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Quantitative Evaluation of Intrinsic Registration Methods for Medical Images

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Abstract: Combining complementary information from two or more images by sitting up geometrical correspondence between them is called image registration. Image registration is one of the important steps in image-guided surgery and several methods have been developed for the accurate registration of medical images. In this paper, we present a comparative analyse of intrinsic registration methods for medical images. The analysis begins by the detail investigation of each registration method, covering their features, advantages, issues and challenges. Then, a comprehensive experimentation is carried out to determine the performance of every registration method. The aim is to provide a comprehensive knowledge on the work that has been developed in a compact form for both researchers and clinicians.

Keywords: Image Registration, Medical Imaging Modalities, Image Guided Surgery, Intrinsic Registration Methods

1. INTRODUCTION

Image registration is one of the essential steps in image-guided surgery in which one to one geometric mappings between features in sets of images are established. In image registration, the sets of images related to a scene may be taken in different modes such as from different angles, with multiple sensors i.e. CT, MRI and PET and in different time-frames. However, the goal is to compare corresponding features and coordinates in each image dimension (Wolberg and Zokai 2000). The process of registration is performed by comparing, analyzing and transforming two or more images (source and target images) (Wang, *et al.* 2001, Pengqiang, *et al.* 2008, El-Baz, *et al.* 2011, Zheng, *et al.* 2011, Sarvaiya, Patnaik *et al.* 2013, Friston, *et al.* 2004).

Image-guided surgery highly depends on the precise registration of medical images (Alam and Rahman 2016, Alam, Rahman *et al.* 2016). Therefore, research reached to a high level in this area, which sees the wide spread use of medical image registration in practices and clinics. The role of image registration in medical imaging modalities i.e. computed tomography (CT), magnetic resonance imaging (MRI), or positron emission tomography (PET) is vital (Alam, *et al.* 2016b). The main reason is the need for the detail information required from images of the internal organs of the human body in three dimensional (3D) form (Maes, *et al.* 2003). Information in 3D form obtain from internal organs of the human body play a crucial role in proper decision-making. As an outcome, the identification of symptoms, treatment planning and an effective medical examination become an easy job for practitioners with accuracy and reliability. (**Fig. 1**) (Rohr 2001) shows the implementation of registration method on 3D images of human head taken at different modalities i.e. CT image (left) and MRI image (middle). The distinction and visibility of different head organs and tissues are clear in the registered image on the right side after transformation.

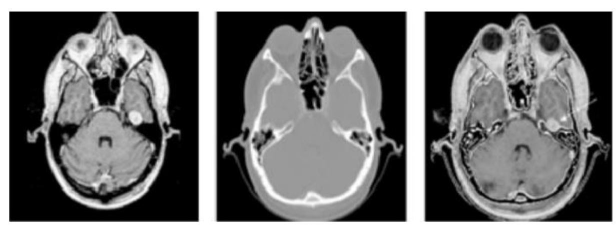

Fig. 1: CT image of human head (left), same MR image (middle) and overlay of both (right) after registration.

The most popular methods in image registration belong to the category of intrinsic property in which information is related to patient's body itself. These methods provide vast area of investigation to resolve complex registration problems which range from simple points to sophisticated 3D shapes (Fookes and Bennamoun 2002). This research paper is aimed to provide a comprehensive review of intrinsic registration used for medical images.. Intrinsic registration methods are beneficial in numerous ways such as to optimize the images, perform registration process quickly and accurately and enable sophisticated software which will share important information obtained from multiple images effectively. This survey paper is covering all of their possible aspects and pros and cons. The study also attempt to find out how these methods can be used

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together to get maximum benefits from them. Main contribution of this paper is togaing practical experience of the common registration methods by evaluating them experimentally and comparing the results based on their accuracy and efficiency.

