Analytical Comparison of Learning Based Methods to Increase the Accuracy and Robustness of Registration Algorithms in Medical Imaging

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Abstract

Image registration refers to finding a geometrical transformation that correspond any point from one image to its homologous on the other image. There are several similarity measures that are classified in two groups based on features and intensity. In medical imaging, accuracy of registration algorithm is important. Since intensity-based methods, are more accurate than feature based ones, we select intensity-based registration; But intensity based methods usually need to global or local similarity measure optimization. Due to large search space, global methods optimization is time-consuming and when image irregularities are large, local methods cannot reach to an optimum amount. Despite these challenges, we found that learning based methods can be an appropriate policy to overcome these problems. Accordingly, in this paper, instead of using a fixed similarity measure, learning based similarity measure methods will present. Using the presented approaches in this paper can have been an effective role in analyzing and evaluating multi modal medical image registration and will increase three main functional measures – accuracy, speed and robustness – in medical image registration.

Keywords: *Image Registration, Multimodal Image Registration, Medical Image Registration, Neural Network, Similarity Measure*

1. Introduction

Image registration is adjustment process of two images and mapping to a common coordinate system to determine changes between two images. One of the important aspects of image registration is multimodal image registration so that different sensors are used for imaging from a scene. In recent years, multimodal image registration is one of the important issues in medical imaging. Due to changes in rotation and size, difference in images clarity or contrast and non-overlapping between two images, for a physician is difficult to mentally combine all image information carefully. Moreover, in radiation, using manual methods for alignment MRI and CT brain images, may require several hours analysis [1] so image registration is needed to transfer all images information to a coordinate system.

For correct alignment of two images, a similarity measure is needed to determine how images are registered through a given location. Similarity measures can be divided into two categories based on feature and intensity [2]. Mutual information is a common intensity based similarity measure for multimodal medical image registration. It is accurate and without pre-processing. This measure is automatic and does not require to user defined levels or special points [3, 4, 5]. Since the corresponding points in images with different modalities, have included different intensities, this method requires estimating the joint histogram between two images which cause to increase computing time significantly. This is one of disadvantages of this method particularly in high-volume images. It is observed that the most common similarity measure in multi modal image registration cannot be a good answer. With further investigation, this result is given that generally intensity based registration techniques needs to global or local similarity measure optimization between images [6].

However, the global methods are time consuming and on the other hand, local methods for images with large irregularities cannot reach to an optimum value. In order to overcome the obstacles, rather than applying a constant and overall similarity measure like mutual information, will try to learn a similarity measure, so that optimally adapted to a given task. Unlike standard information theory methods, which is predefined a similarity measure, in learning based methods, similarity measure is learned of a series of interpreted (annotated) images, where is provided more flexibility in multimodal image registration. Using the presented approaches in this paper can have been an effective role in analyzing and evaluating multi modal medical image registration and will increase three main functional measures – accuracy, speed and robustness – in medical image registration**.** The rest of this paper is organized as follows:

In section 2, the background research and proposed definitions for learning based image registration is introduced. In section 3, learning based methods for multimodal medical image registration described and Section 4 will evaluate various learning registration approaches. Section 5 will express result of this search and future work.

2. Research Background

In recent years, learning based methods have been suggested for general medical registration to impose prior knowledge to achieve more robust and reliable registration. Learning based methods have been widely used in the medical imaging applications for shape based classification [7, 8], shape estimation [9], shape detection [10, 11] for learning the best features to reduce ambiguity in image registration [12]. The first successful approaches in learning similarity functions for medical image registration have been undertaken within a generative framework [13, 14, 15, 16]. Leventon et al. [13] proposed to estimate the underlying joint intensity distribution from registered example image pairs, and then to employ a maximum likelihood (ML) approach to define the alignment measure for new image pairs. Chung et al. [14] minimized the Kullback-Leibler (KL) divergence between the learned joint intensity distribution and the joint distribution of the new images. Similarly, Sabuncu et al. [15] used the entropic graph-based Jensen-R´enyi (JR) divergence for the same minimization problem. Lee et al. [17] worked on supervised learning and used max-margin structured output learning. In this way, we can understand that learning based image registration in recent years is one of the most important fields in increase the image registration algorithms performance**.**

