Image Registration Methods and Validation Techniques

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Abstract - *Image registration shows up in a rich range of application domains, such as medical image analysis (e.g. diagnosis), neuroscience (e.g. brain mapping), computer vision (e.g. stereo image matching for shape recovery), astrophysics (e.g. the alignment of images from different frequencies), military applications (e.g. target recognition), etc Image registration is an important step for a great variety of applications such as remote sensing, medical imaging and multi-sensor fusion based target recognition. It is a prerequisite step prior to image fusion or image mosaic. Its purpose is to overlay two or more images of the same scene taken at different times, from different viewpoints and/or by different sensors. It is also necessary to estimate the accuracy of the image registration process .In this paper we review the different image registration methods as well as the validation techniques.*

Keywords — *Image registration, Validation, Image alignment*

I. INTRODUCTION

In image processing, often, we are interested in the relationship between two or more images. The analysis of this relationship usually becomes tractable once a correspondence is set up between the images. Image registration is the task of setting up this correspondence. The definition of correspondence varies across disciplines and even across individual applications. Over the years, a broad range of techniques has been developed for various types of data and problems. These techniques have been independently studied for several different applications, resulting in a large body of research. Whatever the method used and the area of application, it is essential to estimate the accuracy of the image registration process.

The remaining of the paper is organized as follows. In section 2, introduction to image registration is given. In section 3, the classification and methods of image registration is discussed. In section 4, the validation techniques for image registration is discussed.

II. IMAGE REGISTRATION

Image registration is used to match two or more partially overlapping images and stitch them into one panoramic image of the scene. To register two images, the coordinate transformation between a pair of images must be found from class of transformations. The optimal transformation depends on the types of relation between the overlapping images. To find the relationship between two images we rely on the estimation of the parameters of the transformation model. The number of parameters depends on the chosen transformation model. A common assumption is that the coordinate transformations between two images are rigid planar models. Rigid planar transformation is composed of scaling, rotation, and translation changes, which map the pixel *(x1, y1)* of image *f1* to the pixel *(x2, y2)* of another image *f2*: The rigid transformation is sufficient to match two images of a scene taken from the same viewing angle but from different position. That is, the camera can rotate about its optical axis. In the case of remote sensing, where the distance approaches infinity, the transformation between the captured images behaves like a planar rigid transformation. Image registration is widely used in remote sensing, medical imaging, computer vision etc. Image registration applications can be divided into four main groups according to the manner of the image acquisition namely different viewpoints (multi view analysis), different times (multi temporal analysis) and different sensors (multimodal analysis).

Due to the diversity of images to be registered and due to various types of degradations it is impossible to design a universal method applicable to all registration tasks. Every method should take into account not only the assumed type of geometric deformation between the images but also radiometric deformations and noise corruption, required registration accuracy and application-dependent data characteristics. Nevertheless, the majority of the registration methods consist of four steps namely feature detection, feature matching, mapping estimation and image resampling.

Feature detection also called Control Point (CP) includes selection such as lines, edges, corners, etc. It is necessary to decide what kind of features is appropriate for the given task. The features should be distinctive objects, which are frequently spread over the images and which are easily detectable. Usually, the physical interpretability of the features is demanded. The detected feature sets in the reference and sensed images must have enough common elements, even in situations when the images do not cover exactly the same scene or when there are object occlusions or other unexpected changes. The detection methods should have good localization accuracy and should not be sensitive to the assumed image degradation. In an ideal case, the algorithm should be able to detect the same features in all projections of the scene regardless of the particular image deformation.

Feature matching, includes establishing a match between the control points chosen in step 1. In this step, problems caused by incorrect feature detection or by image degradations can arise. Physically corresponding features can be dissimilar due to the different imaging conditions and/or due to the different spectral sensitivity of the sensors. The choice of the feature description and similarity measure has to consider these factors. The feature descriptors should be invariant to the assumed degradations. Simultaneously, they have to be discriminate enough to be able to distinguish among different features as well as sufficiently stable so as not to be influenced by slight unexpected feature variations and noise. The matching algorithm in the space of invariants should be robust and efficient. Single features without corresponding counterparts in the other image should not affect its performance.

