Medical Image Registration: a Review

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Abstract

This paper presents a review of automated image registration methodologies that have been used in the medical field. The aim of this paper is to be an introduction to the field, provide knowledge on the work that has been developed and to be a suitable reference for those who are looking for registration methods for a specific application. The registration methodologies under review are classified into intensity or feature based. The main steps of these methodologies, the common geometric transformations, the similarity measures, and accuracy assessment techniques are introduced and described.

Keywords: computational methods; image analysis; image alignment, matching, warping; geometrical transformations; similarity measures; optimization

1. Introduction

Image registration, also known as image fusion, matching or warping, can be defined as the process of aligning two or more images. The goal of an image registration method is to find the optimal transformation that best aligns the structures of interest in the input images. Image registration is a crucial step for image analysis in which valuable information is conveyed in more than one image; i.e., images acquired at different times, from distinct viewpoints or by different sensors can be complementary. Therefore, accurate integration (or fusion) of the useful information from two or more images is very important.

Much of the research that has been developed for medical image analysis was devoted to image registration (Pluim and Fitzpatrick, 2003). Applications of image registration in the medical field include: fusion of anatomical images from Computerized Tomography (CT) or Magnetic Resonance Imaging (MRI) images with functional images from Positron Emission Tomography (PET), Single-Photon Emission Computed Tomography (SPECT) or Functional Magnetic Resonance Imaging (fMRI); intervention and treatment planning (Gering et al., 1999; Gering et al., 2001; Staring et al., 2009); computer-aided diagnosis and disease following-up (Huang et al., 2009); surgery simulation (Miller et al., 2010); atlas building and comparison (Freeborough and Fox, 1998; Ganser et al., 2004; Gooya et al., 2011; Joshi et al., 2004; Leow et al., 2006; Wu et al., 2009); radiation therapy (Foskey et al., 2005; Lavely et al., 2004); assisted/guided surgery (Huang et al., 2009; Hurvitz and Joskowicz, 2008; King et al., 2010; Maurer et al., 1997); anatomy segmentation (Collins and Evans, 1997; Dornheim et al., 2005; Frangi et al., 2003; Gao et al., 2010; Isgum et al., 2009; Martin et al., 2008; Oliveira et al., in press; Zhuang et al., 2010); computational model building (Grosland et al., 2009); and image subtraction for contrast enhanced images (Maksimov et al., 2009). For PET and SPECT images, registration has also been useful for correct scatter attenuation and partial volume corrections based on CT images (Bai and Brady, 2011; Hajnal et al., 2001).

Medical image registration has been developed for almost all anatomic parts or organs of the human body: brain (Ashburner, 2007; Auzias et al., 2011; Bhagalia et al., 2009; Cho et al., 2011; Collignon et al., 1997; Duay et al., 2008; Gering et al., 2001; Guimond et al., 2001; Hipwell et al., 2003; Itti et al., 1997; Kassam and Wood, 1996; Liao and Chung, 2010; Mayer et al., 2011; Postelnicu et al., 2009; Shen, 2004; 2007; Shen and Davatzikos, 2002; Studholme et al., 1997; Wu et al., 2006b; Xie and Farin, 2004; Xu et al., 2009; Zhu and Cochoff, 2002), retina (Cideciyan, 1995; Fischer and Modersitzki, 2004; Lin and Medioni, 2008; Matsopoulos et al., 2004; Stewart et al., 2003; Tsai et al., 2010), chest/lung (Bhagalia et al., 2009; Mattes et al., 2003), whole thorax (Loeckx et al., 2003), breast (Karaçali, 2007; Rohlfing et al., 2003; Rueckert et al., 1999; Schnabel et al., 2003; Serifovic-Trbalic et al., 2008; Washington and Miga, 2004), abdomen (liver, kidney and spleen) (Brock et al., 2005), prostate (Alterovitza et al., 2006; Foskey et al., 2005), entire body (Shekhar et al., 2005), cervical (Staring et al., 2009), heart (Dey et al., 1999; Grau et al., 2007; Huang et al., 2009; Ledesma-Carbayo et al., 2005; Rhode et al., 2003; Shekhar and Zagrodsky, 2002; Shekhar et al., 2004), pelvis (Hamilton et al., 1999; Shen, 2004; 2007), wrist (Giessen et al., 2009), vascular structures (Groher et al., 2009; Hipwell et al., 2003; Ruijters et al., 2009), bones (Andreetto et al., 2004; Heger et al., 2005; Hurvitz and Joskowicz, 2008; Tang et al., 2006), knee (Mahfouz et al., 2003; Yamazaki et al., 2004), and spine (Tomazevic et al., 2003).

Recent improvements in medical imaging have allowed the acquisition of temporal image sequences. In comparison to static images, these sequences offer additional information about the motion of the imaged organs, such as the heart. Examples of spatiotemporal image registration of the heart can be found in (Grau et al., 2007; Ledesma-Carbayo et al., 2005; Perperidis et al., 2005; Peyrat et al., 2010), and a solution for temporal plantar pressure image sequences registration is presented in (Oliveira et al., 2011).

In the literature, several reviews on image registration methods can be found: overall image registration in (Brown, 1992; Salvi et al., 2007; Wyawahare et al., 2009; Zitová and Flusser, 2003), medical image registration in general (Bronzino, 2000; Elsen et al., 1993; Fischer and Modersitzki, 2008; Goshtasby, 2005; Hajnal et al., 2001; Hill et al., 2001; Maintz and Viergever, 1998; Modersitzki, 2004; Slomka and Baum, 2009), and hierarchical non-linear medical image registration (Lester and Arridge, 1999). Also there are reviews that focus on specific anatomical parts, such as: cardiac (Mäkelä et al., 2002), retina (Laliberté et al., 2003), breast (Guo et al., 2006) and brain (West et al., 1997). Other surveys focus on the image similarity measure in (Penney et al., 1998; Pluim et al., 2003; Pluim et al., 2004).

A large number of software solutions have been presented for medical image registration; examples of free-open-source software packages include: FAIR (Modersitzki, 2009) – source code in Matlab; AIR (Woods, Roger P. et al., 1998; Woods, Roger P. et al., 1998) – source code in C; ITK (Ibáñez et al., 2005) – source code in C++; 3D Slicer (Gering et al., 1999; Pieper et al., 2004; Pieper et al., 2006) – almost all source code in C++; FLIRT (Jenkinson and Smith, 2001) – source code in C++; and Elastix (Klein et al., 2010) – source code in C++.

Both 3D Slicer and Elastix are based on the ITK library. ART is also a free software package distributed as binary files for Linux and Mac operating systems. The well-known Statistical Parametric Mapping (SPM) (Ashburner and Friston, 1999; Friston, K. J. et al., 1995) software package has been designed for the analysis of brain imaging data sequences, but it also includes a registration tool. An extended list of free software solutions for medical image analysis can be found on the Neuroimaging Informatics Tools and Resources Clearinghouse (NITRC) webpage.

Besides free software for image registration, there are free medical images available for study purposes. For instance, on the BrainWeb project webpage, a simulated brain database with three MRI sequences (T1, T2, and proton-density) is available; and on the PET-SORTEO project webpage, simulated PET images are accessible.

Several comparisons of image registration methodologies have been published. For instance, in (West et al., 1997) twelve registration methodologies, some fully automated and others with user interaction, were compared. Those methodologies were compared for the registration of CT, PET and MR brain volumes. The accuracy of the methodologies under comparison was assessed by relating the geometric transformation found with a gold standard obtained based on fiducial markers attached to the skull. In (Zhilkin and Alexander, 2004) the PA – *Patch Algorithm* (Zhilkin and Alexander, 2000) is compared with the AIR 3.0, COCGV, FLIRT–*FMRIB's*, IR, and SPM algorithms on monomodal registration by using affine geometric transformations. Regarding non-rigid registration, fourteen algorithms were compared in the registration of brains in (Klein et al., 2009), namely: AIR, ANIMAL, ART, Diffeomorphic Demons, FNIRT, IRTK, JRD-fluid, ROMEO, SICLE, SyN, and four different SPM5 algorithms ("SPM2-type" and regular Normalization, Unified Segmentation, and the DARTEL Toolbox). Other comparisons can be found in (Ardekani et al., 2005; Economopoulos et al., 2010; Hellier et al., 2003; McLaughlin et al., 2005; West et al., 1999; Yassa and Stark, 2009).

Image registration is often referred to as image fusion, image matching or image warping; however to avoid any ambiguities these terms will be designated the following definitions for the rest of this paper: image fusion is used to designate the process of combining two or more images into a single image; image matching, as the process of establishing the correspondences among the structures in input images without explicitly aligning them; and image warping, as the application of a geometric transformation on an input image. Also, “fixed image” is designated as the image that remains unchanged, and “moving image” as the image that is transformed using the “fixed image” as a reference.

The main goals of this paper are to introduce the works done on medical image registration, and identify and introduce the key guidelines that have been defined and addressed.

Although several reviews on medical image registration can be found, e.g. (Slomka and Baum, 2009), this review here has a wide coverage and is very general, as no particular attention is given to a specific multimodality image registration application, however, detailed information concerning the main steps of common registration algorithms is given.

The paper is organized as follows: In the next section, the image registration methodologies are classified. Afterwards, common registration methodologies are introduced and explained, focusing on their main features, such as: geometric transformations, similarity measures and optimizers. Then, in section 4, the current techniques for accuracy assessment are presented and, finally, in the last section, a discussion is addressed.

2. Registration methodologies - classification

Basically, the registration of input images requires the selection of the feature space, a similarity measure or alignment quality, a transformation type and a search strategy. A great number of medical image registration methodologies have been presented, and several criteria have been proposed to classify them. Elsen, Pol and Viergever (Elsen et al., 1993) classified the registration methodologies by the data dimensionality (1D, 2D, 3D, 4D, …), source of the image features used to make the registration (intrinsic or extrinsic properties of patients), transformation domain (local or global), transformation elasticity (rigid, affine, projective or curved), tightness of property coupling (interpolating or approximating), parameter determination (direct or search-oriented), and interaction (interactive, semi-automatic or automatic). This classification scheme was further detailed and extended to nine fundamental criteria by Maintz and Viergever (Maintz and Viergever, 1998), where each criterion was divided into one or more sub-criteria (Table 1).

[Insert Table 1 about here]

The registration of images from the same modality, but obtained using different acquisition parameters, such as, the registration of T1-MRI images with T2-MRI or proton density MRI images, are often classified as multimodal.

Registration methodologies are also commonly classified using the feature space image information. This information may be the intensity of the raw voxels, the intensity gradient, statistical information related to the voxel intensity, or structures extracted from the images to be registered, such as, sets of points, edges, contours, graphs, surfaces and volumes.

Registration methodologies based on voxel intensity are commonly known as intensity based, and those based on the geometrical structures extracted from the images as feature based or geometrical based (Hawkes, 2001). Other methodologies use the images in the frequency domain or the Fourier transform properties to achieve optimal registration, and are known as frequency or Fourier based.

Another common classification criterion for registration is based on the amount of image information that is used in the process. A methodology is classified as global, if all voxels presented in the region of the interest (ROI) are used. On the other hand, it is classified as local, if only a part of the voxels in the ROI is used. Usually, the intensity based methods are global and the feature based methods are local.

