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VALIDATION OF A NON-RIGID REGISTRATION ERROR DETECTION ALGORITHM USING CLINICAL MRI KIDNEY IMAGES

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Abstract:

Identification of error in nonrigid registration is a critical problem in the medical image processing community. "Assessing Quality Using Image Registration Circuits" (AQUIRC) method is implemented to identify nonrigid registration errors in clinical MRI kidney images. In this paper, we extend our previous work to assess AQUIRC's ability to detect local nonrigid registration errors and validate it quantitatively at specific clinical landmarks. Non rigid errors can be identified through segmentation of clinical MRI kidney images. Pathology identification can be easily done in the proposed system.

Key Words: Kidney Images, AQUIRC Method, Image Registeration & Validation

1. Introduction:

Although analytical solutions have been derived to estimate error for the point-based rigid-body registration problem [1], no such solution exists for the nonrigid case or even for the rigid case when the transformations are not estimated with homologous points. Assessing the quality of a particular nonrigid registration between image volumes thus remains a difficult and outstanding problem facing the medical imaging community. Few solutions have been proposed that do not require pre-labeled atlases. These solutions generally fall into two broad categories: Bayesian methods and supervised learning techniques.

Bayesian methods have been proposed for instance to estimate registration uncertainty, and have been used to regularize the deformation field in [2], provide confidence information on volumetric measurements in [3], to estimate uncertainty in intra-subject registration in [4] or to estimate lung elasticity in [5]. These techniques require the estimation of posterior distributions, which is done either with Markov Chain Monte Carlo methods [3]–[5], a computationally demanding approach, or mean-field variational Bayesian techniques. In [6] a bootstrap resampling technique is proposed to estimate the variability of an estimated transformation. Evaluation of this technique was limited to 2-D images and simple transformations. Other methods have been proposed that use supervised learning techniques [7]–[9] on image features or manually labeled points to identify registration uncertainty. These techniques, which require a training set for each new application and data set, have been used, for instance, to assess registration accuracy in longitudinal computed tomography (CT) images of the lungs [7], [8] or to detect miss registered regions in simulated brain tumor images [9].

Because assessing the quality of an individual registration is difficult, a number of techniques have been developed over the years to make the transformation estimation process robust and to produce transformations that are likely to be accurate. These include enforcing desirable transformation properties such as inverse consistency and transitivity consistency [10]–[12]. A number of algorithms that enforce inverse consistency have been proposed. A representative set of such algorithms can be found in [13]–[22]. The consistency of three transformations was used by Holden et al. [12], Free borough [24], Woods et al. [11], and Christensen [10] to compare and evaluate several similarity measures and registration algorithms. This technique involves three images A, B, and C and three transformations, i.e., the transformation from A to B, from B to C, and from C to A, respectively. Composing the three transformations maps the coordinate system of image A onto itself through a circuit. If all three transformations are error free, any voxel in image A is mapped exactly onto itself. Errors along the circuit may be detected by computing the distance between a point x and its projection, where. In past work, registration circuits have also been referred to as triplets and loops. Here, we use the term circuit that is used in graph theory.

The inevitability and transitivity properties of transformations were also used by Christensen and Johnson [25] to evaluate nonrigid registration algorithms. In more recent work [16], the same group proposed a registration algorithm called TICMR for transitive inverse consistent manifold registration (TICMR) that jointly estimates a correspondence between three manifolds while minimizing inverse and transitivity consistency. While, undoubtedly, transitivity consistency is a necessary condition for error-free registration around a registration circuit, it is not sufficient. As discussed by Christensen [25], the identity transformation is a trivial example of a useless transformation that would minimize both inverse consistency and transitivity error. Also, transitivity error is an aggregate measure of error across the circuit. It does not identify on which edge in the registration circuit error occurs, and errors may be masked because an error on one edge can be compensated by an error on another edge in the registration circuit. As a consequence, transitivity error has traditionally been used to compare and evaluate algorithms with the assumption that lower transitivity error combined with other checks that would rule out unrealistic or useless transformations is synonymous with a better registration algorithm.

In this work, we calculate transitivity error over multiple registration circuits that have images in common. Thus an individual registration is used in multiple registration circuits; using this redundancy allows for the estimation of error for an individual registration. To the best of our knowledge, transitivity error has not been used to assess the quality of a particular registration between two image volumes until recently [26]–[29]. In this published work, we built on the idea of transitivity error and have shown that it could indeed be used to evaluate the quality of an individual image registration. This algorithm, that we call AQUIRC for assessing quality using image registration circuits, was first proposed in [26] where it was used for global atlas selection.