3. Learning based Method vs Other Image Registration Similarity Measures

Registration algorithms refer to finding a geometrical transformation that correspond any point from one image to its homologous on the other image**.**To maximize similarity measure between transformed input image and reference image, two images are registered. As mentioned earlier, common similarity measures are fixed and predefined and need to initialize**;** besides these methods usually require to global or local similarity measure optimization between images**.** Due to large search space, global methods optimization are time consuming and on the other hand local methods when the amount of irregularities in images are large, cannot reach to an optimum value. The major drawback of standard registration techniques are their sensitivity to initial positioning of images, the issue of dealing with multimodal images and the prohibitive processing time of registration. So, learning based methods can be an appropriate policy to overcome this problem**.** In this way, instead of using a fixed similarity measure, a similarity measure is learned so that input and reference images are achieved to highest degree of similarity.

In a more detailed classification, we divide similarity measures for registration approaches into four groups: landmark based, feature based, intensity based and learning based. Landmark based approaches are based on artificial objects introduced into the scans or by an operator manually which identify anatomical features matching interactivity. Feature based approaches require to volumes segmentation before the registration process. Intensity based approaches work directly on the image intensity values and usually do not require any preprocessing or interaction from the user. In learning based methods, Instead of using a universal and a prior fixed similarity measure such as mutual information, a similarity measure is learned, such that the reference and correctly deformed floating images receive high similarity scores.

In table 1 we analysis basic similarity measure approaches using criterions such as interaction, Parameterization, learning.

Table1. The Analysis of Similarity Measure Approaches

similarity measure approach	Functional Measures						
	User Interaction	Initial Orientation	Feature Selection	Transformation Parameterize	Learning Features	Speed	Accuracy
Landmark based	YES	NO	YES	YES	NO	Low	Low
Feature based	Manual / Automatic	NO	YES	YES	NO	Medium	Medium
Intensity based	NO	YES	NO	YES	NO	Low	High
Learning based	NO	Some ways	Some ways	NO	YES	High	High

4. Learning based Methods for Multimodal Medical Image Registration

There is a growing requirement for multimodal registration for many clinical applications. Existing proposed techniques are used as largely academic research and exist very few methods which being validated for clinical product use. In multimodal images, corresponding points in different images show a distinct intensity values, and dose not exist a mapping between intensity values in an image with corresponding intensity in another image. When the intensity of neighboring pixels in both input and reference images randomly change, mutual information and similarity measure based on intensity histogram will not be able to change the intensity pixel value, While if consider each pixel with its neighbors, it can carry more information than one pixel, thus the goal is to learn a similarity measure so that each location in reference image with corresponding location in input image to be appropriate with extracted features from neighborhood. In multimodal medical image registration there is a reference image I_r and an input image I_f, Such as the equation (1), using a transformation T and a similarity measure S, goal is to find an optimal transformation to maximize the similarity of two images [17].

$$T^* = \arg\max_{T \in \tau} s\,(I_r, I_f \circ T) \qquad (1)$$

Such as Figure 1, the goal is training a similarity function S on a sample of pre-registered patterns so that is minimized the observed irregular on the set of images. However, for brain image registration, due to complex brain structures and large variation of brain structures, local minimum is a critical problem in brain image registration. To overcome this, various registration techniques have been proposed to incorporate statistical information to guide image registration e.g. constraining the shape deformations estimated during the registration procedure [18, 19]. Also, the learned brain deformation information can be used to generate the intermediate template for facilitating the image registration [20].