A common medical image, I, can be defined as a function $I : D \subset R^3 \to R$; that is, I is defined in a subset of a three dimensional space and has values in R. However, in some imaging modalities, like diffusion tensor magnet resonance imaging (DT-MRI), the image can have values in a multidimensional space. In this case, the images are also known as multichannel images, vector images or tensor images. In this work, no distinction has been made for this feature, and all images are assumed to be defined in a 3D space, since volumetric images are the most common image data type in medical imaging and two dimensional images can always be considered in a 3D space.

3. Registration methodologies

Most of the intensity based registration methodologies can be illustrated by the diagram in Figure 1. The main idea is to search iteratively for the geometric transformation that, when applied to the moving image, optimizes i.e. minimizes or maximizes a similarity measure, also known as the cost function. The similarity measure is related to voxel intensity and is computed in the overlapped regions of the input images. The optimizer has the function of defining the search strategy. The aim of the interpolator is to resample the voxel intensity into the new coordinate system according to the geometric transformation found.

Whenever possible, a pre-registration transformation, which makes the moving images closer to the fixed imaged in terms of the similarity measure, is used as an initial solution for the registration algorithm. A good pre-registration allows a faster convergence of the optimizer and decreases the likelihood of convergence to a local optimum.

[Insert Figure 1 about here]

For the feature based registration methodologies there are two main approaches to search for the optimal transformation after the feature segmentation process in the input images: 1) the matching among features is established using some criterion, e.g. based on geometrical, physical or statistical properties. Then, the geometric transformation is established based on the matching found (Figure 2). An example of such approach is when the features extracted, i.e. segmented, from the input images, are sets of points and each point is represented by a descriptor. Then, the “corresponding costs” are the “distances” between the descriptors of the possible point pairs, and the similarity measure between the input images is usually given by the sum of all the “corresponding costs” established (Bastos and Tavares, 2004; Oliveira and Tavares, 2009; Oliveira et al., 2009a). As such, this approach is reliable when the descriptors used are invariant to the geometric transformations to be assessed. 2) the matching and the transformation are defined concurrently based on the optimization of a similarity measure between the features extracted from the input images. The algorithm of this registration approach is quite similar to the algorithm in Figure 1; however, in this case, rather than the original intensity images, the features extracted are used to define the registration result.

[Insert Figure 2 about here]

The registration methodologies based on image moments, such as the principal axes technique (Alpert et al., 1990; Dhawan et al., 1995; Faber and Stokely, 1988), can be classified as feature based, since the basis of the registration is a set of image descriptors extracted from the input images. However, the algorithm used is different from the ones previously presented. Briefly, in this methodology, the translational component of the transform is based on the centres of mass of the images; and the rotational component is based on the eigenvectors of the second order central moments matrix of the images.

In the next sections, the registration algorithms illustrated in Figures 1 and 2 are described.

3.1 Geometric transformations

The choice of the geometric transformation model used is crucial to the success of a registration algorithm, and is highly dependent on the nature of the data to be registered. Usually, the geometric transformations are divided into rigid and non-rigid classes. The rigid transformation is the simplest one, and in a 3D space, it can be defined by 6 parameters or degrees-of-freedom: 3 translational and 3 rotational parameters. The non-rigid transformation class includes the similarity transformation (translation, rotation and uniform scaling), affine (translation, rotation, scaling, and shear), projective, and curved. The curved transformation is also commonly referred to as a deformable, elastic or fluid transformation. The rigid and similarity geometric transformations are subsets of the affine transformation.

A 3D affine transformation $T : R^3 \rightarrow R^3$ is given by $T(X) = DX + S$, where D is a 3×3 matrix representing the rotation, scaling and shearing, and S is a 3×1 vector representing the translation or shift. Sometimes, affine transformations are classified as linear; however, such classification is not mathematically correct, since the function T is linear if, and only if, $T(aX + bY) = aT(X) + bT(Y)$, which implies that the translational component S of the transformation be null. The affine geometric transformation is usually represented with homogeneous coordinates, which has the advantage of using only a 4×4 matrix to represent the whole transformation.

According to the literature, a rigid geometric transformation is mainly applied in two situations. One is in the registration of rigid structures, such as bones (Andreetto et al., 2004; Heger et al., 2005; Livyatan et al., 2003; Tang et al., 2006) and the other is in pre-registration before a more complex geometric transformation (Auer et al., 2005; Hellier and Barillot, 2004; Lötjönen and Mäkelä, 2001; Mattes et al., 2003). The use of affine non-rigid transformations in the final image registration is not common; but, some examples can be found in (Butz and Thiran, 2001; Jenkinson and Smith, 2001; Meyer et al., 1997; Zhilkin and

Alexander, 2000; Zvitia et al., 2010). Like the rigid transformation, the affine non-rigid transformation is also sometimes used in a pre-registration for a final curve registration (Balci et al., 2007; Karaçali, 2007; Zhuang et al., 2010). The affine transformations, both rigid and non-rigid, have been used in the registration of ultrasound images (King et al., 2010; Meyer et al., 1999; Roche et al., 2001; Shekhar and Zagrodsky, 2002; Shekhar et al., 2004), since the low resolution and low signal-to-noise ratio of the ultrasound images makes the accurate registration difficult when more complex transformations are used.

Most approaches for medical image registration are based on curved transformations, since the almost all anatomical parts, or organs, of the human body are, in fact, deformable structures. The simplest curved transformations are based on polynomials of a degree superior to one, and, in a similar way to the affine transformations. Their implementation is very simple as they can be defined by a deformation matrix and a translation vector. However, these transformations are rarely used since they do not usually represent the real deformations involved in the medical images.

Basically, two kinds of curved deformations have been used in medical image registration: free-form transformations, in which any deformation is allowed; and guided deformations, in which the deformation is controlled by a physical model that has taken into account the material properties, such as tissue elasticity or fluid flow. It should be noted that sometimes the registration algorithms based on fluid flow are classified as free-form, since they are able to address almost any deformation.

In many free-form deformation models, a grid of control points is defined in order to determine the deformation involved. The points of such a grid are moved individually in the direction that optimizes the similarity measure, defining local deformations. Transformation between control points is propagated by interpolation; for example, using linear interpolation (Kjems et al., 1999), or other convex kernels (Gaens et al., 1998; Lötjönen and Mäkelä, 2001). The most popular interpolator used for free-form deformation is probably the cubic B-spline (Bai and Brady, 2011; Balci et al., 2007; Bhagalia et al., 2009; Kabus et al., 2004; Khader and Hamza, 2011; Kybic and Unser, 2003; Mattes et al., 2003; Rohlfing and Maurer, 2001; Rohlfing et al., 2003; Rueckert et al., 1999; Studholme et al., 2000; Xie and Farin, 2004); but, B-splines of other degrees can also be used (Loeckx et al., 2010).

Originally, the free-form deformation based on the cubic B-spline was defined in a regular grid of points. Lately, in (Schnabel et al., 2001), a new framework was proposed by extending and generalizing the technique previously presented in (Rueckert et al., 1999). On the other hand, some authors have developed a deformable registration method by defining the global transformation as a series of locally affine transformations (Periaswamy and Farid, 2003; Shekhar et al., 2005).

Some elastic models handle the objects represented in the images as elastic solids (Alexander and Gee, 2000; Christensen and Johnson, 2001; Christensen et al., 1994; Davatzikos, 1997; Gefen et al., 2003). The main idea of image registration methodologies based on elastic solids is straightforward: the internal elastic forces of the solid oppose the deformation, while the external forces driven by the similarity measure try to deform the data to fit the body configuration. Thus, the moving image is deformed until the internal and external forces reach an equilibrium.

Other elastic based registration methods are based on finite element models (Ferrant et al., 2002; Grosland et al., 2009). These models divide the input image into cells and assign a physical description of the tissue property to these cells.

Thin-plate splines (TPS) based registration methodologies are also based on deformable solid properties; however, the fundamentals of the approach are different from the previous ones (Auer et al., 2005; Meyer et al., 1999; Meyer et al., 1997). In these methodologies, a set of control points is moved along the direction that optimizes the similarity measure used. The propagation of the deformation to the neighbours of the control points is defined by the thin-plate model. For point correspondence based registrations, the TPS is based on the correspondences found between the sets. TPS is a interpolation function that minimizes the bending energy (Holden, 2008). Some authors, as in (Rohr et al., 2001; Serifovic-Trbalic et al., 2008), have used approximating TPS rather than interpolating TPS, since the former are more robust to the outliers which can occur in the landmark or point localizations.

The deformable registrations based on TPS are global, that is, when a control point is moved, its new position affects the whole deformation. The registrations based on free-form B-spline deformations are local; however, they also can be classified between a global registration model and a pure local model, since their locality can be controlled by varying the grid or mesh spacing and consequently the number of degrees-of-freedom. Since the free-form B-spline deformations are local, it is essential to correct the global misregistration before computing the deformation involved, for instance, using an affine transformation (Rueckert et al., 1999).

The expression “elastic registration” is sometimes used as a synonym of a curved or deformable registration, however for the rest of this paper it is used just for the registration methodologies whose geometric transformation is based on the elastic properties of solid objects.

In flow based registration algorithms, the registration problem is addressed as a motion problem. As such, the content of an image moves continually towards the other image, and this movement or deformation is driven by the minimization of the energy of the physical model adopted.

Flow based registration algorithms can be divided into two classes: fluid flow and optical flow. Some examples of registration algorithms based on fluid flow can be found in: (Ashburner, 2007; Auzias et al., 2011; Bro-Nielsen and Gramkow, 1996; Chiang et al., 2008; Christensen et al., 1997; Christensen et al., 1994; 1996; D’Agostino et al., 2003; Freeborough and Fox, 1998; Guimond et al., 2002; Hermosillo et al., 2002; Joshi et al., 2004; Leow et al., 2005; Studholme et al., 2006; Tosun and Prince, 2008).

The well-known demons algorithm and its variations (Gooya et al., 2011; Guimond et al., 2002; Guimond et al., 2001; Thirion, 1998; Vercauteren et al., 2007; 2009; Wang et al., 2005; Yeo et al., 2010a) are examples of optical flow based registration algorithms. Other examples of optical flow based algorithms can be found in (Hellier et al., 2001; Tosun and Prince, 2008). The demons algorithm is based on a diffusion process. When applied on monomodal registration, the demons based registration is a variant of the optical flow based approach. If instead of considering the original image intensity values, the image gradients are used, then this algorithm can also be successfully applied on some multimodal image registrations. Further details on demons algorithm can be found in (Pennec et al., 1999).

The fluid based transformations allow larger deformations than the elastic based transformations. Thus, a low-dimensional elastic transformation is sometimes used prior to a high-dimensional fluid registration (Christensen et al., 1997).

The registration algorithms based on B-splines address the image deformations as a combination of basis functions, particularly the B-splines, but other basis functions have also been used (Ashburner and Friston, 1999; Friston, K. J. et al., 1995). Thus, the registration problem can be seen as a problem of finding a set of coefficients for the basis functions that optimizes the similarity measure.

