
A Study of Bio-medical Image Registration Algorithms

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Abstract— Bio-medical Image Registration has greater impact on image analysis. Image Registration technique helps to align two images, which uses intensity of pixels as prime factor for registration. The images used for registration can be either mono-modal or multi-modal. The degradation of image is frequently observed during image acquisition itself, which affects registration considerably. The performance of algorithms should be independent of image degradations. The most commonly used techniques for similarity measures to perform image registration include Sum of Absolute Difference (SAD), Sum of Squared Differences (SSD), and Normalized Cross Correlation (NCC) methods. In this paper a comparative study is done to obtain better algorithm. A set of images were taken for the study and were modified by varying contrast and relative shift. The obtained results show that SAD method is best suited to perform registration of mono-modal images.

Keywords— Image Registration, SAD, SSD, NCC

I. INTRODUCTION

Image Registration plays major role in all applications of medical image analysis and is a basic need to perform image fusion. Registration technique helps for long period abnormality monitoring to determine changes over period [1,2]. Image registration is an optimization procedure that uses similarity measure to find the optimal alignment of two images. Image registration if done on images acquired using same modality then it is called mono-modal registration else it is called multi-modal registration. The accuracy of image registration process depends on geometric transformation and optimization algorithm based on similarity measure [3]. Selection of similarity measure depends on the type of registration used and on intra-/inter-subject perspective. As a result many image similarity measuring techniques have been developed over the time. The most commonly used similarity measures

include Sum of Absolute Difference (SAD), Sum of Squared Differences (SSD), and Normalized Cross Correlation (CC) methods [4, 13].

In the study of registration algorithm, Computed Tomography (CT) image is used and wide framework is considered to perform evaluation of Image Registration techniques. The rest of the paper is organized as follows. Section II, explains suitable theory of the registration algorithms, Section III includes experiment and results of different similarity-measure based on image registration techniques, and section IV brings conclusion of the study.

II. IMAGE REGISTRATION

Image registration is a process of over lapping two or more images of scene taken at different time or from different view point and/or obtained by different sensor [6, 10]. In this section, image registration approach is discussed in detail. First, we introduce geometrical transformation and then discuss different similarity measures utilized in our study. Further, a Levenberg-Marquardt (LM) optimization algorithm is also presented. Finally, the registration algorithm steps are summarized for proposed study.

A. The geometrical transformation model

Image registration uses geometrical transformation to align a references image $I_1(x)$ and source image $I_2(x)$. Geometrical transformation modifies the spatial relationship between pixels in an image. The geometrical transformation is classified in to rigid, affine, and non-rigid based on their degree of freedom. Affine geometrical transform is one which has higher degree of freedom with respect to rigid transformation and lower degree of freedom with respect to non-rigid transformation [5, 6]. Affine

transformation preserves co-linearity ratio between straightness of lines and allows angle between straight lines to change and it is expressed mathematically in equation (1) [2].

$$T(x) = Ax+t \dots\dots\dots (1)$$

Let $x=\{x_1, x_2, x_3 \dots\dots x_n\}$, which defines pixel coordinates in the image. Where A is a 3 X 3 square matrix accounting for rotations and scaling. Displacement is defined by t.

Affine transformation process can be represented using expression (2). Where I2(x) is input image, O(x) is output image and T is affine operator from equation (1).

$$O(x) = I2 (T(x)) \dots\dots\dots (2)$$

B. The similarity measure

The similarity measure plays a vital role in image registration to find similarity of two images according to their underlying intensity patterns of image. Before choosing a similarity measure, it is better to consider how much it is prone to local minima, and its capture range, and how fast it can be computed. In this paper we consider a comparative study of the following intra-modality similarity measure techniques such as,

- 1) Sum of Squared Differences (SSD).
- 2) Sum of Absolute Difference method (SAD).
- 3) Normalized Cross Correlation (NCC).

1) Sum of square difference (SSD):

SSD is a simple commonly used method for same modality image registration. SSD measures intensity at corresponding points between the two images and its mathematical representation is done by

$$SSD = \frac{1}{N} \sum_x |I1(x) - O(x)|^2 \forall x \in I1 \cap O \dots\dots (3)$$

Where image I1(x) is reference image and image O(x) is a transformed source image from equation (2), whereas SSD value is zero for identical images and it increase in misalignment increases [11].