2. INTRINSIC REGISTRATION METHODS

Intrinsic registration is based on the anatomical information and features generated by the subject image itself (Adler 2011). In intrinsic registration, features and information are dug out from subject images through points, curves, snakes, geometrical means, movements and principle axes. Most of the methods related to intrinsic properties of image registration are versatile. The main reason for their versatile nature is their potential for relating images from varying subjects in random poses and over different modalities. Intrinsic registration methods are reliable and explicit because at the time of image acquisition there is no need for any advance measure to avoid possible misfortune. Intrinsic registration methods for medical images are further categorized into landmark based, segmentation based and voxel-based, discussed in the sub-sections below.

2.1 Landmark Based (Point Based) Registration

Intrinsic registration methods based on points or landmarks are non-rigid and takes a consistent set of points or landmarks from the input image and extracts features from them (Liao and Chung 2012). The extracted features are further used for approximate calculation of optimal transformation. Several types of manual, semi-automatic and fully automatic procedures for points selection and extraction are available. However, manual selection and extraction procedures are time consuming, prone to errors and need constant interaction of user (Wan, Bloch *et al.* 2013). Automatic procedures have been developed for landmarks selection and extraction having the capability to globally transform medical images with optimum speed. The speed and efficiency of point-based registration is also good because this method obtained knowledge from the selected landmarks in the initial steps of image registration. Nevertheless, the efficiency and performance become low when landmark based registration methods are applied to register local deformable tissues. The accuracy and effectiveness of the resultant registration always depend on the correct selection of landmarks. However, appropriate selection of landmarks always require more computation time in medical image registration process. Anatomical and geometrical are the two types of landmark based registration, discussed in the sub-sections below.

2.1.1 Anatomical Registration

Anatomical landmarks based registration method is highly capable to deal with medical images with constant variability (Sun, *et al.* 2013). The property of precise mapping mechanism enables this method to automatically identify anatomical features in multimodality images. The use and effectiveness of anatomical landmark registration is in several clinical applications including bimaxillary surgery, brain MR surgery, lateral skull based and temporal bone surgery. Anatomical landmarks based registration also work successfully In bimaxillary surgery, this method localizes the joints of the transverse and sigmoid sinuses for keyhole craniotomy. Furthermore, anatomical landmarks based registration when presented to the surgeons with an appropriate user interface, can give an improved results by identify the locations of anatomical points located at various levels. On the other hand, in some situations, small numbers of points are defined in this method, which produce erroneous results during the identification and selection of anatomical landmarks as registration points. The cranium and cross skull are among them, which always suffer due to less number of anatomical registration points. Therefore, one can say that the anatomical landmarks in both image and patient dataset can be detected perfectly if the experience of clinical operator is high.

2.1.2 Geometrical Registration

Geometrical registration is another important type of landmark-based registration widely used in multidimensional and multimodality medical images. In this method, image registration is done on the principle of differential geometry i.e. identification of key feature point and their position in multimodality images, establishing correspondence between key points and the measurement of optimal geometrical transformation between corresponding images (Thomas 2012). The registration processes is performed on geometrical cost functions and on discriminative feature descriptors. Landmark registration based on geometry of objects, can easily solve both global and local differences in 2D and 3D medical images.

Identification of key points in this registration scheme is simple and strait forward due to the availability of geometric invariance properties. Geometrical registration process is also performed automatically with high speed and cannot require expertise for interaction. On the down side, this registration method always requires the correct selection and extraction of geometrical features such as corners, line intersections and local curvatures. Furthermore, the presence of disperse features such as noise and artifacts in some medical images when used for the creation of consistent landmarks also effects the accuracy of registration (Liu, *et al.* 2012).