To preserve the topology of the structures represented in the images to be registered, the geometric transformation needs to be a diffeomorphism; that is, to be invertible and differentiable mapping with differentiable inverse. The registration methodologies that use diffeomorphic transformations are known as diffeomorphic image registration methodologies. The set of elastic-solid based registration methodologies are examples of these methodologies. The free-form and flow based registration methodologies can also be diffeomorphic if a penalty term is added to the similarity measure or adequate constraints are used in order to avoid undesirable deformations. If not degenerated, the affine transformations are also diffeomorphic. Examples of registration algorithms that include diffeomorphic transformations can be found in (Ashburner, 2007; Auzias et al., 2011; Beg et al., 2005; Geng et al., 2011; Joshi and Miller, 2000; Marsland and Twining, 2004; Rao et al., 2004; Vercauteren et al., 2007; 2009; Yeo et al., 2010a; Yeo et al., 2009).

A comparative study among transformation functions for non-rigid medical image registration based on points correspondence is presented in (Zagorchev and Goshtasby, 2006). Additionally, a study on geometric transformations for non-rigid image registration can be found in (Crum et al., 2004) and a review in (Holden, 2008). Closely related to the medical image registration is the computational anatomy, that is, the computational models of organ deformations. A study on this subject can be found in (Miller et al., 2002).

3.2 Similarity measures

The similarity measures here are dived into two classes, the intensity and feature based methods. Depending on the features used, some similarity measures can be included in both classes.

Normally, the similarity measure used for deformable image registration is composed of at least two terms: one related to the voxel intensity or structures similarity, and the other one to the deformation field (Ashburner et al., 1999; Auzias et al., 2011; Collins and Evans, 1997; Hermosillo et al., 2002; Lötjönen and Mäkelä, 2001; Lu et al., 2004; Rohlfing and Maurer, 2001; Rohlfing et al., 2003; Rueckert et al., 1999). As such, the final similarity measure, or cost function, is a trade-off between the “voxel intensity or structures similarity” and the constraints imposed on the deformation field. The constraint term is usually known as penalty or regularization term.

Particularly in non-rigid registration, the choice of the fixed and moving images could produce distinct registration results. This is mainly a consequence of the large number of local optimums that the similarity measure used can have. Such problems are known as inverse inconsistency and indicate an error in, at least, one of the registration directions. Several solutions have been proposed to overcome this problem (Ashburner et al., 1999; Christensen and Johnson, 2001; Rogelj and Kovacic, 2006; Shen and Davatzikos, 2002).

3.2.1 Intensity based similarity measures

The most commonly used similarity measures are based on intensity differences, intensity cross-correlation and information theory.

The measures based on the intensity difference are usually based on the sum of squared differences (SSD) or their normalizations (Ashburner and Friston, 1999; Friston, K. J. et al., 1995; Hajnal et al., 1995; Woods, Roger P. et al., 1998). The assumption behind the SSD computed from the voxel intensity is that the corresponding structures in both images should have identical intensities. Thus, the lower the SSD is, the better the registered images is.

The cross-correlation and its derived measures, such as the Pearson's correlation coefficient or correlation ratio, have also been used as image similarity measures (Cideciyan, 1995; Collins and Evans, 1997; Hermosillo et al., 2002; Orchard, 2007b; Roche et al., 1998). The cross-correlation is based on the assumption that there is a linear relation between the intensities of the corresponding structures in both images. Thus, the larger the cross-correlation is, the better the registered image is.

The SSD, the cross-correlation and their variants are similarity measures appropriate for monomodal image registration. Besides the assumptions previously referred to, these measures are also based on suppositions of independence and stationarity of the intensities from voxel to voxel. Recently, to overcome these requirements, a new similarity measure, called the residual complexity, was proposed in (Myronenko and Song, 2010).

The information theory based similarity measures are mostly based on the mutual information (MI) or derived measures. The MI was simultaneously proposed for image registration by Viola and co-workers (Viola and Wells, 1995; Wells et al., 1996) and Collignon and co-workers (Collignon et al., 1995; Collignon et al., 1997). A few years later, a normalized mutual information (NMI) was proposed in (Studholme et al., 1999), which is less sensitive to the dimensions of the overlapped image regions. The MI is based on the Shannon entropy that is computed from the joint probability distribution of the image voxel intensity.

Mutual information registration has received so much attention that, a few years after being proposed for image registration, a state-of-the-art image registration based on mutual information was presented in (Pluim et al., 2003) addressing almost two hundred works on that topic. A comparative study on the mutual information and other similarity measures based on the information theory is described in (Pluim et al., 2004), and a study on medical image registration based on mutual information is presented in (Maes et al., 2003).

Mutual information (MI) is usually defined as $MI(X,Y) = H(X) + H(Y) - H(X,Y)$, where X and Y are two random variables, $H(X)$ and $H(Y)$ are the Shannon's entropy of the X and Y variables, respectively, and $H(X,Y)$ is the joint Shannon's entropy of the joint probability histogram. Other equivalent definitions of the MI exist, see, for example, (Pluim et al., 2003).

Mutual information is a measure on how well one image explains the other image, that is, it is based on the simple assumption that there is a functional between the variables involved, e.g. between the intensities of both images. The MI can be applied for both intra and inter-modal registration, and should have the highest value when the input images are correctly registered.

Figure 3 shows a registration example based on the maximization of MI. In this example, the MI was computed in a ROI that did not contain the frame that was supporting the heads to be registered. It should be noted that the low registration accuracy based on the affine transformation is because this kind of transformation cannot model the image deformation adequately and not because of the similarity measure used. However, better accuracy could be achieved by tuning the parameters of the registration methodology more carefully.

[Insert Figure 3 about here]

Mutual information is computed on a voxel by voxel basis, thus it takes into account only the relationships between corresponding individual voxels, and consequently does not take into consideration relevant spatial information that is inherent to the original images. To overcome this drawback, variations of the mutual information have been proposed. In (Pluim et al., 2000) two similarity measures are suggested, one based on a combination of MI and gradient information, and the other one based on NMI and gradient information. Other solutions based on mutual information have also been proposed in (Russakoff et al., 2004; Studholme et al., 2006), by defining a regional mutual information, and in (Loeckx et al., 2010), using the conditional mutual information.

Mutual information has proven to be a very robust and reliable similarity measure for intensity-based registration of multimodal images. However, it faces difficulties for registration of small sized images. To overcome this limitation, for instance, in (Andronache et al., 2008) the MI was used for global registration and the cross-correlation to register the small image patches.

Besides the Shannon's entropy, other divergence measures have been used, for instance, Rény's entropy (He et al., 2003; Wachowiak et al., 2003), Tsallis' entropy (Khader and Hamza, 2011; Sun et al., 2007; Tsallis, 1988) and Havrda-Charvat's entropy (Wachowiak et al., 2003).

The joint intensity distribution, which is the basis for the MI, is also used in the definition of other similarity measures. For example, in (Chung et al., 2002; Leventon and Grimson, 1998; Zhang et al., 2005) the registration methodologies described use prior information on the expected joint intensity distribution of the input images when registered to address the geometric transformation search. On the other hand, in (Leventon and Grimson, 1998) the log likelihood is maximized and in (Chung et al., 2002) the Kullback-Leibler distance is minimized. In (Orchard, 2008) the geometric transformation is driven with the goal to build compact clusters of the joint intensity scatter plot.

For DT-MRI images, the similarity measure can be computed as the sum of the similarity of the individual channels. For instance, in (Alexander and Gee, 2000; Guimond et al., 2002) the normalized SSD computed on all the image channels was considered as the similarity measure; however, in (Alexander and Gee, 2000), other similarity measures were also considered. In (Cao et al., 2005) the similarity measure used is based on the Euclidean distance between the principal eigenvectors of the diffusion tensors. On the other hand, in (Chiang et al., 2008) the diffusion tensors are matched based on the minimization of the symmetrised Kullback-Leibler divergence between the Gaussian probability density functions whose covariance matrices are given by the diffusion tensors.

To guarantee that the registration process is mainly influenced by the anatomical part that should be registered, or to avoid image artefacts or different fields of view (FOV) corrupting the registration process, the similarity measure can be computed over only a region of interest

(ROI) (Elen et al., 2010; Huang et al., 2009). Also, to increase the computational speed of the registration process, the similarity measure is frequently evaluated only on an image sample.

Several comparative studies among similarity measures have been carried out (Jenkinson and Smith, 2001; Penney et al., 1998; Pluim et al., 2004). In the study presented in (Pluim et al., 2004), the mutual information is compared against other similarity measures based on the information theory, and a survey on image registration based on mutual information is presented in (Pluim et al., 2003).

3.2.2 Feature based similarity measures

As aforementioned, depending on the structures extracted from the original images, the similarity measures based on intensity can be used in their registration; for example, after the segmentation of an organ from the input images, instead of using the binary images representing the organ shapes to drive the registration process, the voxel intensities of the organ can be used. A similar situation occurs when the segmentation process divides the input images into smaller image patches or volumes, and the similarity or "distance" among those patches is assessed using intensity based similarity measures.

As for the SSD, the similarity measure used in the feature based registration is often computed as the sum of the "distances" associated to each correspondence established. These distances can be related to the spatial position of the corresponding structures, or related to other attributes, as in the case of the patch segmentation described above.

For spatial distance, the Euclidean distance is a common choice. For instance, most of the iterative closest point (ICP) algorithms found in the literature use this solution. Other examples in which the Euclidean distance is used can be found in (Gefen et al., 2003; Ostuni et al., 1997). Additionally, the chamfer distance has also been used in image registration solutions (Borgefors, 1988; Itti et al., 1997).

In (Shen and Davatzikos, 2002) the distance is computed based on a set of rotation invariant moments in the neighbourhood of the voxels that drive the transformation. On the other hand, similarity measures based on the curvature have been used in surface matching (Tosun and Prince, 2008).

In (Zvitia et al., 2010) the correlation ratio is considered as the similarity measure used to register sets of fibres extracted from brain white matter images. The MI can also be used in feature based registration; for instance, in (Butz and Thiran, 2001) the MI is computed using the image gradient fields.

3.2.3 Regularization terms

There are several regularization terms, but one of the most used is related to the second-order derivatives of the transformation, which are related to the bending energy of the transformation (Lötjönen and Mäkelä, 2001; Rohlfing et al., 2003; Shen and Davatzikos, 2002).

The Jacobian of the transformation has also been used (Christensen et al., 1997; Noblet et al., 2005; Rohlfing and Maurer, 2001; Rohlfing et al., 2003); in this case, if the Jacobian is equal to one, then the deformation is categorized as incompressible.

In (Collins and Evans, 1997) the regularization term is based on the motion of each point of the moving image. On the other hand, in (Kim et al., 2003) the regularization term used is based on the sum of the squared first-order derivatives of the transformation.

3.3 Optimization

The similarity measure can be understood as an n-dimensional function, where n is the number of degrees of freedom of the transformation involved. For the registration proposed, the optimum of this function is assumed to correspond to the transformation that correctly registers the input images. The goal of the optimization algorithm used is to search for the maximum or minimum value of the similarity measure adopted. Usually, the similarity measures are defined in such a way that the optimal registration is accomplished when their value is minimized. Thus, the registration problem can be mathematically defined as: $\min_T D\left[I_0, T\left(I_1\right)\right]$, where D is the distance or similarity measure function, I_0 and I_1 are the images or structures to be registered, and T is the transformation.