Mapping estimation consists of estimating the best parameters responsible for registering the sensed image to the reference one. The type of the mapping functions should be chosen according to the a priori known information about the acquisition process and expected image degradations. If no a priori information is available, the model should be flexible and general enough to handle all possible degradations which might appear. The accuracy of the feature detection method, the reliability of feature correspondence estimation, and the acceptable approximation error need to be considered too. Moreover, the decision about which differences between images have to be removed by registration has to be done. It is desirable not to remove the differences we are searching for if the aim is change detection. This issue is very important and extremely difficult.

Image resampling, consists of transforming the sensed image using the optimal parameters found in the previous step. The choice of the appropriate type of resampling technique depends on the trade-off between the demanded accuracy of the interpolation and the computational complexity. The nearest-neighbor or bilinear interpolation are sufficient in most cases; however, some applications require more precise methods.

III. CLASSIFICATION

Image registration methods can be classified based on the feature space employed and the warp space employed.

3.1. Based on Feature Space.

Based on the feature space employed, the image registration algorithms can be classified as pixel-based, transform-based and feature-based.

3.1.1. Pixel based Image Registration.

Pixel-based algorithms work directly with the pixel values of the images being registered. Preprocessing is often used to suppress the adverse effects of noise and differences in acquisition [1] or to increase or uniformise pixel resolution [2]. It is possible to work directly with the pixel values on the discrete coordinate grid. However, to get a sub pixel resolution, the problem is often cast into the continuous framework. The images are considered as functions of real arguments, the image coordinates. The correspondence between the discrete and continuous versions of the image is established using interpolation. The crudest method is the nearest-neighbor, and the most often used one is linear interpolation. Among the high-end methods, spline interpolation [3] provides the best tradeoff between accuracy and the computational cost. Occasionally, the image model occupies more dimensions than the original data. The main advantage of this approach is a more global vision of the algorithm, which increases its robustness.

3.1.2. Transform based Image Registration.

Transform-based algorithms exploit properties of the Fourier, Wavelet, Hadamard and other transforms, making use of the fact that certain deformations manifest themselves more clearly in the transform domain. These methods are used mainly in connection with linear deformation fields. Nevertheless, there are examples of methods that estimate locally linear optical flow using Gabor filters [4] and B-spline wavelets [5]. Typical characteristics of the transforms employed are linearity and independence on the actual image contents.

3.1.3. Feature based Image Registration.

Feature-based algorithms work on a set of characteristic features extracted from the images. The dimensionality of the features is usually drastically smaller than the dimensionality of the original image data. The extraction process is highly non-linear, mostly using thresholding. Landmark based methods [6-9] use a relatively small and sparse set of landmarks. These are important points which can be (manually or automatically) identified in both images. Extrinsic markers refer to specifically designed artificial features attached to the object (or subject, in medical imaging) before acquisition to serve as landmarks. Unfortunately, extrinsic markers are difficult to deploy. In medical imaging they are not patient friendly either. If extrinsic markers are not available, we have to content ourselves with features intrinsic to the images. In that case, however, the automatic landmark identification suffers from lack of robustness. The manual landmark identification is often tedious, time-consuming, imprecise, and unreproducible. If the images cannot be characterized using points, it might be more appropriate to use curves such as edges [10] or volume boundaries [11]. Likewise, in the case of 3D data, surfaces can be used instead of working with the complete volumes. Popular features are also templates, small sub-images of important regions [12], which can be used directly, or which can form a higher level feature map [13].

3.2. Search Space based Classification.

One of the important factors to categorize registration algorithms is the search space used. We also call it a warp space, because it contains warping functions. Warping functions are candidate solutions of the registration problem. From the analogy between warping and deformation, the deformation (warping) functions play also the role of correspondence functions. Because we work with finite memory computers, every warping function from the search space is described by a finite set of real parameters (from a set of permissible values) by means of a warping model. We classify the warping models according to the number of parameters and the spatial extent of the area influenced by a single parameter.

3.2.1. Local Models.

The deformation function sought after is basically unconstrained, or belongs to a very large and unrestrictive functional space. We seek the values of this deformation at a very fine grid, usually coinciding with pixel locations. These methods are formulated either as variational, defining a scalar criterion to minimize, or more generally using partial differential equations (PDE). The continuously defined deformation function minimizes a given criterion, or solves a given PDE. The essence of these methods is thus entirely in the criterion. The PDE come from the optical flow approach (gradient methods) [14], viscous fluid model [15-17], and elastic deformations with physical analogs or without it. Sometimes the deformation function is also modeled indirectly. For example, it can be modeled using a potential field [18]. This reduces the dimensionality of the problem, at the expense of reduced generality of the deformation. Discretization allows for integer only displacements at pixel points [19].