2.2 Segmentation Based (Surface Based) Image Registration

Surface/segmentation based registration is performed by dividing into segments important features of images captured from same or different modalities into single more informative image. In segmentation /surface based image registration, an accurate translation and rotation between two images are performed. These registration methods are more robust then other types of registration such as point based. The important reason of their robustness is the strong preservation and manageability of segmented information inside the edges of images. Segmentation based registration methods deals with images of different nature but in some cases accuracy is compromised. These cases include continuous splitting in the edge segments and absence or partial appearance of single position in one of the images (Coiras, Santamarı´a *et al.* 2000). However, methods such as grouping of segments in source and destination image have been developed which can perform accurate transformation and matching. Redundancy in the surface of medical images makes these methods a better choice for registration against point-based registration because the differentiation of non-rigid motion in redundant surface is more easy than others. Segmentation based image registration is further categorized into rigid models and deformable models, discussed in the sub-sections below.

2.2.1 Rigid Models Based Registration

Image registration based on rigid models relies on image features such as points, curves and surfaces. In rigid registration, the correspondence between two images is established by the translation and rotation of objects i.e. points, curves and surfaces present inside the images. In medical imaging, registration is performed based on the segmentation of organs into geometrical shapes such as point, curves and surfaces (Le Guyader and Vese 2011). Registration is performed by sitting information in the segments of source image and mapping them to the corresponding information in the reference image.

2.2.2 Deformable Models Based Registration

Image registration based on deformable models has been widely used in medical image processing. In deformable registration best possible mapping scheme between source and target images are available. The elimination and integration of image boundaries elements belonging to the same structure and making a reliable model of the structure is a challenging task in image registration and segmentation (McInerney and Terzopoulos 1996). Such type of challenges need expertise in the field and often produces awkward object boundaries. The main reason of inappropriateness of these model free methods is the reliance on local information. Deformable models such as snakes and nets are non-rigid competent methods for medical image registrations which can locate, match and divide medical images into proper segments. The inconsistency of images over time and across multiple individuals often creates problems in medical image registration. Therefore, deformable models based methods were developed which can precisely make distinction between variability of shapes in objects. Moreover, surgeons and medical practitioners can easily interact and apply their expertise during image guided surgery due to flexible and user friendly interface provided by these methods.

Deformable models when appear in 3D form are also called nets. It is mainly used for the features integration of segmentation methods such as region based and boundary based. Deformable nets models are the appropriate methods for the registration of several types of medical subjects such as inter-subject, atlas and for the registration of template obtain from human anatomy (Balci 2006). However, for proper movement and convergence in image space these methods strongly rely on good initial position. Deformable models also produce erroneous results in local deformation of the template when there is strong difference between target structure and the template structure.

2.3 Intensity (Voxel) Based Registration

Feature based registration methods such as points and surfaces relay on images prominent and special objects, the accuracy of which requires consistent localization of a sufficient number of matching points in every modality. User interaction and proper segmentation of related surfaces are also required in feature based image registration methods. The identification of related segments and surfaces are challenging task in these methods because some functional modalities such as PET cannot properly isolate them (Maes, *et al.* 2003).

Image registration by using the methods of voxel or intensity measure has the potential to highly optimize the registration process with accuracy (Maes, *et al.* 2003). Intensity or voxel based methods uses either entire content of images for registration or work directly on image gray scale values without segmentation. The feature calculations and correspondence in voxel based methods are simple and strait forward and are not limited by surface and segmentation errors. Reductive registration and using full image contents registration are the two popular types of intensity based image registration, are described in the sub-sections below.

2.3.1 Reductive Registration

Reductive registration such as moments and principle axes play an important role in image registration process because they contain information about the image which is further used for analysis. Movements and principle orientations based registration methods are rigid due to their restriction to translation and rotation of images. Contrast to segmentation based methods which require dividing images into segments for registration, movements and principle orientations methods directly operate on image gray values (Wilson and Laxminarayan 2007). Registration methods based on moments and principle orientations are also called reduction to scalars/vectors registration methods because in these methods image gray levels are directly reduce to representative scalars/ vectors. In other words, these methods depend on the center of gravity, angular mass and the principle moments for registration.