2) Sum of Absolute Difference method (SAD):

SAD takes the absolute value of the difference between each pixel in the original image I1(x) and with corresponding pixel in the transformed image O(x). The mathematical representation is given by

$$SAD = 1/N \sum_x (I1(x)-O(x)) \forall x \in I1 \cap O \dots\dots\dots (4)$$

Where SAD results zero for identical image and its value increases as dissimilarity in image increases [11].

3) Normalized Cross Correlation (NCC):

Another approach is to characterize the relationship between I1(x) and O(x). NCC has been used as similarity measure for registration of intra-modality application. The expression for normalized cross correlation coefficient is given by.

$$NCC = \frac{1}{N} \frac{\sum_x (I1(x)-\bar{I})(O(x)-\bar{O})}{(\sum_x (I1(x)-\bar{I})^2 \sum_x (O(x)-\bar{O})^2)^{1/2}} \forall x \in I1 \cap O \dots\dots\dots (5)$$

Where NCC value is equal to one for identical images and its, value decreases as dissimilarity increases [11].

C) The Optimization technique:

A spatial optimization technique helps in optimising local and global registration. Optimization algorithm generates sequence of iteration in optimization and it terminates when either no more progress could be done or when the solution is approximately sufficient. It is found that Levenberg-Marquardt Optimization is an effective optimization method that provides high accuracy and precision. This method is designed using sum of squares of nonlinear functions [7]. The Newton's method for optimizing the transformation index T(x) is

$$x_{m+1} = x_m - A_m^{-1} S_m$$

Whereas, $A_m = \nabla^2 T(x)|_{x=x_m}$ and $S_m = \nabla T(x)|_{x=x_m}$

Assuming that T(x) is a sum of square function, then gradient can be written in matrix form as

$$\nabla T(x) = 2J^T(x)I1(x) \dots\dots\dots (6)$$

The next value of x_m can be calculated as

$$x_{m+1} = x_m - [2J^T(x_m)J(x_m)]^{-1} 2J^T(x_m)I1(x_m) \dots\dots (7)$$

Where $J^T(x_m) = \frac{d}{d}$ and E(x) takes value of similarity measure SSD, SAD or NCC. The equation (7) represents gauss-Newton expression. For optimization process, Hessian matrix can be approximated as

$$G = H + \lambda I$$

This leads to Levenberg-Marquardt algorithm

$$x_{m+1} = x_m - [J^T(x_m)J(x_m) + \lambda_m I]^{-1} J^T(x_m)I1(x_m) \dots\dots (8)$$

Where λ_m is a positive scalar parameter and I is the identity matrix. The free parameter λ_m works as an adjustment of the step length during the iteration. The parameter has great impact on convergence of the similarity measure [8].

The proposed different similarity based medical image registration algorithm is described in the following steps:

Step 1: Load the reference image $I_1(x)$ and source image $I_2(x)$

Step 2: Apply the affine transformation to source image $I_2(x)$, the result of the transformed source image is $O(x)$.

Step 3: Calculating the similarity measure between reference and transformed image.

Step 4: If result is not optimized, then LM optimization algorithm is used to optimize the affine transformation matrix.

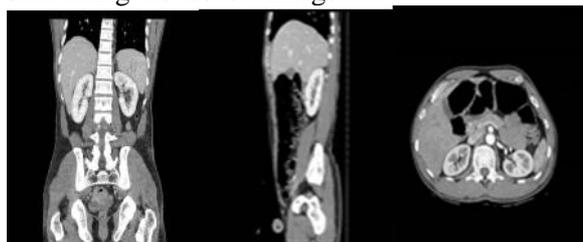
Step 5: Optimization terminates when it reaches desired value or no more progress can be done on the registration process.

Step 6: Resulted image is registered.

III. EXPERIMENT AND RESULT

A. Data acquisitions

The computed tomography (CT) image is a non-invasive technique with good spatial resolution and high signal to noise ratio, this nature made radiologist to prefer computed tomography imaging in diagnosis of abdominal abnormalities. Computed tomography image data set is created from human subjects, which are scanned for abdominal region using CT scanner. These images are obtained for our study. The test set is generated for few images of size 512 X 512 from different Patients. The obtained images are acquired from axes like axial, coronal, and sagittal mode. Theset of test images are shown in Fig.1 and another set of images for registration is generated by simulating the test set image.