Several optimization algorithms have been used in the field of medical image registration, including: the Powell's method (Auer et al., 2005; Collignon et al., 1997; Lavely et al., 2004; Maes et al., 1997; Meyer, 2007; Oliveira and Tavares, 2011; Pluim et al., 2000; Pluim et al., 2004; Sun et al., 2007), the downhill simplex method (Dey et al., 1999; Jenkinson and Smith, 2001; Shekhar and Zagrodsky, 2002; Shekhar et al., 2004), the Gauss-Newton (Ashburner and Friston, 1999), the Levenberg-Marquardt (Kabus et al., 2004; Thévenaz and Unser, 2000), the gradient ascent or descent (Balci et al., 2007; Karaçali, 2007; Rohlfing and Maurer, 2001; Rueckert et al., 1999; Tang et al., 2006), the quasi-Newton (Khader and Hamza, 2011; Loeckx et al., 2010; Mattes et al., 2003), the stochastic algorithms (e.g. simulated annealing) (Loeckx et al., 2003; Nikou et al., 1999), and evolutionary algorithms (Butz and Thiran, 2001; Pataky et al., 2008; Ruijters et al., 2009). Almost all the optimization algorithms previously indicated are described in (Press et al., 2007).

For deformable medical image registration, the similarity measure used is frequently addressed as the energy functional. Therefore, the goal of such registration approaches is to find the displacement field that minimizes the energy functional used. The minimization problem is frequently converted into a problem of solving a set of partial differential equations (PDE). Thus, specialized techniques, such as the finite difference method (Beg et al., 2005; Lu et al., 2004), finite element method (Alterovitza et al., 2006; Brock et al., 2005; Niculescu et al., 2009), variational method (Hermosillo et al., 2002), and Green's functions based method (Marsland and Twining, 2004), can be used.

Sometimes the optimization problem is converted into a problem of solving a set of linear equations simultaneously. Thus, the solution can be achieved directly, for instance, by using the singular value decomposition (Zhilkin and Alexander, 2000) or the least squares technique (Friston, K. J. et al., 1995).

Some authors have used the support vector machine (SVM) technique in their image registration algorithms (Qi et al., 2008; Zhang et al., 2005). These algorithms are frequently based on prior information obtained from the joint intensity distribution between two or more registered images. This prior knowledge is used in the registration process to estimate the similarity measure in function of the geometric transformation. Because the optimization based on SVM is a sparse problem, this technique can be very efficient in terms of computational time.

Generally, the similarity measure as a function is not smooth, as it contains many local extremes. Some of these local extremes represent local best solutions, but others are a consequence of the approach implemented, such as interpolation imperfections and lack of robustness of the similarity measure.

The iterative optimization algorithms are frequently implemented with a multi-resolution or pyramidal strategy. This strategy uses a coarse-to-fine approach. Usually, the process starts by defining a pair of image pyramids that are used to down-sample the fixed and moving images.

Then, the registration starts by registering the images from the lower to the higher resolution images. In each step, the transformation found in the previous step is used as the new initial registration. Relatively to the methods that just use the original images, this approach has some advantages, such as: higher convergence radius (also known as capture range), more robust to local optimums, and usually faster. Some examples of works in which a multi-resolution strategy has been used are in (Hellier and Barillot, 2004; Hipwell et al., 2003; Loeckx et al., 2010; Mattes et al., 2003; Orchard, 2008; Rueckert et al., 1999; Shekhar et al., 2005; Staring et al., 2009; Studholme et al., 1997; Thévenaz et al., 1998; Thévenaz and Unser, 2000).

For the point correspondence based registration algorithms, the optimal transformation between two input images can be directly determined based on the matching established. The well-known Procrustes method (Hill and Batchelor, 2001) is an example of this kind of minimization strategy. Similar solutions are the ones based on the least squares techniques. Optimization algorithms based on assignment algorithms have also been presented (Bastos and Tavares, 2004; Oliveira and Tavares, 2008; Oliveira et al., 2009b).

A comparison among eight optimization algorithms for non-rigid medical image registration based on cubic B-spline and the maximization of the mutual information is described in (Klein et al., 2007).

3.4 Interpolation

In the registration process, when a point is mapped from one space into another space by a transformation, it is generally allocated a non-grid position. Thus, it is necessary to evaluate the image intensity at the new mapped position. The goal of the interpolation step is to estimate the intensity at that new position.

The interpolation solution used can affect the accuracy and speed of the registration process. To increase the speed, a simple interpolation algorithm is usually used in the optimization step, as the ones based on the nearest neighbour or linear interpolations, and then an interpolation solution of higher quality is used to obtain the final registered image, such as the ones based on cubic B-spline or windowed sinc interpolators. In cases when the smoothness or robustness of the similarity measure is significantly affected by imperfections of the interpolation solution, a superior interpolation solution should also be used during the optimization step.

A study on image interpolation function can be found in (Thévenaz et al., 2000). Additionally, in (Tsao, 2003) eight interpolation solutions are compared in a multimodal image registration based on maximization of mutual information.

3.5 Pre-registration

A bad initial registration can compromise the registration speed or even make it worse, it can impede the convergence of the optimization algorithm used in the registration. Thus, in most applications, it is important that the initial fixed and moving images are not badly misregistered or a good pre-registration solution should be applied to the optimization algorithm used.

Except for the situations where the image features extracted from the images are invariant to the geometric transformations, large initial misregistrations between the input images should be avoided. An initial pre-registration can be defined manually by the user or by a fully automated approach using, for example, image moments as in (Itti et al., 1997; Pan et al., 2011).

3.6 Segmentation

Image segmentation consists of extracting relevant information from the input images. This information can be simply established by sets of points, edges, lines, contours, surfaces, areas, volumes, medial axes, etc., or descriptors on the objects represented in the images, such as distances, lengths, angles, moments or shape signatures or even more complex structures containing information about the objects, such as graphs, skeletons or diagrams in the images.

In some cases, segmentation is an easy task, such as the extraction of fiducial markers placed in patients' bodies with the goal to carry out the registration based on those fiducial markers (Maurer et al., 1997), or points of high gradient magnitude (Ostuni et al., 1997). However, in the most cases, robust image segmentation is not a trivial task.

Several image segmentation techniques exist, which can be broadly classified as region or border based. Examples of region-based techniques are: thresholding methods (Otsu, 1979; Wellner, 1993), watershed (Beucher, 1991; Grau et al., 2004), and region growing (Adams and Bischof, 1994). Usual border-based segmentation techniques include edge detectors based on image gradient (Canny, 1986; Marr and Hildreth, 1980), corner detectors, line detectors based on the Hough transform; deformable models, like active contours, usually known as snakes, (Cootes and Taylor, 1992; Gonçalves et al., 2008; Kass et al., 1988; McInerney and Terzopoulos, 1996; Xu and Prince, 1998) and level set methods (Han et al., 2009; Wang et al., 2007; Wang and Wang, 2006).

Reviews on image segmentation techniques can be found in (Gonzalez and Woods, 2008; Ma, Zhen et al., 2010; Monteiro, 2007; Zhang and Lu, 2004; Zhang, 2001).

3.7 Matching

In the intensity based registration methodologies previously referred to, a dense matching is automatically established based on the geometric transformation found. However, in this section, the matching between the features extracted from both input images is considered sparse.

Matching can be established independently of the geometric transformation or iteratively based on it. In both cases, a similarity measure between the features to be matched is optimized. For the iterative matching optimization, besides the optimization algorithms previously indicated, common algorithms are the ICP (Besl and McKay, 1992) and its variations (Andreetto et al., 2004; Giessen et al., 2009; Pan et al., 2011; Stewart et al., 2003; Tsai et al., 2010).

The HAMMER algorithm (Shen and Davatzikos, 2002) establishes the matching in a similar fashion to the free-form deformation, that is, based on a local search for the best matching. In (Wu et al., 2006a) this algorithm is integrated with a machine learning based technique, where features are learned from different types of local image descriptors that are selected from a training set of registered images.

For the matching algorithms where the matching is established independently, the geometric transformations are also based on the optimization of a similarity or “distance” measure. The “distance” among the features to be matched is based on their particular characteristics. Dedicated optimization solutions can be used to establish the matching among features, such as self-organizing maps (Matsopoulos et al., 2004), simulated annealing (Bayro-Corrochano and Rivera-Rovelo, 2009), quasi-orientation maps (Wong et al., 2006), approaches based on the Procrustes method (Hill and Batchelor, 2001; Rangarajan et al., 1997), fuzzy clustering (Tarel and Boujemaa, 1999), homothetic boundary mapping (Davatzikos et al., 1996), or contours mapping via dynamic programming (Oliveira and Tavares, 2008). To match relational structures, such as graphs, dynamic programming can be used as in (Maksimov et al., 2009). Figure 4 shows an example of registration of two brain images (slices) based on contour matching and using dynamic programming.

[Insert Figure 4 about here]

In some matching algorithms, before the computation of the optimal geometric transformation, it is important to consider an algorithm to remove outlier matches. The random sample consensus (RANSAC) (Fischler and Bolles, 1981) is an example of this kind of algorithm, and is applied, for example, in (Wong and Orchard, 2006) to enhance the robustness of the matching process.

3.8 Frequency based methodologies

The SSD and cross-correlation based similarity measures can be efficiently evaluated in the frequency domain using the Fourier transform and its properties. Both measures can be directly evaluated in function of an arbitrary shift (Andreetto et al., 2004; Cideciyan, 1995; Oliveira et al., 2010; Orchard, 2007a), which is less time demanding than the solution based on iterative optimization. The rotational and the scaling of 2D images, can also be achieved by transforming the original image spectrums into polar or log-polar coordinate systems (Andreetto et al., 2004; Cideciyan, 1995; Kassam and Wood, 1996; Oliveira et al., 2010).

The well-known phase correlation technique (Kuglin and Hines, 1975) can also be used to estimate the optimal registration between two images (Grau et al., 2007; Hoge, 2003; Oliveira et al., 2010).

Also the Fourier transform and wavelet transforms have been used in some image registration methodologies (Gefen et al., 2003; Xu and Chen, 2007).

The image registration techniques based on the optimization of the SSD and cross-correlation in the frequency domain can be clearly classified as intensity based; however, since the computation is done in the frequency domain, they have been included in this category.

3.9 Hybrid methodologies

Various authors have combined two or more registration methodologies/strategies in their algorithms (Andreetto et al., 2004; Auer et al., 2005; Chen et al., 2010; Christensen et al., 1997; Davatzikos et al., 1996; Kim et al., 2003; Liao et al., 2011). Some use feature and intensity based registration methodologies concurrently. Sometimes, the similarity measure used contains information on the voxel intensity distributions and information on the features extracted from the input images simultaneously.

A common solution is the use of a feature based algorithm for a coarse registration and then the use of an intensity based methodology for a fine registration as described in (Chen et al., 2010; Liao et al., 2011; Oliveira and Tavares, 2011; Postelnicu et al., 2009). For example, in (Postelnicu et al., 2009), to optimally register volumetric brain images, relevant geometrical information is initially extracted from the segmented surfaces of cortical and subcortical structures, and afterwards the surfaces are registered and the deformation found is applied to the rest of the volume data. This deformation is then refined in the non-cortical regions with an intensity driven optical flow procedure, preserving the initial registration in the cortical region.