In image-guided surgery, these methods are used to register medical images by mapping their corresponding volumes or points or surfaces (Maciunas). Speed, easy implementation and automatic behavior make these methods suitable choice for the registration of images which cannot need more accuracy. Moreover, multimodal brain images obtained from PET, CT and MR can be registered accurately using voxel-based methods. On the other hand, the presence of whole image data in both source image and target image is essential for the precise computation of principle orientations. In other words, missing some image data can cause inaccurate registration results. Other limitations include sensitivity for surgeons in some image guided therapy such as marginal hypo-metabolic swelling in PET, poor handling of dissimilarities in scanned volume and image to image registration.

2.3.2 Using Full Image Contents Registration

Using full image contents is widely used voxel property based registration method for medical images due to its flexible and automatic behavior. Contrast to reduction method in which prior reduction of image gray value content are performed in registration, full image content-based method uses whole image gray value information in registration process. In this registration method, similarity measures such as cross-correlation, ratio image uniformity, square intensity differences and intensity variance are used for transformation and establishing correspondence between images. Full image content based registration is used for both inter-subject and atlas registration and allow improved visualization of the subject voxel. However, their computation cost is high in some clinical application such as 3D-3D. Moreover, in time-constrained applications such as intra-operative 2D-3D registration this registration method has not been introduced yet.

3. EXPERIMENTAL EVALUATION AND DISCUSSION

We have performed experimental evaluation of intrinsic registration methods in terms of accuracy and efficiency. Experimental evaluation of intrinsic registration methods will provide more in-depth and useful information to the users about this challenging area of research. In the experimental analysis, registrations algorithms were tested on the set of 2D benchmark images of brain MRI, obtained from National Library of Medicine 1 and Kitware 2. The parameters for analyzing the performance of each algorithm are accuracy and efficiency. In this experiment, accuracy and efficiency of image registration algorithm are estimated from Root Mean Square (RMS) error and memory occupied by the registration algorithm respectively. We have tested every algorithm on three sets of images i.e. images with 0% Gaussian noise, 1% Gaussian noise and 2% Gaussian noise. The purpose was to get more in-depth information about the performance of each algorithm and the effect of Gaussian noise on it. All the registration algorithms are programmed using Insight Segmentation and Registration Toolkit 4.6.0 on Intel(R) Core (TM) i5-3210M CPU @2.50 GHz with 4 GB of RAM.

We have performed our experiments on anatomical registration using Evangelidis and Psarakis (Evangelidis and Z.Psarakis OCTOBER 2008) algorithms and on geometrical registration using. Baker and Matthews (Baker 2001) algorithm. For the experimental evaluation of rigid, deformable, reductive and full image content based registration, we take algorithms from Insight Registration and Segmentation Toolkit (ITK) software guide (Johnson, McCormick *et al.* July 23, 2014). In our experiments, translation errors, computational time, occupied memory spaces, total iterations and RMS errors were computed for all the registration algorithms as shown in **(Table 1)**. Throughout all testing, estimation of the translation errors and RMS errors were the most difficult and error prone phases due to the complex mathematical and statistical calculations.

The RMS errors at noise (0%, 1% and 2%) estimated in Table 1 were listed in Table 2 to find out the accuracy of each algorithm at different noise levels. One of the important metric for estimating the accuracy of registration method is RMS error value i.e. the minimum RMS error a more accurate will be the registration method. It is shown in Table 2 that in most registration algorithms, the RMS error increases with introduction of noise on images. In the experiments, we obtained minimum RMS error values while testing deformable and rigid registration on images (without the presence of noise and at minimum level i.e. 1%). Therefore, the accuracy of these two registration methods is high in our case as compared to others. On the other hand, RMS error values obtained from full image contents based registration are high due to which its accuracy is low. In **(Table 2)**, high RMS error values

[1] http://www.nlm.nih.gov/nlmhome.html

at different noise levels represent low accuracy while low RMS error values represent high accuracy.