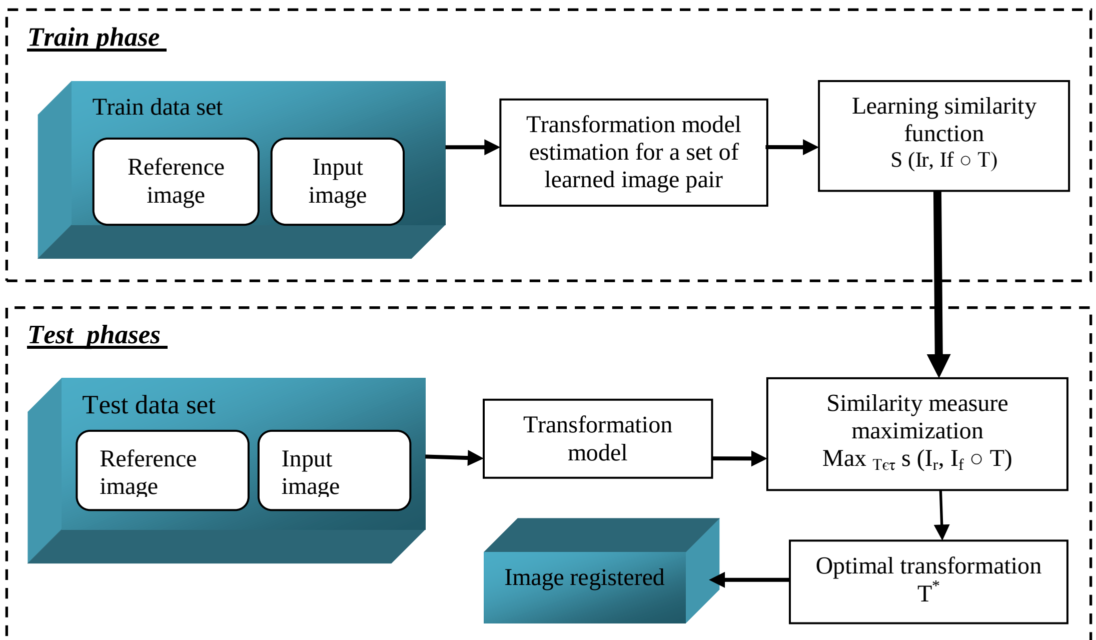


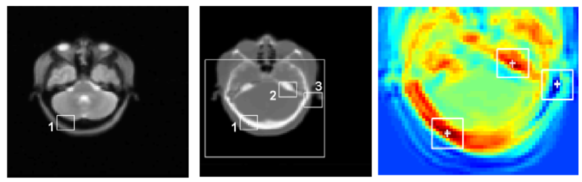
Figure1. Learning based Multimodal Medical Image Registration Phases

The most common learning algorithms for similarity measure in the field of medical image registration are as follows:

- Max-Margin Algorithm
- Kull back – Leibler
- Jensen –Shannon Divergence
- Genetic Algorithm
- PSO
- Neural Network

4.1. Max-margin Algorithm

This algorithm uses a joint kernel method for mapping the input - output image space so that offers a statistical representation of images with different quality that should be registered**.** Figure 2 shows a reference image of human MR image and corresponding input CT image**.** A place on X1 in reference image is selected and values of S (X1, y) for all y samples, is selected from the CT image [17]**.**



(Reference Image) (Input Image) (Learned Image)

x_1 y_1 y_2 y_3

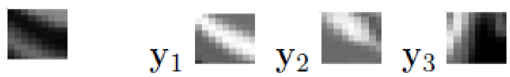


Figure 2. Learned Image with Max- Margin [17]

4.2. Kullback-liebler

This method is based on prior knowledge from expected joint intensity histogram distribution of the set of aligned training images. The goal is to align of both input and reference images so that expected and observed joint intensity histogram distribution to be matched with each other remarkably. The difference between two distributions is measured with Kullback-Leibler distance measure**.** This measure is expressed in equation (2):

$$D(PT||Pref) = \sum_{i1,i2=0}^{255} PT(i1,i2) log \frac{PT(i1,i2)}{Pref(i1,i2)} \quad (2)$$