In [27] we have shown that it could be used to detect errors in intensity-based rigid body registration problems. In [28] we presented preliminary and qualitative results on simulated data suggesting that this approach could be used to detect local registration error. In [29], we used the estimation of error at the local error for local atlas selection. Herein, we extend upon the work in [28]. We apply AQUIRC to a data set of 109 medical images with manually identified ground truth, treating nine images as atlas images and the remaining 100 as target images. We use five popular registration algorithms to provide a wide range of error that is representative of what might be expected when using a registration algorithm in practice. Using these data and algorithms, we show that AQUIRC's quality measure correlates well with the ground truth at the anterior commissure (AC) and the posterior commissure (PC) points. The AC and PC are two reference points used clinically for brain normalization to, for instance, guide the placement of deep brain stimulation (DBS) electrodes. We use the AC and PC points, which can be localized accurately in MR images, as this allows us to correlate our results with a known target registration error locally. Also, we [26], [29] as well as others [30] have used other error measures such a DICE to evaluate our approach. In [26], we applied AQUIRC to global atlas selection and showed that it can be used to improve the DICE value over majority vote as well as over a residual global NMI atlas selection method. We also found in [29] that AQUIRC can be used to improve upon the DICE value over majority vote in the context of local atlas selection for the brainstem and performs comparably to cutting edge atlas selection techniques on other brain structures.

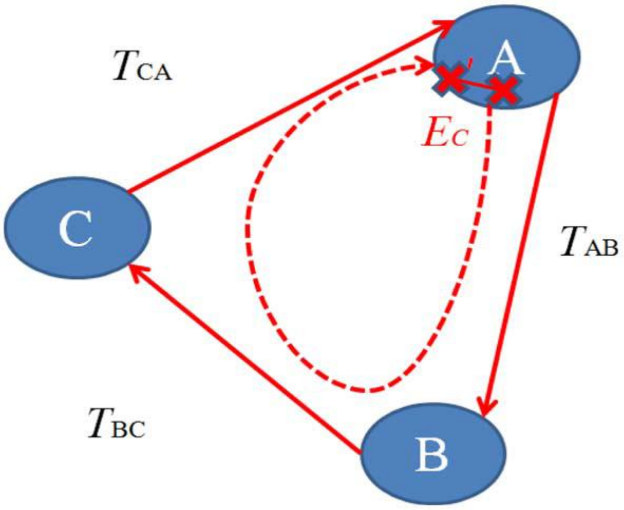

Figure 1: An example of one registration circuit, with the transformations between each image represented by T_{AB}, T_{BC}, and T_{CA}. Distance between the red X and X ` represents the registration circuit consistency error.

2. Ease of Use:

- **Data Preparation:**

Image registration involves more than two images that maybe acquired using different modalities or at different parameters, so in order to achieve consistent input data for the registration process, appropriate data preparation is sometimes needed prior to the registration process. These may include data format conversion; coordinate transformation, intensity correction, distortion correction and so on. Sometimes it may also be necessary to preprocess the data, for example image segmentation, to provide the registration algorithms with appropriate input information.

Many current registration algorithms are not robust in the presence of large intensity variations across the images, so that it may be necessary to apply intensity correction schemes prior to registration. These are typically based on low pass filtering the data to suppress image structure and obtain an estimate of the underlying spatial intensity variations, which can then be used to normalize the intensity of the original images. The result is a much more homogeneous appearance, which is likely to avoid failures of registration algorithms. Blurring is also applied to correct for differences in the intrinsic resolution of the images. Some methods resample the images is otropically to achieve similar voxel sizes in all image dimensions; others resample to obtain similar voxel sizes in the images to be registered.

- **Image Registration Algorithms:**

Registration algorithms compute image transformations that establish correspondence between points or regions within images, or between physical space and images. This section briefly introduces some of these methods. As stated above, based on the registration basis, there are image-based registration and non-imaged based registration. Image-based registration can be further divided into extrinsic and intrinsic, it can also be broadly divided into algorithms that use corresponding points, corresponding surfaces or operate directly on the image intensities.

- **Edge Based Registration:**

Intrinsic registration can also be based segmentation where anatomically the same structures (mostly surfaces) are extracted from both images to be registered, and used as sole input for the alignment procedure. In these algorithms corresponding surfaces are delineated in the two imaging modalities and a transformation computed that minimizes some measure of distance between the two surfaces. At registration this measure should be minimum. The first widely used method was the "head and hat" algorithm[i], but most methods are now based on the iterative closest point algorithm.

- **Non-Rigid Registration Algorithms:**

The main difference between rigid and non-rigid registration techniques is the nature of the transformation. The goal of rigid registration is to find the six degrees of freedom (3 rotations and 3 translations) of a transformation which maps any point in the source image into the corresponding point in the target image. An extension of this model is the affine transformation model which has twelve degrees of freedom and allows for scaling and shearing. These affine or linear transformation models are often used for the registration of images for which some of the image acquisition parameters are unknown, such as voxel sizes or gantry tilt or to accommodate a limited amount of shape variability. By adding additional degrees of freedom (DOF), such a linear transformation model can be extended to nonlinear transformation models.