In (Christensen et al., 1997) the registration is established in two steps. First, the global transformation is determined by using a low-dimensional elastic model; then, the local higher deformation is obtained using the Navier-Stokes fluid model. On the other hand, in (Auer et al., 2005) a coarse initial registration is defined by maximizing the mutual information using the Powell’s method combined with a multi-resolution strategy, and then a fine point-based registration is accomplished using an elastic TPS.

4. Registration accuracy assessment

Registration is of low value if its accuracy cannot be evaluated. To assess the registration accuracy, several approaches have been proposed. Since the image registration problem is commonly defined as an optimization problem, the image similarity measure optimization can be used as a crude accuracy measure. However, most similarity measures frequently used have no geometric/physical significance.

A simple and generally used approach is to apply a transformation to an image and then use the registration algorithm to re-align both images (Balci et al., 2007; Bhagalia et al., 2009; D’Agostino et al., 2003; Wang et al., 2005). Then, the applied transformation is used as ground-truth.

An approach closely related to the later is based on synthesizing images by simulating the imaging acquisition physics or/and material properties and then evaluating the registration algorithm on the synthetic images produced. For example, in (Schnabel et al., 2003) physically plausible biomechanical tissue deformations of the breast are simulated using the finite element method.

Other more reliable solutions are by manually identifying a set of corresponding points in both input images, e.g. fiducial markers placed into the patients or the organs, and use them to assess the registration accuracy (Collignon et al., 1997; Maes et al., 1997; Mattes et al., 2003; Penney et al., 1998; Pluim et al., 2000; West et al., 1999; West et al., 1997).

The target registration error (TRE) is an important measure of the accuracy of the performed registration. It evaluates the registration accuracy based on points correspondence. Since its value is given in terms of Euclidean distance between the corresponding points, it has an immediate physical meaning. Its drawback is its dependency on the fiducial localization error (FLE). Studies evaluating the registration errors associated to this kind of registration can be found in (Danilchenko and Fitzpatrick, 2011; Dorst, 2005; Fitzpatrick et al., 1998; Ma, Burton et al., 2010; Moghari and Abolmaesumi, 2009a; b; Wiles et al., 2008).

In some studies phantoms are used to assess the accuracy (Rhode et al., 2003; Studholme et al., 2000; Wang et al., 2005) since they allow accurate control/simulation of the patients' movements.

In (Hub et al., 2009), a stochastic approach is proposed to detect areas in which the monomodal B-spline based registration performs well and those in which the accuracy is lower. Another evaluation on the accuracy of the B-spline registration based approach is carried out using synthetic images deformed by the finite element method in (Schnabel et al., 2003).

The Dice similarity coefficient (DSC) quantifies the amount of overlapping regions and has also been used to assess the registration accuracy (Alterovitza et al., 2006; Loeckx et al., 2010; Vercauteren et al., 2007).

Since the image registration task is classically formulated as an optimization problem with a multiple set of tuneable parameters, its accuracy also depends on those parameters. Usually, such parameters are adjusted manually by observing the registration results, which does not always guarantee that the best combination is achieved. A solution to overcome this limitation is proposed in (Yeo et al., 2010b).

Researchers and students can freely download the “Vanderbilt Database” (West et al., 1997), hosted by the Retrospective Image Registration Evaluation Project, and test the accuracy of their rigid registration algorithms. This project is design to compare CT-MR and PET-MR intra-subject registration techniques using brain images from the Vanderbilt Database. The ground-truth transforms have been defined using fiducial markers.

5. Conclusions

In the last few years, the use of the intensity based registration methods has grown considerably compared to the feature based methods. The turning point came with the introduction of the mutual information as the similarity measure. Before this introduction, multimodal registration was done mainly on segmented images, since no intensity similarity measure had been proposed that could be generally and efficiently applied to multimodal registration.

Another important factor that boosted the intensity based registration methods was the advance in terms of computational resources, particularly, processing speed and memory capacity. Ten or twenty years ago, computers needed hours or days to register two image volumes when using intensity based methodologies. Using the same computer resources, the registration problem could be solved in less time using feature based methods, since these methods use only a small amount of the data from the original images. Today, a simple laptop is able to solve the same intensity based registration problem in a few seconds or minutes.

The growing importance of the intensity based registration methods is also a consequence of their simplicity, as there is no need for image segmentation that is usually subject to errors and can be complex.

The growth in computational speed and the high accuracy of the intensity based registration methods have stimulated many authors to use them as an initial step in image segmentation procedures, since, if the orientation and position of a structure in an input image is previously known, the segmentation task can become significantly easier. However, it should be noted that, in this case, instead of the segmentation being carried out to allow the registration afterwards, as happens in the feature based registration methodologies, here it is the registration procedure that facilitates the segmentation task.

In the field of medical image analysis, image registration is still one of the most active topics. If the registration of static images is now well established, the registration of dynamic images still presents several difficulties, demanding significant improvements in terms of computational speed and registration accuracy.

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References

Adams R, Bischof L. 1994. Seeded region growing. IEEE Transactions on Pattern Analysis and Machine Intelligence 16(6):641-647.

Alexander DC, Gee JC. 2000. Elastic matching of diffusion tensor images. Computer Vision and Image Understanding 77:233-250.

Alpert NM, Bradshaw JF, Kennedy D, Correia JA. 1990. The principal axes transformation - a method for image registration. The Journal of Nuclear Medicine 31(10):1717-1722.

Alterovitza R, Goldberg K, Pouliot J, Hsu I-CJ, Kim Y, Noworolski SM, Kurhanewicz J. 2006. Registration of MR prostate images with biomechanical modeling and nonlinear parameter estimation. Medical Physics 33(2):446-454.

Andreetto M, Cortelazzo GM, Lucchese L, 2004. Frequency domain registration of computer tomography data. In Proceedings of the 2nd International Symposium on 3D Data Processing, Visualization, and Transmission (3DPVT’04). p. 550-557.

Andronache A, Siebenthal Mv, Székely G, Cattin P. 2008. Non-rigid registration of multi-modal images using both mutual information and cross-correlation. Medical Image Analysis 12:3-15.

Ardekani BA, Guckemus S, Bachman A, Hoptman MJ, Wojtaszek M, Nierenberg J. 2005. Quantitative comparison of algorithms for inter-subject registration of 3D volumetric brain MRI scans. Journal of Neuroscience Methods 142:67-76.

Ashburner J. 2007. A fast diffeomorphic image registration algorithm. NeuroImage 38:95-113.

Ashburner J, Andersson JLR, Friston KJ. 1999. High-dimensional image registration using symmetric priors. NeuroImage 9:619-628.

Ashburner J, Friston KJ. 1999. Nonlinear spatial normalization using basis functions. Human Brain Mapping 7:254-266.

Auer M, Regitnig P, Holzapfel GA. 2005. An automatic nonrigid registration for stained histological sections. IEEE Transactions on Image Processing 14(4):475-486.

Auzias G, Colliot O, Glaunès JA, Perrot M, Mangin J-F, Trouvé A, Baillet S. 2011. Diffeomorphic brain registration under exhaustive sulcal constraints. IEEE Transactions on Medical Imaging 30(6):1214-1227.

Bai W, Brady SM. 2011. Motion correction and attenuation correction for respiratory gated PET images. IEEE Transactions on Medical Imaging 30(2):351-365.

Balci SK, Golland P, Wells WM, 2007. Non-rigid groupwise registration using B-Spline deformation model. In Proceedings of the International Conference on Medical Image Computing and Computer Assisted Intervention, Brisbane, Australia, p. 105-121.

Bastos LF, Tavares JMRS, 2004. Improvement of modal matching image objects in dynamic pedobarography using optimization techniques. In: Perales, FJ and Draper, BA (Eds.), Articulated Motion And Deformable Objects - Lecture Notes in Computer Science, Volume 3179/2004. Springer Verlag, p. 39-50.

Bayro-Corrochano E, Rivera-Rovelo J. 2009. The use of geometric algebra for 3D modeling and registration of medical data. Journal of Mathematical Imaging and Vision 34:48-60.

Beg MF, Miller MI, Trouvé A, Younes L. 2005. Computing large deformation metric mappings via geodesic flows of diffeomorphisms. International Journal of Computer Vision 61(2):139-157.

Besl PJ, McKay ND. 1992. A method for registration of 3-D shapes. IEEE Transactions on Pattern Analysis and Machine Intelligence 14(2):239-256.

Beucher S, 1991. The watershed transformation applied to image segmentation. In Proceedings of the 10th Pfefferkorn Conference on Signal and Image Processing in Microscopy and Microanalysis, Cambridge, UK, 1992, p. 299-314.

Bhagalia R, Fessler JA, Kim B. 2009. Accelerated nonrigid intensity-based image registration using importance sampling. IEEE Transactions on Medical Imaging 28(8):1208-1216.

Borgefors G. 1988. Hierarchical chamfer matching: a parametric edge matching algorithm. IEEE Transactions on Pattern Analysis and Machine Intelligence 10(6):849-865.

Bro-Nielsen M, Gramkow C, 1996. Fast fluid registration of medical images. In Proceedings of the 4th International Conference on Visualization in Biomedical Computing - VBC'96, Hamburg, Germamy, September 22–25, p. 265-276.

Brock KK, Sharpe MB, Dawson LA, Kim SM, Jaffray DA. 2005. Accuracy of finite element model-based multi-organ deformable image registration. Medical Physics 32(6):1647-1659.

Bronzino J, 2000. Handbook of Medical Imaging: Processing and Analysis, New York.

Brown LG. 1992. A survey of image registration techniques. ACM Computing Surveys 24(4):325-376.

Butz T, Thiran J-P, 2001. Affine registration with feature space mutual information. In Proceedings of the 4th International Conference on Medical Image Computing and Computer-Assisted Intervention - MICCAI 2001, Utrecht, The Netherlands, October 14-17, p. 549-557.

Canny J. 1986. A computational approach to edge detection. IEEE Transactions on Pattern Analysis and Machine Intelligence PAMI-8(6):679-698.

Cao Y, Miller MI, Winslow RL, Younes L. 2005. Large deformation diffeomorphic metric mapping of vector fields. IEEE Transactions on Medical Imaging 24(9):1216-1230.