(a) (b) (c)
Fig. 1: Bio-medical image

The biomedical image obtained are usually found to be distorted based on various factors like; light source, motion due to breathing causes slight blurred image, noise interference and because of change in intensity value in the corresponding images. To perform test analysis, other set of images for registration is constructed by applying changes to the test set image of fig.1.

The change in orientation is obtained by applying shift $\Delta I(x,y)$ to the image. This is represented mathematically in equation (9)

$$I(x,y) = I(x,y) + \Delta I(x,y) \dots \dots (9)$$

Motion blurring is due to relative motion between recording device and scene. When an object or the camera is moved during light exposed, motion blurring may be in form of rotation, translation, a sudden change in scale, or may be the combination of these [12]. Then motion blurring function is given by equation (10)

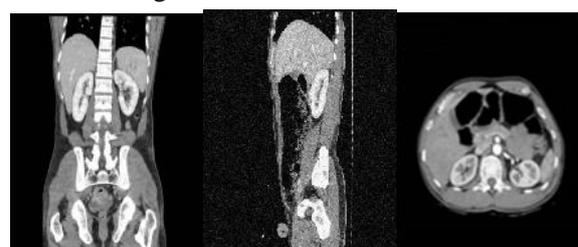
$$I(x,y) = \begin{cases} \frac{1}{L} & \text{if } \sqrt{x^2 + y^2} \leq \frac{L}{2} \text{ and } \frac{x}{y} = -\tan\phi \\ 0 & \text{otherwise} \end{cases} \dots \dots (10)$$

$$\text{Where } L = V_r \times T_e$$

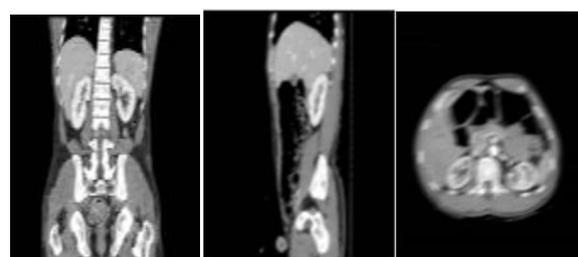
T_{exposure} = Object exposure time interval.

V_{relative} = Camera at relative constant velocity.

L = length of motion.



(a) (b) (c)



(d) (e) (f)

Fig. 2: test set generated a, b & c shows the translated and d, e & f shows motion blurred Image of Fig. 1.

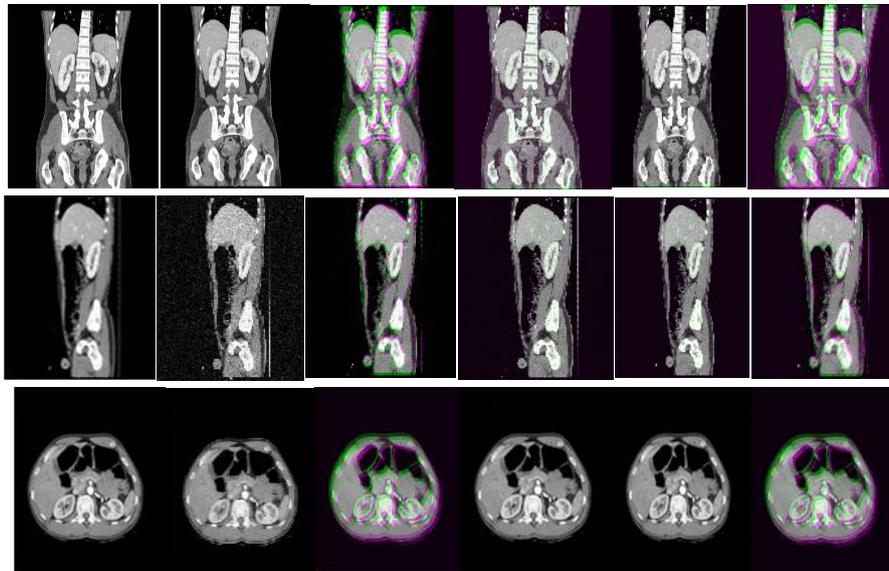


Fig.3: first column shows reference image, second column shows source image (translated), third column before registration, fourth, fifth, and sixth column shows result of the registration with different similarity measure, Sum of Square Difference, Sum of absolute difference, and normalized cross correlation.