According to equation (3), the goal is to find a T0 transformation so that is minimized the KLD value between expected joint intensity histogram distribution "P ref" and observed joint intensity histogram distribution "PT "[21].

$$T0 = \arg \min T\ D\ (P_T \,||\, P_{ref}) \quad (3)$$

4.3. Jensen –Shannon Divergence

Jensen–Shannon Divergence (JSD) is a learning based method that incorporates the prior information on the expected joint intensity histogram for robust registration. JSD is used to quantify the statistical similarity between the observed and expected joint histogram and provides a more suitable measure than KLD in quantifying histogram discrepancy because some histogram bins may vanish for the training data but not for the observed data or vise versa, in which case KLD is undefined. Depending on how well the a prior represents the observed data, the registration process is driven by a compounding effect of the statistical consistency of the observed joint histogram to the learned prior and the statistical dependence between the individual intensity distributions of the images being registered; There is no need to image segmentation and labeling as done in [22], whose error can lead to further errors in subsequent registration. Instead, an automatic nonlinear histogram mapping is done iteratively during the matching process to handle the intensity discrepancy between the observed data and the training data.

4.4. Genetic Algorithm

The genetic algorithms are computational models that provide good behavior in learning parameters. In this method, the mapping function can be described with learning nearest neighbors [23]**.** With CT and MRI imaging of human head, we consider an image as reference image and another image is taken as input**.** The desired features are extracted from each of images**.** Such as Figure 2, extracted features are given to a genetic algorithm until two images are registered. With generating a random population of chromosomes, the fitness of each chromosome is evaluated**.** As in genetic algorithms, initial solutions are encoded in N chromosomes representing the initial population. The difference in our algorithm is that each chromosome does not encode only one solution but all the possible solutions by putting them within a superposition.

A new population is generated by selecting two parent chromosomes from the population until new population is completed. A new child is generated from the combined parent and if we do not have combination, a copy of one parent is child. New children are accepted in a new population. The new population is replaced to the previous population to algorithm is again repeated. If algorithm has reached to end condition, the algorithm is stopped and the best solution is returned of the current population [24]. The main drawback of a GA is:

- The risk of premature convergence to a local extremum
- Bad initialization of the search space
- The choice of the stopping criterion
- How long must it take have a good accuracy quickness ratio?
- Time complexity
- population size
- iteration number

