Semi-automatic Registration of Mammographic Images for Breast Cancer Progression Assessment

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ABSTRACT
Breast cancer is the most common cancer among women. Despite significant advances in the medical field and its related technologies, cancer remains one of the biggest problems in medical science. Point common in all cancers need to do surgery and remove the tumor in advanced cases. Unfortunately, the surgery is not successful in some cases and later re-released in the body. Sometimes changing in the patient's tissues hides from human sight. One of the problems of comparing images taken at different times is change in imaging condition that causes distortion in the image and the difference between the textures in the image. To solve this problem and reduce the error, in this paper a semi-automatic method is presented for mammographic images registration. In this method using feature extraction of a mammogram such as brightness of the image, transformation distance, and also information that the user presents, can obtain the actual relationship between images and determines the differences between the images with less error. The proposed method will run on a sample of 27 mammograms from the Parto Teb Azma Imaging Center. We will show that in addition to maximizing similarities and minimizing differences between two images, the second image retains its overall shape. Generally correlation coefficient of mammograms after image registration in the semi-automatic method increase to 0.2670 and the difference squared in the semi-automatic method will decrease to 0.0968.

KEYWORDS: Image processing, Mammogram registration, Non-rigid registration, Mutual Information, change detection.

1. INTRODUCTION

Breast cancer is the most incident cancer and the fifth cause of death due to malignancies among Iranian women with approximately 8500 incident cases per year. The breast cancer rate is 11 percent of the whole malignancies among both genders[1].

Despite significant advances in the medical field and its related technologies, cancer remains one of the biggest problems in medical science. Each cancer has its own characteristics and treatment methods, but their common point is needed to do surgery and remove the tumor in advanced cases. Unfortunately, surgery is not successful in some cases and later re-released in the body. Sometimes changing in patient tissues is negligible from a human perspective, but the trend of these changes represents a fundamental change in the condition of the patient. One of the problems in comparing images taken at different times from the breast is change in imaging condition. The difference between the patient's condition or imaging device settings cause distortion in image.

The best way to detect these changes is to use computers to help doctors diagnose. Methods based on image registration can be a good option to solve this problem.

Image registration is the process to get optimal converting function and variables that make a connection between picture cells of two or several pictures and make maximized their similarities and minimize their differences.

Rueckert et al. [2] Proposed the non-rigid image registration using FFD based on B-splines for three-dimensional images of breast MR images. In their model, Normalized mutual information is used as a voxel-based similarity measure which is insensitive to intensity changes as a result of the contrast enhancement. The Marias et.al [3] Proposed the scheme as ‘Registration and matching of temporal mammograms for detecting abnormalities ‘. Their method was for detecting abnormalities after aligning a pair of mammograms using thin-plate spline interpolation based on corresponding points on the breast boundary. They also suggested a method for the automatic detection of landmarks within the breast tissue.

In 2004, a project Was presented by the Marias et.al [4], which was an image analysis method that could detect and measure breast density from digitized mammograms. The results show that present methods for measuring mammographic density fail to characterize temporal changes. Castillo et al. [5], proposed a semi-automatic method for non-rigid image registration. In this scheme, Supplementary information provide to the user to identify the corresponding points. This method run on various images such as brain, lung and satellite images that error rate is high.

Yang et al. [6], proposed a semi-automatic method in 2011 which is used to non-rigid image registration of the brain. In this method for improving the quality of the image registration, for each checkpoint, several multi-awarded point are obtained and extracted corresponding points are weighted. In this method, maximum error rate is 36.21 that are very high.

A new algorithm based on SIFT feature and GTM methods was introduced [7]. In this method, features are extracted from the mammogram images by scale invariant feature transform method and then this method use graph transformation matching approach for obtaining more accurate image information. But error remains high.

2. MAMMOGRAM REGISTRATION SCHEME

Mammogram registration is an important step in the processing of automatic detection of breast cancer, therapy planning, and guidance of surgery. In this paper, a semi-automated method for non-rigid registration of mammographic images will be proposed. This approach with using extracted features from the mammogram such as image brightness and important areas of the breast like the nipple, will extract corresponding points on the two images. These points are given as input to the transformation function. In Figure 1, the flowchart of proposed method is given.

2.1. Pre-processing of Mammogram Images

The pre-processing is one of the important steps in the mammogram registration due to poor captured mammogram image quality. Preprocessing Mammographic images before image registration is used to increase the quality of the image. Preprocessing causes improving the accuracy and reduces the processing time of image registration. The proposed method uses image segmentation to extract the most important areas and remove non-important area.