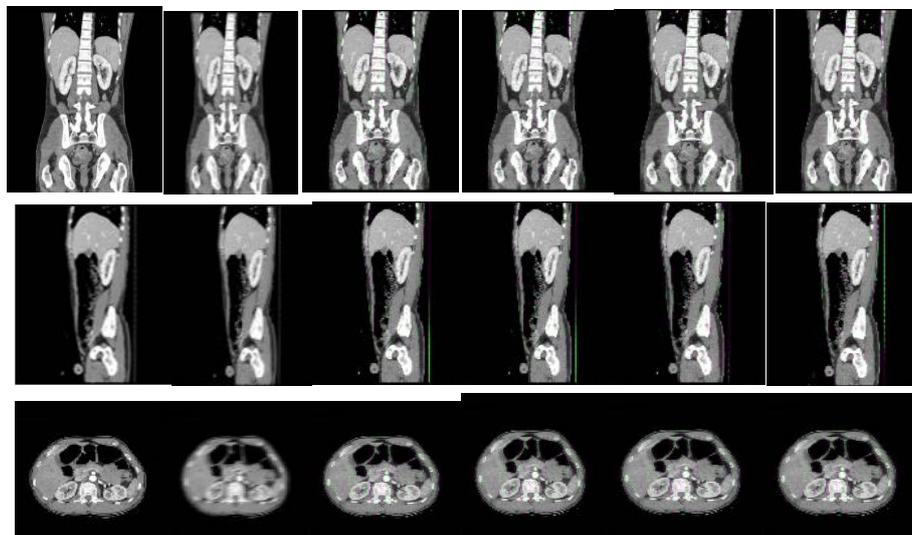


Fig.4: first column shows reference image, second column shows source image (motion blurred), third column before registration, fourth, fifth and sixth column shows result of the registration with different similarity measure, Sum of Square Difference, Sum of absolute difference, and normalized cross correlation

Similarity Measure	Mean Error	Standard deviation error	Time (sec)
Sum of square Difference	0.629	0.7829	86
Sum of Absolute Difference	0.0101	0.354	45
Normalized cross Correlation	0.201	0.451	40

Table: 1 shows the mean error and standard deviation error obtained for test data set and total time elapsed during execution

Similarity Measure	Mean Error	Standard deviation error	Time (sec)
Sum of square Difference	-0.14	0.735	56
Sum of Absolute Difference	0.06	0.389	53
Normalized cross Correlation	-0.0201	0.482	30

Table: 2. shows the mean error and standard deviation error obtained for test data set and total time elapsed during execution

B. Result and Discussion:

The Image registration is performed using MatLab2013a software on system Intel i3 processor with 4GB RAM on windows 7 32-bit based platform. Bio-medical Image registrations help in monitoring changes in size, shape or image intensity over the interval of time. The patient is monitored for abnormality like tumors, for a long treatment period. Abdominal CT image is used to study liver, kidney, stomach or spleen abnormalities. Image registration result is shown in Fig. 3 for degraded image & Fig. 4 for shifted images, the first and second column in figure corresponds to reference and source image, the third column shows result before image registration. The other fourth, fifth, and sixth column shows registration results obtained by using Sum of Square Difference, Sum of Absolute difference, Normalized cross correlation. The registration results suggest that, those images registered are employed with different similarity based approach, which made the evaluation feasible to trace. Mean error is used to measure registration accuracy and standard deviation error is used to measure registration precision, the result is summarized in Table: 1 & 2 from this we notice that, SAD method based similarity measure provides a good accuracy and small standard deviation error with respect to other image registration method. NCC is computationally fast but accuracy and precision is comparatively very low with respect to SAD and SSD.

IV. CONCLUSION

In this paper, we discussed mono-modal Image registration technique using different similarity measure. Image Registration technique is used significantly in the medical image analysis. A set of CT images were taken for the study and were

modified by varying contrast and providing relative shift to generate other set of image. The experimental results insist us to conclude that SAD based registration technique performs well compared to SSD or NCC based registration method. Other than statistical comparison, the visual quality of registered image also insists the same Conclusion.

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