Chen T, Wang X, Chung S, Metaxas D, Axel L. 2010. Automated 3D motion tracking using Gabor filter bank, robust point matching, and deformable models. IEEE Transactions on Medical Imaging 29(1):1-11.
Chiang M-C, Leow AD, Klunder AD, Dutton RA, Barysheva M, Rose SE, McMahon KL, Zubicaray GId, Toga AW, Thompson PM. 2008. Fluid registration of diffusion tensor images using information theory. IEEE Transactions on Medical Imaging 27(4):442-456.
Cho Y, Seong J-K, Shin SY, Jeong Y, Kim JH, Qiu A, Im K, Lee JM, Na DL. 2011. A multi-resolution scheme for distortion-minimizing mapping between human subcortical structures based on geodesic construction on Riemannian manifolds. NeuroImage 57:1376-1392.
Christensen GE, Johnson HJ. 2001. Consistent image registration. IEEE Transactions on Medical Imaging 20(7):568-582.
Christensen GE, Joshi SC, Miller MI. 1997. Volumetric transformation of brain anatomy. IEEE Transactions on Medical Imaging 16(6):864-877.
Christensen GE, Rabbitt RD, Miller MI. 1994. 3D brain mapping using a deformable neuro anatomy. Physics in Medicine and Biology 39(3):609-618.
Christensen GE, Rabbitt RD, Miller MI. 1996. Deformable templates using large deformation kinematics. IEEE Transactions on Image Processing 5(10):1435-1447.
Chung ACS, Wells WM, Norbash A, Grimson WEL, 2002. Multi-modal image registration by minimising Kullback-Leibler distance. In Proceedings of the 5th International Conference on Medical Image Computing and Computer-Assisted Intervention - MICCAI 2002, Tokyo, Japan, September 25-28, p. 525-532.
Cideciyan AV. 1995. Registration of ocular fundus images: an algorithm using cross-correlation of triple invariant image descriptors. IEEE Engineering in Medicine and Biology Magazine 14(1):52-58.
Collignon A, Maes F, Delaere D, Vandermeulen D, Suetens P, Marchal G, 1995. Automated multimodality image registration using information theory. In Proceedings of the XIVth International Conference on Information Processing in Medical Imaging (IPMI'95), Ile de Berder, France, p. 263-274.
Collignon A, Maes F, Vandermeulen D, Marchal G, Suetens P. 1997. Multimodality medical image registration by maximization of mutual information. IEEE Transactions on Medical Imaging 16(2):187-198.
Collins DL, Evans AC. 1997. ANIMAL: validation and applications of non-linear registration-based segmentation. International Journal of Pattern Recognition and Artificial Intelligence 11(8):1271-1294.
Cootes TF, Taylor CJ, 1992. Active shape models: smart snakes. In Proceedings of the British Machine Vision Conference (BMVC92), Leeds, UK, p. 267-275.
Crum WR, Hartkens T, Hill DLG. 2004. Non-rigid image registration: theory and practice. The British Journal of Radiology 77:S140-S153.
D'Agostino E, Maes F, Vandermeulen D, Suetens P. 2003. A viscous fluid model for multimodal non-rigid image registration using mutual information. Medical Image Analysis 7:565-575.
Danilchenko A, Fitzpatrick JM. 2011. General approach to first-order error prediction in rigid point registration. IEEE Transactions on Medical Imaging 30(3):679-693.
Davatzikos C. 1997. Spatial transformation and registration of brain images using elastically deformable models. Computer Vision and Image Understanding 66(2):207-222.
Davatzikos C, Prince JL, Bryan RN. 1996. Image registration based on boundary mapping. IEEE Transactions on Medical Imaging 15(1):112-115.

Dey D, Slomka PJ, Hahn LJ, Kloiber R. 1999. Automatic three-dimensional multimodality registration using radionuclide transmission CT attenuation maps: a phantom study. Journal of Nuclear Medicine 40:448-455.

Dhawan AP, Arata LK, Levy AV, Mantil J. 1995. Iterative principal axes registration method for analysis of MR-PET brain images. IEEE Transactions on Biomedical Engineering 22(11):1079-1087.

Dornheim L, Tönnies KD, Dixon K, 2005. Automatic segmentation of the left ventricle in 3D SPECT data by registration with a dynamic anatomic model. In Proceedings of the 8th International Conference on Medical Image Computing and Computer Assisted Intervention - MICCAI 2005, Palm Springs, California, USA, October 26 to October 30, p. 335-342.

Dorst L. 2005. First order error propagation of the Procrustes method for 3D attitude estimation. IEEE Transactions on Pattern Analysis and Machine Intelligence 27(2):221-229.

Duay V, Houhou N, Gorthi S, Allal AS, Thiran J-P, 2008. Hierarchical image registration with an active contour-based atlas registration model. In Proceedings of the 16th European Signal Processing Conference, Lausanne, August 25-29, p.

Economopoulos TL, Asvestas PA, Matsopoulos GK. 2010. Automatic correspondence on medical images: a comparative study of four methods for allocating corresponding points. Journal of Digital Imaging 23(4):399-421.

Elen A, Hermans J, Ganame J, Loeckx D, Bogaert J, Maes F, Suetens P. 2010. Automatic 3-D breath-hold related motion correction of dynamic multislice MRI. IEEE Transactions on Medical Imaging 29(3):868-878.

Elsen PA, Pol E-JD, Viergever MA. 1993. Medical image matching - a review with classification. IEEE Engineering in Medicine and Biology Magazine 12(1):26-39.

Faber TL, Stokely EM. 1988. Orientation of 3-D structures in medical images. IEEE Transactions on Pattern Analysis and Machine Intelligence 10(5):626-633.

Ferrant M, Nabavi A, Macq B, Black PM, Jolesz FA, Kikinis R, Warfield SK. 2002. Serial registration of intraoperative MR images of the brain. Medical Image Analysis 6:337-359.

Fischer B, Modersitzki J. 2004. Intensity-based image registration with a guaranteed one-to-one point match. Methods of Information in Medicine 43:327-330.

Fischer B, Modersitzki J. 2008. Ill-posed medicine - an introduction to image registration. Inverse Problems 24(3):1-16.

Fischler M, Bolles R. 1981. Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. Communications of the ACM 24(6):381-395.

Fitzpatrick JM, West JB, Maurer CR. 1998. Predicting error in rigid-body point-based registration. IEEE Transactions on Medical Imaging 17(5):694-702.

Foskey M, Davis B, Goyal L, Chang S, Chaney E, Strehl N, Tomei S, Rosenman J, Joshi S. 2005. Large deformation 3D image registration in image-guided radiation therapy. Physics in Medicine and Biology 50(24):5869-5892.

Frangi AF, Laclaustra M, Lamata P. 2003. A registration-based approach to quantify flow-mediated dilation (FMD) of the brachial artery in ultrasound image sequences. IEEE Transactions on Medical Imaging 22(11):1458-1469.

Freeborough PA, Fox NC. 1998. Modeling brain deformations in alzheimer disease by fluid registration of serial 3D MR images. Journal of Computer Assisted Tomography 22(5):838-843.

Friston KJ, Ashburner J, Poline JB, Frith CD, Heather JD, Frackowiak RSJ. 1995. Spatial registration and normalization of images. Human Brain Mapping 2:165-189.

Friston KJ, Holmes AP, Worsley KJ, Poline J-P, Frith CD, Frackowiak RSJ. 1995. Statistical parametric maps in functional imaging: a general linear approach. Human Brain Mapping 2:189-210.

Gaens T, Maes F, Vandermeulen D, Suetens P, 1998. Nonrigid multimodal image registration using mutual information. In Proceedings of the First International Conference onS Medical Image Computing and Computer-Assisted Intervention - MICCAI 1998, Massachusetts Institute of Technology, Cambridge MA, USA, October 11-13, p. 1099-1106.

Ganser KA, Dickhaus H, Metzner R, Wirtz CR. 2004. A deformable digital brain atlas system according to Talairach and Tournoux. Medical Image Analysis 8:3-22.

Gao Y, Sandhu R, Fichtinger G, Tannenbaum AR. 2010. A coupled global registration and segmentation framework with application to magnetic resonance prostate imagery. IEEE Transactions on Medical Imaging 29(10):1781-1794.

Gefen S, Tretiak O, Nissanov J. 2003. Elastic 3-D alignment of rat brain histological images. IEEE Transactions on Medical Imaging 22(11):1480-1489.

Geng X, Ross TJ, Gu H, Shin W, Zhan W, Chao Y-P, Ching-Po Lin, Schuff N, Yang Y. 2011. Diffeomorphic image registration of diffusion MRI using spherical harmonics. IEEE Transactions on Medical Imaging 30(3):747-758.

Gering D, Nabavi A, Kikinis R, Grimson W, Hata N, Everett P, Jolesz F, Wells W, 1999. An integrated visualization system for surgical planning and guidance using image fusion and interventional imaging. In Proceedings of the International Conference on Medical Image Computing and Computer-Assisted Intervention - MICCAI 1999, Cambridge, UK, September 19-22, p. 809-819.

Gering DT, Nabavi A, Kikinis R, Hata N, O'Donnell LJ, Grimson WEL, Jolesz FA, Black PM, Wells WM. 2001. An integrated visualization system for surgical planning and guidance using image fusion and an open MR. Journal of Magnetic Resonance Imaging 13:967-975.

Giessen Mvd, Streekstra GJ, Strackee SD, Maas M, Grimbergen KA, Vliet LJv, Vos FM. 2009. Constrained registration of the wrist joint. IEEE Transactions on Medical Imaging 28(12):1861-1869.

Gonçalves PCT, Tavares JMRS, Jorge RMN. 2008. Segmentation and simulation of objects represented in images using physical principles. Computer Modeling in Engineering & Sciences 32(1):45-55.

Gonzalez RC, Woods RE, 2008. Digital Image Processing. Prentice Hall.

Gooya A, Biros G, Davatzikos C. 2011. Deformable registration of glioma images using EM algorithm and diffusion reaction modeling. IEEE Transactions on Medical Imaging 30(2):375-390.

Goshtasby AA, 2005. 2-D and 3-D Image Registration for Medical, Remote Sensing, and Industrial Applications. Wiley-Interscience, Hoboken, New Jersey, USA.

Grau V, Becher H, Noble JA. 2007. Registration of multiview real-time 3-D echocardiographic sequences. IEEE Transactions on Medical Imaging 26(9):1154-1165.

Grau V, Mewes AUJ, Alcañiz M, Kikinis R, Warfield SK. 2004. Improved watershed transform for medical image segmentation using prior information. IEEE Transactions on Medical Imaging 23(4):447-458.

Groher M, Zikic D, Navab N. 2009. Deformable 2D-3D registration of vascular structures in a one view scenario. IEEE Transactions on Medical Imaging 28(6):847-860.

Grosland NM, Bafna R, Magnotta VA. 2009. Automated hexahedral meshing of anatomic structures using deformable registration. Computer Methods in Biomechanics and Biomedical Engineering 12(1):35-43.

Guimond A, Gutrmann CRG, Warjield SK, Westin C-F, 2002. Deformable registration of DT-MRI data based on transformation invariant tensor characteristics. In Proceedings of the IEEE International Symposium on Biomedical Imaging, Washington (DC), USA, July 7-10, p. 761-764.

Guimond A, Roche A, Ayache N, Meunier J. 2001. Three-dimensional multimodal brain warping using the demons algorithm and adaptive intensity corrections. IEEE Transactions on Medical Imaging 20(1):58-69.

Guo Y, Sivaramakrishna R, Lu C-C, Suri JS, Laxminarayan S. 2006. Breast image registration techniques: a survey. Medical & Biological Engineering & Computing 44:15-26.

Hajnal JV, Hill D, Hawkes DJ, 2001. Medical image registration. CRC Press.

Hajnal JV, Saeed N, Oatridge A, Williams EJ, Young IR, Bydder GM. 1995. Detection of subtle brain changes using subvoxel registration and subtraction of serial MR images. Journal of Computer Assisted Tomography 19(5):677-691.

Hamilton RJ, Blend MJ, Pelizzari CA, Milliken BD, Vijayakumar S. 1999. Using vascular structure for CT-SPECT registration in the pelvis. Journal of Nuclear Medicine 40(2):347-351.