2.2. Selecting a set of control points

Using user information increase accuracy and reduces process time of image registration. This is one of the most important goals of using user information in non-rigid image registration as semi-automatic with regarding medical criteria. Correspondingcc points

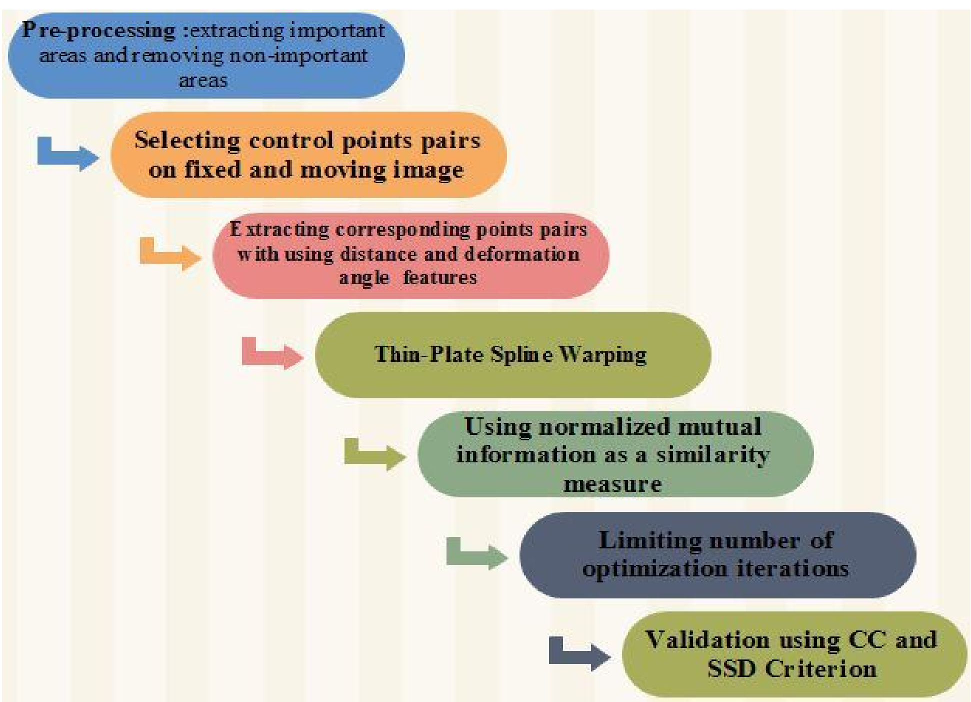

Fig. 1 Flow chart of the proposed algorithm for the registration of mammograms

as a coefficient of geometrical conversion have a basic role in semi-automatic registration and for this reason; accuracy and process time of registration image has a direct relation with the number and quality of the Correspondingcc points.

The control points extracted from images should show the most important area in the image. These areas in medical images are important tissue. By using the resemblance of tissue reformative can determine corresponding point in two images with accepted value. For diagnosing approximately corresponding points in two images can sampled a few points regard to the importance of them as medical view and after comparing the change amount of moving specified by user in the area, the corresponding points are extracted.

One of the most important characteristics of breast tissues is different levels of illumination intensity. Because of this; the characteristics can be used to diagnose the corresponding control points of breast image. Figure 2 shows a sample of selecting initial control points by user.

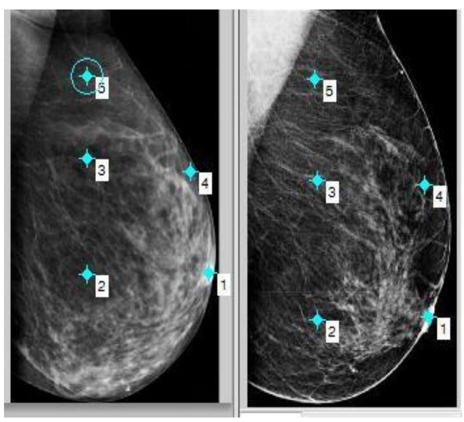

Fig 2. Selecting the initial controlling points by user (on the left side of image, fixed image and the right image moving image)

2.3. Extracting corresponding points Pairs

After the selection of control point by user, corresponding points is found by algorithm. Here to find the best corresponding points Pairs we used two sets of features, Euclidean distance and deformation angle. In this step, first Search Scope is determined. To find corresponding points, only points are examined that are in certain distance from the first point in fixed image. Then, after comparing the deformation angle CPs based on their computed features the final corresponding points are identified.