We have experimentally evaluates the efficiency of each method by estimating its occupied space in computer memory. The memory space occupied by each registration method at different noise levels is also shown in **(Table 1).** All the values obtained in Table 1 are listed in Table 3, in which high values for memory space at different noise levels represent low efficiency while low memory space values represent high efficiency. It is shown in **(Table 3)** that the most efficient method in our experiment is rigid registration because it take less memory space during execution. Furthermore, the minimum values obtained for full image contents based registration also shows its high efficiency. On the other hand, the memory space occupied by the reductive registration is more due to which its efficiency is low.

We have tested intrinsic registration methods on sets of 2D benchmark images. In the experimental evaluation, we have identified the accuracy and efficiency of each registration method as shown in the Table 1. This is done by determining the translation errors, computational time, memory space and RMS error at different noise levels. Table 1 is further elaborated in Table 2 and Table 3 to precisely identify the accuracy and efficiency of each method respectively. In the experimental evaluation, minimum RMS values were obtained for rigid and deformable registration, which shows their high accuracy. On the other hand, RMS values obtained in case of full image content based registration is much high which shows its low accuracy.

Table 1: Experimental Evaluation of Intrinsic Registration Methods

Parameters	Anatomical Registration			Geometrical Registration			Rigid Registration			Deformable Registration			Reductive Registration			Using Full Image Content Based Registration		
	Noise (0%)	Noise (1%)	Noise (2%)	Noise (0%)	Noise (1%)	Noise (2%)	Noise (0%)	Noise (1%)	Noise (2%)	Noise (0%)	Noise (1%)	Noise (2%)	Noise (0%)	Noise (1%)	Noise (2%)	Noise (0%)	Noise (1%)	Noise (2%)
Translation Errors (mm)	0.191	0.697	0.810	0.239	0.895	0.897	-0.534	1.741	-17.249	-0.094	-0.102	-0.191	-14.397	-15.442	-16.319	-16.575	-16.730	-16.823
Computational Time (sec)	1.518	1.521	1.607	1.631	1.643	1.665	0.862	4.011	3.137	0.585	0.570	0.602	0.199	0.166	0.187	0.280	0.134	0.239
Memory (kb)	14018	14491	15102	15360	16384	16384	644	628	728	16064	16140	16080	19705	20927	20992	29976	2984	2984
Iteration	20	25	31	16	17	23	76	400	321	20	20	20	23	16	16	21	12	12
Root Mean Square Error (mm)	64.186	65.917	67.261	67.078	66.990	66.385	34.453	44.682	81.852	22.019	27.868	74.883	60.472	73.710	75.484	62.556	80.018	81.852

Table 2: RMS errors (mm) for the registration methods at different noise levels

	Anatomical	Geometrical	Rigid	Deformable	Reductive	Full Image Contents
Noise (0%)	64.186	67.0788	34.453	22.019	60.472	62.556
Noise (1%)	65.917	66.990	44.682	27.868	73.710	80.018
Noise (2%)	67.261	66.385	81.852	74.883	75.484	81.852

Table 3: Memory space (kb) taken by the registration methods at different noise levels

	Anatomical	Geometrical	Rigid	Deformable	Reductive	Full image content
Noise (0%)	14018	15102	644	16140	19705	2997
Noise (1%)	14491	16360	628	16080	20927	2984
Noise (2%)	15103	16384	728	19705	20992	2984

4. CONCLUSIONS

In general, every type of intrinsic registration method provide flexibility, efficiency, accuracy and automation by integrating and analyzing information from multiple sources in image guided surgery. It was augmented by the critics that the leading factors effecting the efficiency, reliability and accuracy of registering medical images are physical associations between the source and target image, complex optimization procedures, intensive computation, transformation mechanisms (rigid and non-rigid), invasiveness, compatibility issues, missing or partial data and difficult target localization. Therefore, for the reliable, fast and accurate registration of medical images, more advance and general registration methods are needed which could be used for any type of registration problem. Nevertheless, the introduction of such advanced technologies and their use in clinics is difficult and still needs a massive amount of research contributions from the research communities.

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