3.2.2. Global Models.

Global methods describe the correspondence function using a global model with a relatively small number of parameters [20]. The model mostly consists of expressing the warping function in a linear [21], global polynomial [22] or harmonic basis [23,24]. For these methods, the deformation model corresponding to a specific warp space is as important as the criterion being minimized.

3.2.3. Semi Local Method

In between the two extremes are semi-local models, using a moderate number of parameters with local influence. A grid of control points is placed over the image. Their spacing corresponds loosely to knot or landmark density. By changing the spacing, we can approach either of the limit cases or choose a compromise offering the best tradeoff. Such models were used in the context of motion estimation [25]. B-spline models have also been independently used [26].

3.2.4. Image Dependent Models.

It is sometimes useful to adapt the warping model to the images considered. Quadtree based deformation model [27] is refined only where it is needed. In feature based methods, the basis functions of the warping model can be placed where the features are. The deformation field is interpolated in regions where no information is available. Typical examples are radial basis functions such as thin plate splines [28].

3.2.5. Elastic Registration

In this method, introduced by Bajcsy [29] et al the estimation of the geometric deformation is reduced to the search for the 'best' parameters. Here the images are viewed as pieces of a rubber sheet, on which external forces stretching the image and internal forces defined by stiffness or smoothness constraints are applied to bring them into alignment with the minimal amount of bending and stretching. The feature matching and mapping function design steps of the registration are done simultaneously. Fluid registration methods make use of the viscous fluid model to control the image transformation. The reference image is here modeled as a thick fluid that flows out to match the sensed image under the control of the derivative of a Gaussian sensor model. This approach is mainly used in medical applications. Other examples of non-rigid methods are diffusion based registration, level sets registration, and optical flow based registration.

IV. VALIDATION TECHNIQUES

One of the challenges in the development of image registration algorithms is their validation. It is essential to provide an estimate of the accuracy of the image registration. Errors can occur in the registration process in each of its stages. There might be physical differences in the images which might be hard to distinguish from registration inaccuracies. In this section we discuss the basic error classes and validation strategies.

4.1. Basic Error classes.

The errors that can occur in the image registration can be brought under the classes of localization error, matching error and alignment error. Localization error is due to the displacement of the CP coordinates due to their inaccurate detection. Though it cannot be measured directly for a given image, the expected localization error can be estimated from the computer simulation studies of various image types. Localization error can be reduced by selecting an optimal feature detection algorithm for the given data but usually there is a tradeoff between the number of detected CP candidates and the mean localization error. Matching error is measured by the number of false matches when establishing the correspondence between CP candidates. This error often leads to failure of the registration process and can be avoided by the use of robust matching algorithms. Alignment error denotes the difference between the mapping model used for the registration and the actual between-image geometric distortion.

4.2. Validation Techniques

In this section, we discuss the validation of image registration algorithms. The ideal validation data for image registration of two images would have the true displacement vector for each point of the first image that would bring it to the corresponding point in the second image. In addition, the accuracy of the data has to be known, since validation data without known accuracy is useless. In most practical cases such data is impossible to obtain. Researchers have used a number of methods to assess the quality of image registration algorithms. Several validation strategies have been suggested.

4.2.1. Visual Assessment.

In many applications, the only practical approach for estimation of the registration accuracy is to visually inspect the images. Observers look at the registered images, using contour overlays for inter-modality registration [30] or difference images for intra-modality registration [31-36] and then qualitatively classify the registration solution as good, average or poor. This is a subjective and qualitative measure and it does not provide true displacement vectors between the two images.

4.2.2. Gold Standard.

If the true (gold standard) geometric transformation between the two images is known, then the accuracy of the image registration algorithm can be obtained by comparing the calculated transformation to the gold standard one.

4.2.3. Simulation.

A displacement field is generated, referred to as true displacement field, and is applied to an image to obtain a deformed image. The image registration algorithm can be run using the original and the deformed image, and the computed displacements can be compared to the true ones.

V. CONCLUSION

In this paper we have discussed the various image registration techniques, classes of errors that can occur in the image registration process and validation strategies for the registration process. Though many techniques are available there is no hard and fast rule for selecting a technique for a particular application. Also the automation of image registration process is also under research. New methods like polar transforms, sub pixel, swarm optimization, ant colony algorithms have been proposed. A combination of the methods can also be considered for specific applications.

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