We use distance and angle of control point that are selected by user as reference for the comparison of control points in two images. Equation1is used to calculate the distance between two points[8].

$$ED = \sqrt[2]{(x_2 - x_1)^2 + (y_2 - y_1)^2} \qquad (1)$$

Where x and y are point coordinates, also equation2 is used to calculate the deformation angle.

$$DA = arctg\left(\frac{y_2 - y_1}{x_2 - x_1}\right) \qquad (2)$$

Between points which are in certain distance and angle from source points, some points diagnose as corresponding points that have the nearest distance value and Angular transformation to reference distance and reference transformation angle.

2.4. Thin-Plate Spline Warping

After identifying corresponding points, we use Thin-Plate Spline transformation function to warp the fixed image into the moving image. Corresponding points pairs are given as input to the TPS transformation function. In Eq.3 TPS transformation function is considered[9].

$$T(x,y,z) = \alpha_1 + \alpha_2 x + \alpha_3 y + \alpha_4 z \sum_{i=1}^{n} b_i\, \theta(|\Phi_i - (x,y,z)|) \qquad (3)$$

In the above equation, a coefficients relate to the affine component and the summation term refers the non-affine component of the transformation. θ is a basic function. The combination of Basic key functions makes each of the thin plate Spline function that affect the functions on the whole process of image registration. By Using Eq. Spline, source image can be transformed in ways that change their overall shape which is preserved and has uniform textures. Another important feature of the Thin-plate Spline is local supporting for image transformation.

2.5. The Optimization of similarity measure

In Non-rigid image registration as semi-automated, a standard normalized mutual information as the similarity measure is used. Using normalized mutual information function is greatly affected by changing Common areas to solve the problem[10]. To increase the performance of similarity measurement in mutual information, probability distribution function values are calculated as local form and by dividing image in some parts firstly the facture of its image are registered to over the maximum possible level of changing locally by the process of image registration. To limit optimization process, the numbers of optimized circle are reduced as the size to able of recovering first Correspondence to prevent tissue changes. A common form of NMI can be noted by [2], that is shown in Equ4.

$$NMI(A,B) = \frac{(H(A) + H(B))}{H(A,B)} \qquad (4)$$

Where A and B are the fixed and moving images and H is the entropy value.

2.6. Testing and Validation

After registering mammogram images, the performance of proposed method are measured with two correlation coefficient (CC) and SSD (Sum of squared differences).

3. DATA BASE

These photos were provided by the imaging medicine ray of Qom.7 patients were enrolled in the center's database of both breast and had a mammogram in full view of the CC and the OBL images. Finally, 27 samples were obtained mammograms. The mammograms were converted to DICOM format to JPG and then converted to the size 6000*1200.

Mammograms were then taken for readability of the database created for this paper were summarized. For example, in Fig, 3, 1fccr that shows first column represents the mammogram of patient No.1.The second column is the first letters(fix) indicating the mammogram is the first image or fixed image and cc expressed that this image correlate to cc view and r represents the right breast mammogram.

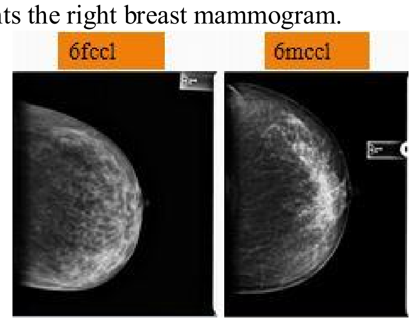

Fig 3. Naming mammography in database

4. EXPERIMENTAL RESULTS

We implemented the proposed method on mammograms database. Results of the proposed method on mammograms in the database are shown in Table1. In this table, the first column corresponds to the number of mammograms in the database.CC1 is correlation coefficient between the fixed and moving images before registration. SSD1 is related to the difference between fixed and moving image. CC2 is correlation coefficient between the fixed image and registered image. SSD2 related to the difference between the fixed and registered image.

In Table2 the results of the proposed approach on various views of mammograms come together. Mean values of each indicator is given in the table below.

By implementing the proposed approach, the highest reduction mean in error in view of the ccr and the highest increase in the correlation coefficient is in ccl view. The lowest error reduction average is related to ccl and the lowest increase in the correlation coefficient was in oblr view.

Diagram 1 shows the correlation coefficient between mammograms registered before and after registering image.CC1andCC2 is the correlation coefficient between fixed and moving images andcc2 is the correlation coefficient between the fixed and registered image.