Han X, Xu C, Prince JL. 2009. A moving grid framework for geometric deformable models. International Journal of Computer Vision 84:63-79.

Hawkes DJ, 2001. Registration methodology: introduction. In: Hajnal, JV, Hill, D and Hawkes, DJ (Eds.), Medical Image Registration. CRC Press, p.

He Y, Hamza AB, Krim H. 2003. A generalized divergence measure for robust image registration. IEEE Transactions on Signal Processing 51(5):1211-1220.

Heger S, Portheine F, Ohnsorge JAK, Schkommodau E, Radermacher K. 2005. User-interactive registration of bone with A-mode ultrasound. IEEE Engineering in Medicine and Biology Magazine 24(2):85-95.

Hellier P, Barillot C. 2004. A hierarchical parametric algorithm for deformable multimodal image registration. Computer Methods and Programs in Biomedicine 75(2):107-115.

Hellier P, Barillot C, Corouge I, Gibaud B, Goualher GL, Collins DL, Evans A, Malandain G, Ayache N, Christensen GE, Johnson HJ. 2003. Retrospective evaluation of intersubject brain registration. IEEE Transactions on Medical Imaging 22(9):1120-1130.

Hellier P, Barillot C, Mémin E, Pérez P. 2001. Hierarchical estimation of a dense deformation field for 3-D robust registration. IEEE Transactions on Medical Imaging 20(5):388-402.

Hermosillo G, Chefd'Hotel C, Faugeras O. 2002. Variational methods for multimodal image matching. International Journal of Computer Vision 50(3):329-343.

Hill DLG, Batchelor P, 2001. Registration methodology: concepts and algorithms. In: Hajnal, JV, Hill, D and Hawkes, DJ (Eds.), Medical image registration. CRC Press, p.

Hill DLG, Batchelor PG, Holden M, Hawkes DJ. 2001. Medical image registration. Physics in Medicine and Biology 46:R1-R45.

Hipwell JH, Penney GP, McLaughlin RA, Rhode K, Summers P, Cox TC, Byrne JV, Noble JA, Hawkes DJ. 2003. Intensity-based 2-D–3-D registration of cerebral angiograms. IEEE Transactions on Medical Imaging 22(11):1417-1426.

Hoge WS. 2003. A subspace identification extension to the phase correlation method. IEEE Transactions on Medical Imaging 22(2):277-280.

Holden M. 2008. A review of geometric transformations for nonrigid body registration. IEEE Transactions on Medical Imaging 27(1):111-128.

Huang X, Ren J, Guiraudon G, Boughner D, Peters TM. 2009. Rapid dynamic image registration of the beating heart for diagnosis and surgical navigation. IEEE Transactions on Medical Imaging 28(11):1802-1814.

Hub M, Kessler ML, Karger CP. 2009. A stochastic approach to estimate the uncertainty involved in B-spline image registration. IEEE Transactions on Medical Imaging 28(11):1708-1716.

Hurvitz A, Joskowicz L. 2008. Registration of a CT-like atlas to fluoroscopic X-ray images using intensity correspondences. International Journal of Computer Assisted Radiology and Surgery 3:493-504.

Ibáñez L, Schroeder W, Ng L, Cates J, (2005) 'The ITK software guide', (Clifton Park, NY: Kitware, Inc.).

Isgum I, Staring M, Rutten A, Prokop M, Viergever MA, Ginneken Bv. 2009. Multi-atlas-based segmentation with local decision fusion – application to cardiac and aortic segmentation in CT scans. IEEE Transactions on Medical Imaging 28(7):1000-1010.

Itti L, Chang L, Mangin J-F, Darcourt J, Ernst T. 1997. Robust multimodality registration for brain mapping. Human Brain Mapping 5:3-17.

Jenkinson M, Smith S. 2001. A global optimisation method for robust affine registration of brain images. Medical Image Analysis 5(2):143-156.

Joshi S, Davis B, Jomier M, Gerig G. 2004. Unbiased diffeomorphic atlas construction for computational anatomy. NeuroImage 23:S151-S160.

Joshi SC, Miller MI. 2000. Landmark matching via large deformation diffeomorphisms. IEEE Transactions on Image Processing 9(8):1357-1370.

Kabus S, Netsch T, Fischer B, Modersitzki J, 2004. B-spline registration of 3D images with Levenberg-Marquardt optimization. In Proceedings of the Medical Imaging 2004: Image Processing, San Diego, CA, USA, p. 304-313

Karaçali B. 2007. Information theoretic deformable registration using local image information. International Journal of Computer Vision 72(3):219-237.

Kass M, Witkin A, Terzopoulos D. 1988. Snakes: active contour models. International Journal of Computer Vision 1(4):321-331.

Kassam A, Wood ML. 1996. Fourier registration of three-dimensional brain MR images: exploiting the axis of rotation. Journal of Magnetic Resonance Imaging 6(6):894-902.

Khader M, Hamza AB, 2011. An entropy-based technique for nonrigid medical image alignment. In Proceedings of the 14th International Workshop Combinatorial Image Analysis - IWCIA 2011, Madrid, Spain, May 23-25, p. 444-455.

Kim JS, Lee JM, Kim JJ, Choe BY, Oh C-H, Nam SH, Kwon JS, Kim SI. 2003. Non-linear registration for brain images by maximising feature and intensity similarities with a Bayesian framework. Medical & Biological Engineering & Computing 41:473-480.

King AP, Rhode KS, Ma Y, Yao C, Jansen C, Razavi R, Penney GP. 2010. Registering preprocedure volumetric images with intraprocedure 3-D ultrasound using an ultrasound imaging model. IEEE Transactions on Medical Imaging 29(3):924-937.

Kjems U, Strother SC, Anderson J, Law I, Hansen LK. 1999. Enhancing the multivariate signal of [^{15}O] water PET studies with a new nonlinear neuroanatomical registration algorithm. IEEE Transactions on Medical Imaging 18(4):306-319.

Klein A, Andersson J, Ardekani BA, Ashburner J, Avants B, Chiang M-C, Christensen GE, Collins DL, Gee J, Hellier P, Song JH, Jenkinson M, Lepage C, Rueckert D, Thompson P, Vercauteren T, Woods RP, Mann JJ, Parsey RV. 2009. Evaluation of 14 nonlinear deformation algorithms applied to human brain MRI registration. NeuroImage 46:786-802.

Klein S, Staring M, Murphy K, Viergever MA, Pluim JPW. 2010. elastix: A toolbox for intensity-based medical image registration. IEEE Transactions on Medical Imaging 29(1):196-205.
Klein S, Staring M, Pluim JPW. 2007. Evaluation of optimization methods for nonrigid medical image registration using mutual information and B-splines. IEEE Transactions on Image Processing 16(12):2879-2890.
Kuglin CD, Hines DC, 1975. The phase correlation image alignment method. In Proceedings of the International Conference Cybernetics and Society, p. 163-165.
Kybic J, Unser M. 2003. Fast parametric elastic image registration. IEEE Transactions on Image Processing 12(11):1427-1442.
Laliberté F, Gagnon L, Sheng Y. 2003. Registration and fusion of retinal images - an evaluation study. IEEE Transactions on Medical Imaging 22(5):661-673.
Lavely WC, Scarfone C, Cevikalp H, Li R, Byrne DW, Cmelak AJ, Dawant B, Price RR, Hallahan DE, Fitzpatrick JM. 2004. Phantom validation of coregistration of PET and CT for image-guided radiotherapy. Medical Physics 31(4):1083-1092.
Ledesma-Carbayo MJ, Kybic J, Desco M, Santos A, Sühling M, Hunziker P, Unser M. 2005. Spatio-temporal nonrigid registration for ultrasound cardiac motion estimation. IEEE Transactions on Medical Imaging 24(9):1113-1126.
Leow A, Yu CL, Lee SJ, Huang SC, Protas H, Nicolson R, Hayashi KM, Toga AW, Thompson PM. 2005. Brain structural mapping using a novel hybrid implicit/explicit framework based on the level-set method. NeuroImage 24:910- 927.
Leow AD, Klunder AD, Jack CR, Toga AW, Dale AM, Bernstein MA, Britson PJ, Gunter JL, Ward CP, Whitwell JL, Borowski BJ, Fleisher AS, Fox NC, Harvey D, Kornak J, Schuff N, Studholme C, Alexander GE, Weiner MW, Thompsona PM. 2006. Longitudinal stability of MRI for mapping brain change using tensor-based morphometry. NeuroImage 31(2):627-640.
Lester H, Arridge SR. 1999. A survey of hierarchical non-linear medical image registration. Pattern Recognition 32:129-149.
Leventon ME, Grimson WEL, 1998. Multi-modal volume registration using joint intensity distributions. In Proceedings of the First International Conference on Medical Image Computing and Computer-Assisted Intervention - MICCAI 1998, Massachusetts Institute of Technology, Cambridge MA, USA, October 11-13, p. 1057-1066.
Liao S, Chung ACS. 2010. Feature based nonrigid brain MR image registration with symmetric alpha stable filters. IEEE Transactions on Medical Imaging 29(1):106-119.
Liao Y-L, Sun Y-N, Guo W-Y, Chou Y-H, Hsieh J-C, Wu Y-T. 2011. A hybrid strategy to integrate surface-based and mutual-information-based methods for co-registering brain SPECT and MR images. Medical & Biological Engineering & Computing 49:671-685.
Lin Y, Medioni G, 2008. Retinal image registration from 2D to 3D. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition - CVPR 2008, Anchorage, Alaska, USA, 23-28 June, p. 1-8.
Livyatan H, Yaniv Z, Joskowicz L. 2003. Gradient-based 2-D/3-D rigid registration of fluoroscopic X-ray to CT. IEEE Transactions on Medical Imaging 22(11):1395-1406.
Loeckx D, Maes F, Vandermeulen D, Suetens P. 2003. Temporal subtraction of thorax CR images using a statistical deformation model. IEEE Transactions on Medical Imaging 22(11):1490-1504.
Loeckx D, Slagmolen P, Maes F, Vandermeulen D, Suetens P. 2010. Nonrigid image registration using conditional mutual information. IEEE Transactions on Medical Imaging 29(1):19-29.

Lötjönen J, Mäkelä T, 2001. Elastic matching using a deformation sphere. In Proceedings of the 4th International Conference on Medical Image Computing and Computer-Assisted Intervention - MICCAI 2001, Utrecht, The Netherlands, October 14-17, p. 541-548.

Lu W, Chen M-L, Olivera GH, Ruchala KJ, Mackie TR. 2004. Fast free-form deformable registration via calculus of variations. Physics in Medicine and Biology 49(14):3067-3087.

Ma B, Moghari MH, Ellis RE, Abolmaesumi P. 2010. Estimation of optimal fiducial target registration error in the presence of heteroscedastic noise. IEEE Transactions on Medical Imaging 29(3):708-723.

Ma Z, Tavares JMRS, Jorge RMN, Mascaranhas T. 2010. A review of algorithms for medical image segmentation and their applications to the female pelvic cavity. Computer Methods in Biomechanics and Biomedical Engineering 13(2):235-246.

Maes F, Collignon A, Vandermeulen D, Marchal G, Suetens P. 1997. Multimodality image registration by maximization of mutual information. IEEE Transactions on Medical Imaging 16(2):187-198.