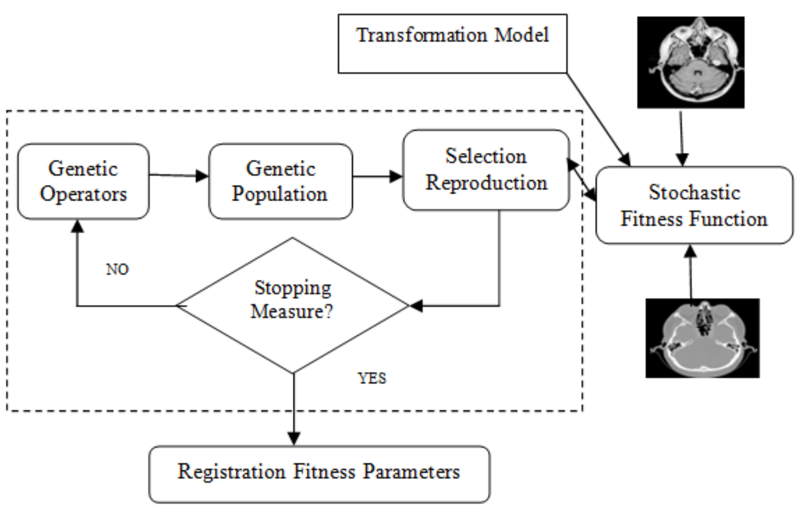


Figure 2. Registration Phase with Genetic Algorithm

4.5. PSO

Particle swarm optimization (PSO) refers to a relatively new family of algorithms that may be used to find optimal solutions to numerical and qualitative problems. It is easily implemented and has proven both very effective and quick when applied to a diverse set of optimization problems. PSO technique can be used for image registration. To achieve a refined enhancement, PSO is used to optimally determine the local camera models associated with a generalized geometric transform. The optimization process is driven using the minimization of entropy between the multimodal images. Test and validation of this alignment process is achieved using a forward model producing known geometric artifacts in the images and afterwards using a PSO algorithm to demonstrate the ability to identify and correct for these artifacts. Specifically, the forward model introduces local translational, rotational, and magnification changes within the image. PSO alignment algorithm is effective in autonomously determining and mitigating these geometric modifiers. Studies show that global image threshold binarization provides rapid and superior convergence characteristics relative to that of morphologically based methods [24].

4.6. Neural Network

In neural network based image registration, network will be learned based on reference image and learned similarity measure between input and reference and network error rate is calculated. The goal of network learning is aligning the network weights to minimize cost function. In supervised multi-layer neural network, a set of samples used to train the network as a model of system [25]. In order to avoid of network training by local features, characteristic points should be distributed among the entire image. For example when characteristic points in PET images are network input neurons, characteristic points in MRI images are output neurons. In each experiment, a train set was extracted from the reference image within a predefined range and is translated, rotated and scaled randomly. Similarly, a test set was generated for each of the evaluated signal to- noise ratios. NN structure has the smallest MSE to register MRI and PET images [26].

An example of neural network based image registration is principal component analysis (PCA) neural network [27]. In this method, firstly a statistical deformation model is built using a PCA method of a set of educational fields. Thus, this statistical deformation model is applied to fit the pattern regression models to make a correlation between deformation and twisting of images. Because of efficient transformation using PCA and a small number of coefficients, can be seen that transformation coefficients to be significantly reduced.The regression coefficients of education is easier with the use of regression models [27].

5. Evaluation

In this section, we evaluate learning based multimodal medical image registration according to main functional measures. Our evaluation is summarized in Table 2.

The functional measures that considered in our evaluation of learning based are as follows:

- ***Computational time:*** This property express that how many iteration dose the algorithm need to find the optimal solution
- ***Accuracy:*** A multimodal image registration approach must provide high accuracy in dealing with medical data.

- ***Speed of convergence:*** A multimodal image registration method must guarantee high speed.
- ***Robustness:*** This property express that how many iteration dose the algorithm need to find the optimal solution

Table2. The Evaluation of Learning based Multimodal Medical Image Registration

Evaluation Measure / Method	*Computational time*	*accuracy*	*Speed of convergence*	*Robustness*	*Basic Challenge*
Max-Margin Algorithm	Median	Median	Low	Low	Window Size
Kull back – Leibler	Median	Median	Low	Low	Local Minimums
Jensen–Shannon Divergence	Median	Median	Low	Median	Pre-alignment
Genetic Algorithm	Median	Median	Median	Median	Initialization
PSO	High	Median	Low	Median	Low Convergence
Neural Network	High	High	High	High	Training

6. Conclusion and Future Work

The paper has presented an analytical comparison of learning based methods to increase the accuracy, speed and robustness of registration algorithms in medical imaging. Common registration schemes utilize some form of similarity measures in order to evaluate transformation parameters. In this paper, we found that learning based methods can be employed as a means of providing translation, rotation and scaling parameters with respect to reference and observed image sets. Results with several deformed and noisy images indicate that learning based algorithms are both accurate and remarkably robust to diverse noisy conditions. In this study we proposed some functional measures according to this classification to evaluate learning based similarity measure for multimodal medical image registration. The proposed evaluation is comprehensive and could guide researchers to develop more efficient methods in this field.

For future work, we plan to register PET and CT images by neural network with new idea based on increasing accuracy and robustness registration algorithm.

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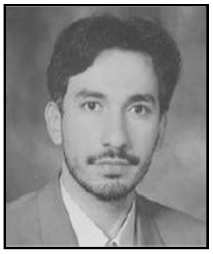

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