Table1: implementing the proposed method on database mammograms

	fixed with moving image		fixed with registered image			
Mammogram	CC1	SSD1	CC2	SSD2	cc2-cc1	|SSD2 - SSD1|
1ccr	0.6831	0.0349	0.99	0.0145	0.3069	0.0204
1obll	0.6055	0.1266	0.9269	0.0297	0.3214	0.0969
1oblr	0.5726	0.0513	0.9836	0.0131	0.411	0.0382
2ccl	0.6605	0.0576	0.9918	0.0239	0.3313	0.0337
2ccr	0.6529	0.1129	0.7972	0.0848	0.1443	0.0281
2obll	0.6486	0.0786	0.962	0.0217	0.3134	0.0569
2oblr	0.5797	0.0996	0.8839	0.0463	0.3042	0.0533
3ccl	0.7463	0.2397	0.9748	0.0177	0.2285	0.222
3ccr	0.4916	0.2219	0.7977	0.0474	0.3061	0.1745
3obll	0.6284	0.221	0.7001	0.0773	0.0717	0.1437
3oblr	0.5863	0.0919	0.7244	0.073	0.1381	0.0189
4ccl	0.7062	0.2315	0.868	0.0538	0.1618	0.1777
4ccr	0.5745	0.2108	0.8872	0.0512	0.3127	0.1596
4obll	0.4028	0.0769	0.8849	0.0512	0.4821	0.0257
4oblr	0.457	0.1295	0.7288	0.1135	0.2718	0.016
5ccl	0.6412	0.2559	0.8788	0.1026	0.2376	0.1533
5ccr	0.4745	0.2905	0.9885	0.0326	0.514	0.2579
5obll	0.6291	0.1503	0.7441	0.129	0.115	0.0213
5oblr	0.7051	0.1498	0.982	0.0203	0.2769	0.1295
6ccl	0.6268	0.1834	0.8505	0.0169	0.2237	0.1665
6ccr	0.4896	0.1551	0.9948	0.0046	0.5052	0.1505
6obll	0.2874	0.1075	0.7327	0.0669	0.4453	0.0406
6oblr	0.4899	0.142	0.7104	0.127	0.2205	0.015
7ccl	0.6676	0.1833	0.7675	0.1416	0.0999	0.0417
7ccr	0.7067	0.2835	0.9875	0.0261	0.2808	0.2574
7oblr	0.7542	0.0677	0.8985	0.0487	0.1443	0.019
MEAN	0.594927	0.152065385	0.870638	0.055207692	0.26701	0.096857692
MAX	0.7542	0.2905	0.9948	0.1416	0.514	0.2579
MIN	0.2874	0.0349	0.7001	0.0046	0.0717	0.015

Table 2: The results of implementing semi-automatic method on the four facades of mammograms

MEAN	ccl	ccr	obll	Oblr
CC2-CC1	0.2138	0.14977	0.06418	0.04141
SSD2-SSD1	0.1324	0.3385	0.2914	0.2524