- **Validation:**

Validation is an essential part of the registration process. Several measures of error including target registration error (TRE) which is the disparity in the positions of two corresponding points after registration can be used to evaluate the registration. TRE may vary with the registration situation such as the imaging modalities, the anatomy and the pathology. So experimental validation of a registration system should be limited to a clinical situation matches the experimental one. The degree of the required match will vary with the registration system, but the same modality pair should always be used.

While visual assessment has also often been used as a standard, the most commonly accepted strategy for validation is to compare the system to be validated against a gold standard, which is defined to be any system whose accuracy is known to be high. Gold standards may be based on computer simulations, typically by acquiring one image and generating a second with a known geometrical transformation, on phantom images, or on pairs of patient images. The former category provides arbitrarily accurate geometrical transformations but, like phantoms, suffers in comparison to the latter category in realism. Simulations should also be approached with great care in nonrigid validations because of the bias of such validations in favor of registration methods that employ similar nonrigid transformations, whether or not they are physically meaningful. Validations based on pairs of acquired patient images represent the most desirable class of standards because of the inclusion of all the physical effects of the patient on image acquisition, but it suffers from the difficulty of establishing the true transformation between acquired images. The simplest method for establishing the transformation between acquired images is based on the target feature, which is any object that can be localized independently in each view. The root-mean-square (RMS) disparity in the two localizations of the target feature after registration provides an upper bound on the RMS of TRE at the location of the feature. A more desirable method for rigid-body registration is based on a registration system that employs several fiducial features as registration cues. The major advantage of this type of system as a validation standard is that its accuracy can be determined without reference to other standards. This feat is accomplished by exploiting theoretically established statistical relationships among fiducial localization error FLE, fiducial registration error FRE, and TRE to translate self-consistency into accuracy. FRE plays an important role in this translation, but is itself a poor measure of registration error.

3. Architecture:

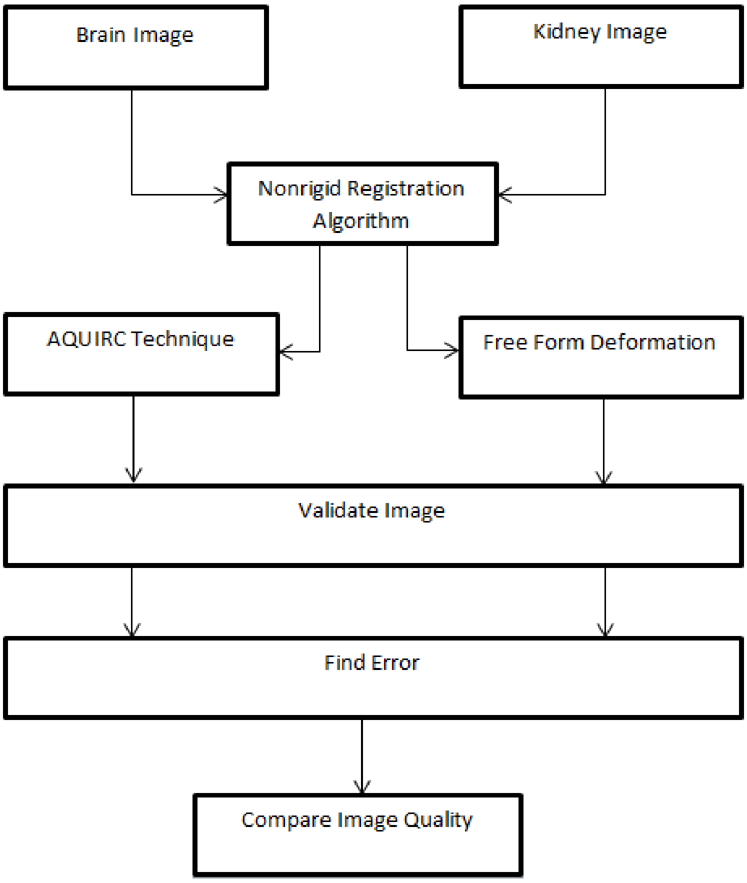

Figure 2: Architecture of kidney image validation Process

4. Conclusion and Future Work:

In the proposed work error detection in biomedical kidney images can be validated by AQUIRC method. Query kidney image is compared with Dataset images to validate the kidney image and to detect errors in it. Non Rigid registration technique is used to validate the kidney images. Image segmentation plays a crucial role in many medical imaging applications by automating or facilitating the delineation of anatomical structures and other regions of interest. Computed tomography (CT) is images with low contrast and with heavy noise. To handle these types of images for the purpose of kidney tumor delineation, we propose a new technique called AQUIRC is used. Non rigid registration errors are identified by this method. By combining and refining state-of-the-art techniques we demonstrate the possibility of building an algorithm that meets these requirements.

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