea that motivates the employment of entropy information measures quantifying the quality of alignment is simple: Corresponding features extracted from the images should become statistically more dependent with better alignment.

Relative Entropy (RE) is a concept from information theory and its application as a cost-function in similarity-measure based approaches to registration was first suggested by Viola [23]. It has been extensively exploited for the task of matching images of the brain [22]. It expresses the amount of information that one image contains about a second image. In this paper we consider the relative entropy for model based alignment of target image with respect to reference image. Motivated by the effectiveness of the region-based energies to register the MRI images with spatial correspondence, as described in [18], we follow the model based approach that incorporates a region-based energy as

the distance measure between the template and reference model. Specifically we propose the distance measure which is based on the



(a) (b) (c) (d) (e)

*A) **Relative Entropy***

Relative Entropy is a measure of how much information two images have in common. Maximizing the mutual information can be thought of as minimizing the joint entropy H (A, B) relative to the marginal entropies H(A) and H(B) in the overlapping region of the images. This is given by:

$$RE(A,B) = H(A) + H(B) - H(A,B) \qquad (4)$$

$$RE(A,B) = \sum_{a\in A}\sum_{b\in B} p_{AB}(a,b)\,log[\frac{p_{AB}(a,b)}{p_A(a).p_B(b)}] \qquad (5)$$

The optimal parameters of the spatial transformation T_α which brings the images into registration are found by maximizing the mutual information:

$$T_\alpha = arg \,{}^{max}_{t}\, RE(A,B^t) \qquad (6)$$

Where $RE(A,B^t)$ is the mutual information of image A And image B transformed using parameter t and

T_α is the position at which $RE(A,B^t)$ is maximized.

The optimal registration parameters T_α are found by maximization $RE(A, B^t)$ using exhaustive searching.

4 Results

4.1 Visual Validation:

Fig.2 presents the algorithm resultant images of HDR mammogram image registration. The processing steps of an image are shown from (b)-(e). To show the algorithm's performance the resultant image (e) is compared with an image (d) which is before registration process. It can be seen that the details that are evidently seen at each and every intensity range, appear prominently in the final single image as well.

4.2 Comparison to other Algorithms

The performance of various registration algorithm can be accurately compared to our algorithm, in the feature preservation aspect, since its code is available in MATLAB software. In future work, the distributed Segmentation Algorithm [26, 27] can be used to speed up the process.

Table 1: Comparison of Registration Algorithms based on computation time.

Registration Algorithms	**Computation time (in microseconds)**
Affine	13.02
Similarity	12.91
Rigid	15.05
Non-Rigid	26.937
MBNRF	8.685

Fig.3 represents the registration algorithm's performance. It shows fairly good and somewhat similar results to those appearing in the full size images. However, if we zoom the resultant image in a specific region of interest, it can be seen, that the fine details are better exposed with our framework. (Such zooming is often used in order to find micro calcifications).

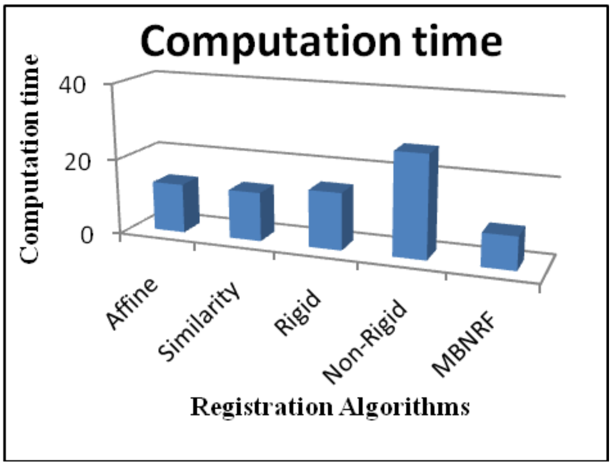


Figure 3. Performance of various Algorithm based on time

We have compared the accuracy of the registration of proposed framework with previous algorithm using specificity and sensitivity values.

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