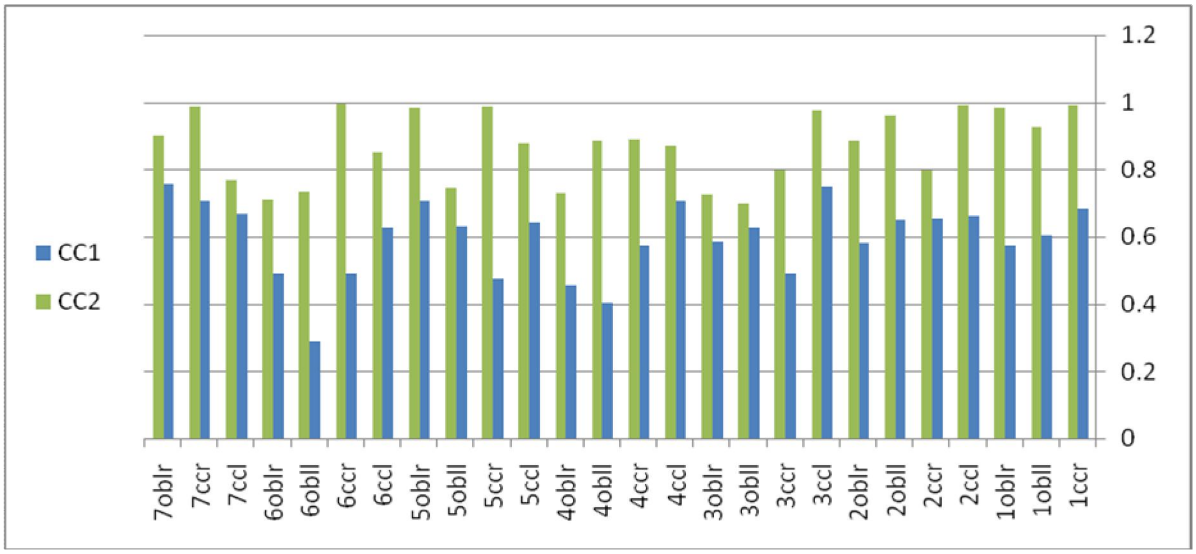

Diagram 1: the comparison on correlation coefficient between mammograms: cc1 correlation coefficient between fixed and moving mammograms and cc2 cc1 correlation coefficient between fixed and registered mammograms in semi-automated method.

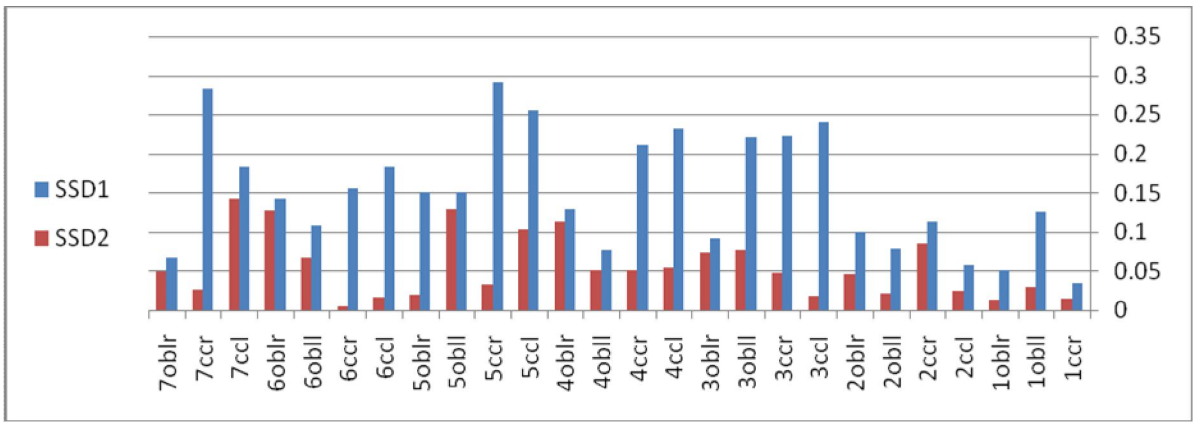

Diagram 2: the comparison on Sum of squared differences between mammograms: ssd1 Sum of squared differences between fixed and moving mammograms and ssd2 Sum of squared differences between fixed and registered mammograms in semi-automated method

Diagram 1 shows that the registration of mammographic image with proposed method on database mammogram cause increasing the correlation coefficient.

Diagram 2 shows that registering mammography images with semi-automated approach, has caused to reduce SSD. The maximum amount of reducing SSD in mammogram is in 5ccr that is 0.2579 and the minimum amount of reduction SSD is 0.015 in 6oblr. Totally the average reduction SSD is 0.0968.

The maximum correlation coefficient is 0.522 and the minimum amount of increasing is related to 5ccr mammograms that are 0.514 and the minimum amount of increasing cc is 0.0717 that is occurred in 3pbll mammogram. Totally the average increase in mammograms, 3obll happened. Overall, the average increase in the correlation coefficient is 0.2670.

In Diagram 2 the results of the performance evaluation of the proposed method on mammograms database using a standard SSD is shown.

Fig4 is registered image of moving mammogram on fixed mammogram. The observed differences after registering image is related to variations due to location, context change due to breathing and also changing the position of the patient. Semi-automatic registration of the two images using the proposed method has large layover come these differences. In High Mammograms correlation coefficient (CC) between fixed and moving image is 0.4745 and between tow registered and fixed mammogram is 0.9885 that is increased. Also, Squared difference (SSD) between fixed and moving is 0.2905 and is 0.0326 between fixed and registered image that is represents the difference of tow images.

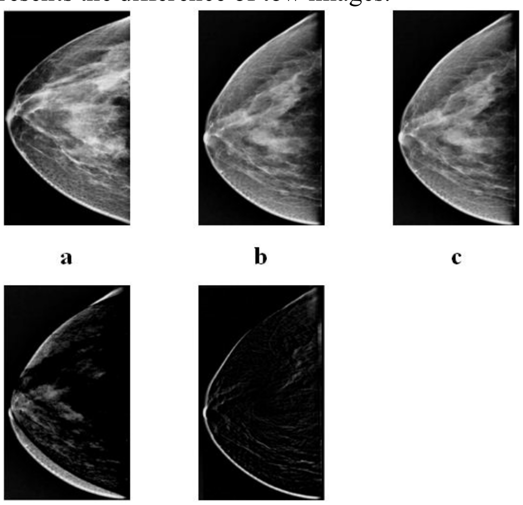

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Fig 4. Non-rigid registration results of mammograms with the proposed method: a) fixed mammogram b) moving mammogram c) registered mammogram d) the difference between fixed and moving mammogram d) the difference fixed and registered image.

In table 3, four existing methods is compared with proposed method.

Table 3 the comparison of proposed method with existing methods

Method name	Image type	Mean CC	Mean SSD	Max CC	Min SSD
method AD[11]	ultrasound	**0.71**	**0.77**		
method CD[11]	ultrasound	**0.75**	**0.67**		
method External Features [12]	mammogram			**0.977**	**0.026**
method Internal Features [12]	mammogram			**0.994**	**0.002**
method Proposed	mammogram	**0.87**	**0.05**	**0.995**	**0.004**

In table 3 using the four-variable Max CC, which represents the maximum correlation coefficient between the fixed and registered image. Min SSD is the minimal differences between the fixed and registered image. Mean CC is average correlation coefficient between the fixed and registered image. SSD Mean is the average difference between the fixed and registered image.

As shown in the above table, the proposed method in this paper is more efficient than other methods.

Diagram 3 and 4 as well as the method proposed by Yang [7] is compared.

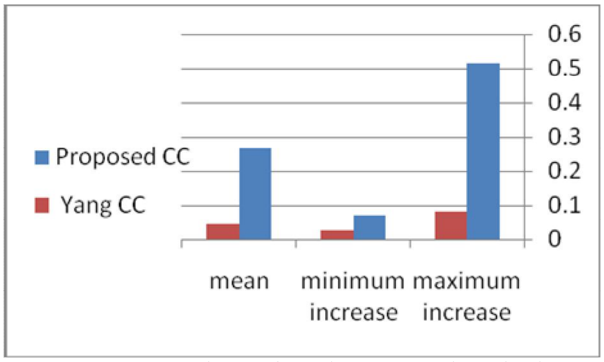

Diagram 3: Comparison of semi-automated method using Yang correlation coefficient

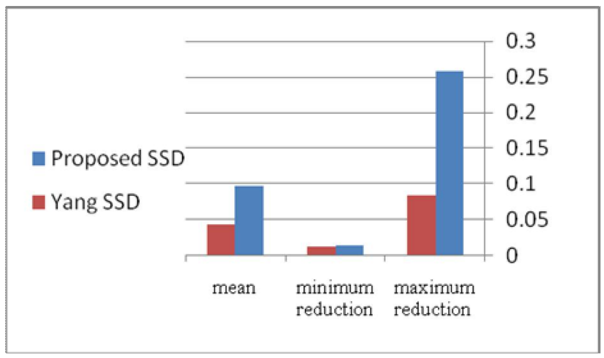

Diagram 4: Comparison of the sum squared difference between semi-automatic techniques with Yang

As figures 3 and 4 show, the average correlation coefficient for the semi-automated method higher than Yang method.

5. CONCLUSION

In this paper, a semi-automated method for mammographic image registration was presented that registered image by helping user to select control points. The proposed method in the MATLAB software was implemented using image processing tool box.

To evaluate the proposed approach, two CC and SSD measures is used. The experimental results have demonstrated that the proposed method maximizes similarities and minimizes differences between two images; also the second image retains its overall shape. Comparisons with existing work were also shown that the correlation coefficient increases while the differences are small. By implementing the proposed approach, the highest reduction mean in error in view of the ccr and the highest increase in the correlation coefficient is in ccl view. The lowest error reduction average is related to ccl and the lowest increase in the correlation coefficient was in oblr view.

Overall, the average correlation coefficient mammogram after the semi-automatic image registration is increased to 0.0968.

Our proposed method in Non-rigid Image Registration is able to eliminate whole initial factors in lack of correspondence and without changing in shape and mass of tissue, can increase the similarity of two images.

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