Maes F, Vandermeulen D, Suetens P. 2003. Medical image registration using mutual information. Proceedings of the IEEE 91(10):1699-1722.

Mahfouz MR, Hoff WA, Komistek RD, Dennis DA. 2003. A robust method for registration of three-dimensional knee implant models to two-dimensional fluoroscopy images. IEEE Transactions on Medical Imaging 22(12):1561-1574.

Maintz JBA, Viergever MA. 1998. A survey of medical image registration. Medical Image Analysis 2(1):1-36.

Mäkelä T, Clarysse P, Sipilä O, Pauna N, Pham QC, Katila T, Magnin IE. 2002. A review of cardiac image registration methods. IEEE Transactions on Medical Imaging 21(9):1011-1021.

Maksimov D, Hesser J, Brockmann C, Jochum S, Dietz T, Schnitzer A, Düber C, Schoenberg SO, Diehl S. 2009. Graph-matching based CTA. IEEE Transactions on Medical Imaging 28(12):1940-1954.

Marr D, Hildreth E. 1980. Theory of edge detection. Proceedings of the Royal Society of London 207:187-217.

Marsland S, Twining CJ. 2004. Constructing diffeomorphic representations for the groupwise analysis of nonrigid registrations of medical images. IEEE Transactions on Medical Imaging 23(8):1006-1020.

Martin S, Daanen V, Troccaz J. 2008. Atlas-based prostate segmentation using an hybrid registration. International Journal of Computer Assisted Radiology and Surgery 3:485-492.

Matsopoulos GK, Asvestas PA, Mouravliansky NA, Delibasis KK. 2004. Multimodal registration of retinal images using self organizing maps. IEEE Transactions on Medical Imaging 23(12):1557-1563.

Mattes D, Haynor DR, Vesselle H, Lewellen TK, Eubank W. 2003. PET-CT image registration in the chest using free-form deformations. IEEE Transactions on Medical Imaging 22(1):120-128.

Maurer CR, Fitzpatrick JM, Wang MY, Galloway RL, Maciunas RJ, Allen GS. 1997. Registration of head volume images using implantable fiducial markers. IEEE Transactions on Medical Imaging 16(4):447-462.

Mayer A, Zimmerman-Moreno G, Shadmi R, Batikoff A, Greenspan H. 2011. A supervised framework for the registration and segmentation of white matter fiber tracts. IEEE Transactions on Medical Imaging 30(1):131-145.

McInerney T, Terzopoulos D. 1996. Deformable models in medical image analysis: a survey. Medical Image Analysis 1(2):91-108
McLaughlin RA, Hipwell J, Hawkes DJ, Noble JA, Byrne JV, Cox TC. 2005. A Comparison of a similarity-based and a feature-Based 2-D–3-D registration method for neurointerventional use. IEEE Transactions on Medical Imaging 24(8):1058-1066.
Meyer CR, Boes JL, Kim B, Bland PH, Lecarpentier GL, Fowlkes JB, Roubidoux MA, Carson PL. 1999. Semiautomatic registration of volumetric ultrasound scans. Ultrasound in Medicine & Biology 25(3):339-347.
Meyer CR, Boes JL, Kim B, Bland PH, Zasadny KR, Kison PV, Koral K, Frey KA, wahl RL. 1997. Demonstration of accuracy and clinical versatility of mutual information for automatic multimodality image fusion using affine and thin-plate spline warped geometric deformations. Medical Image Analysis 1(3):195-206.
Meyer J, 2007. Histogram transformation for inter-modality image registration. In Proceedings of the 7th IEEE International Conference on Bioinformatics and Bioengineering, Boston, MA, USA, 14-17 October p. 1118-1123.
Miller K, Wittek A, Joldes G, Horton A, Dutta-Roy T, Berger J, Morriss L. 2010. Modelling brain deformations for computer-integrated neurosurgery. International Journal for Numerical Methods in Biomedical Engineering 26:117-138.
Miller MI, Trouvé A, Younes L. 2002. On the metrics and Euler-Lagrange equations of computational anatomy. Annual Review of Biomedical Engineering 4:375-405.
Modersitzki J, 2004. Numerical Methods for Image Registration (Numerical Mathematics and Scientific Computation). Oxford University Press, New York, USA.
Modersitzki J, 2009. FAIR: Flexible Algorithms for Image Registration. SIAM, Philadelphia.
Moghari MH, Abolmaesumi P. 2009a. Distribution of fiducial registration error in rigid-body point-based registration. IEEE Transactions on Medical Imaging 28(11):1791-1801.
Moghari MH, Abolmaesumi P. 2009b. Distribution of target registration error for anisotropic and inhomogeneous fiducial localization error. IEEE Transactions on Medical Imaging 28(6):799-813.
Monteiro FJC, 2007. Region-based spatial and temporal image segmentation. Universidade do Porto, Pages.
Myronenko A, Song X. 2010. Intensity-based image registration by minimizing residual complexity. IEEE Transactions on Medical Imaging 29(11):1882-1891.
Niculescu G, Nosher JL, Schneider MDB, Foran DJ. 2009. A deformable model for tracking tumors across consecutive imaging studies. International Journal of Computer Assisted Radiology and Surgery 4:337-347.
Nikou C, Heitz F, Armspach J-P. 1999. Robust voxel similarity metrics for the registration of dissimilar single and multimodal images. Pattern Recognition 32:1351-1368.
Noblet V, Heinrich C, Heitz F, Armspach J-P. 2005. 3-D deformable image registration: a topology preservation scheme based on hierarchical deformation models and interval analysis optimization. IEEE Transactions on Image Processing 14(5):553-566.
Oliveira FPM, Pataky TC, Tavares JMRS. 2010. Registration of pedobarographic image data in the frequency domain. Computer Methods in Biomechanics and Biomedical Engineering 13(6):731-740.
Oliveira FPM, Sousa A, Santos R, Tavares JMRS. 2011. Spatio-temporal alignment of pedobarographic image sequences. Medical & Biological Engineering & Computing 49(7):843-850.
Oliveira FPM, Sousa A, Santos R, Tavares JMRS. in press. Towards an efficient and robust foot classification from pedobarographic images. Computer Methods in Biomechanics and Biomedical Engineering.

Oliveira FPM, Tavares JMRS. 2008. Algorithm of dynamic programming for optimizations of the global matching between two contours defined by ordered points. Computer Modeling in Engineering & Sciences 31(1):1-11.
Oliveira FPM, Tavares JMRS. 2009. Matching contours in images through the use of curvature, distance to centroid and global optimization with order-preserving constraint. Computer Modeling in Engineering & Sciences 43(1):91-110.
Oliveira FPM, Tavares JMRS. 2011. Novel framework for registration of pedobarographic image data. Medical & Biological Engineering & Computing 49(3):313-323.
Oliveira FPM, Tavares JMRS, Pataky TC. 2009a. Rapid pedobarographic image registration based on contour curvature and optimization. Journal of Biomechanics 42(15):2620-2623.
Oliveira FPM, Tavares JMRS, Pataky TC, 2009b. A versatile matching algorithm based on dynamic programming with circular order preserving. In Proceedings of the VIPimage 2009 – II ECCOMAS Thematic Conference on Computational Vision and Medical Image Processing, Porto, Portugal, 14-16 October, p. 269-274.
Orchard J. 2007a. Efficient least squares multimodal registration with a globally exhaustive alignment search. IEEE Transactions on Image Processing 16(10):2526-2534.
Orchard J, 2007b. Globally optimal multimodal rigid registration: an analytic solution using edge information. In Proceedings of the IEEE International Conference on Image Processing, San Antonio, TX, USA, September 16 - October 19, p. 485-488.
Orchard J. 2008. Multimodal image registration using floating regressors in the joint intensity scatter plot. Medical Image Analysis 12:385-396.
Ostuni JL, Levin RL, Frank JA, DeCarli C. 1997. Correspondence of closest gradient voxels - a robust registration algorithm. Journal of Magnetic Resonance Imaging 7(2):410-415.
Otsu N. 1979. A threshold selection method from gray-level histogram. IEEE Transactions on Systems Man Cybernetics 9:62-66.
Pan M-s, Tang J-t, Rong Q-s, Zhang F. 2011. Medical image registration using modified iterative closest points. International Journal for Numerical Methods in Biomedical Engineering 27:1150-1166.
Pataky TC, Goulermas JY, Crompton RH. 2008. A comparison of seven methods of within-subjects rigid-body pedobarographic image registration. Journal of Biomechanics 41(14):3085-3089.
Pennec X, Cachier P, Ayache N, 1999. Understanding the “demon’s algorithm”: 3D non-rigid registration by gradient descent. In Proceedings of the Medical Image Computing and Computer-Assisted Intervention - MICCAI'99, Cambridge, UK, September 19-22, p. 597–606.
Penney GP, Weese J, Little JA, Desmedt P, Hill DLG, Hawkes DJ. 1998. A comparison of similarity measures for use in 2-D-3-D medical image registration. IEEE Transactions on Medical Imaging 17(4):586-595.
Periaswamy S, Farid H. 2003. Elastic registration in the presence of intensity variations. IEEE Transactions on Medical Imaging 22(7):865-874.
Perperidis D, Mohiaddin R, Rueckert D. 2005. Spatio-temporal free-form registration of cardiac MR image sequences. Medical Image Analysis 9(5):441-456.
Peyrat J-M, Delingette H, Sermesant M, Xu C, Ayache N. 2010. Registration of 4D cardiac CT sequences under trajectory constraints with multichannel diffeomorphic demons. IEEE Transactions on Medical Imaging 29(7):1351-1368.
Pieper S, Halle M, Kikinis R, 2004. 3D Slicer. In Proceedings of the IEEE International Symposium on Biomedical Imaging: From Nano to Macro, Arlington, Virginia, USA, 15-18 April, p. 632-635.

Pieper S, Lorensen B, Schroeder W, Kikinis R, 2006. The NA-MIC Kit: ITK, VTK, pipelines, grids and 3D Slicer as an open platform for the medical image computing community. In Proceedings of the 3rd IEEE International Symposium on Biomedical Imaging: From Nano to Macro, Arlington, Virginia, USA, 6-9 April, p. 698-701.

Pluim JPW, Fitzpatrick JM. 2003. Image registration. IEEE Transactions on Medical Imaging 22(11):1341-1343.

Pluim JPW, Maintz JBA, Viergever MA. 2000. Image registration by maximization of combined mutual information and gradient information. IEEE Transactions on Medical Imaging 19(8):809-814.

Pluim JPW, Maintz JBA, Viergever MA. 2003. Mutual information based registration of medical images: a survey. IEEE Transactions on Medical Imaging 22(8):986-1004.

Pluim JPW, Maintz JBA, Viergever MA. 2004. f-Information measures in medical image registration. IEEE Transactions on Medical Imaging 23(12):1508-1516.

Postelnicu G, Zöllei L, Fischl B. 2009. Combined volumetric and surface registration. IEEE Transactions on Medical Imaging 28(4):508-522.

Press WH, Teukolsky SA, Vetterling WT, Flannery BP, 2007. Numerical Recipes: The Art of Scientific Computing. Cambridge University Press, New York.

Qi W, Gu L, Zhao Q, 2008. Effective 2D-3D medical image registration using Support Vector Machine. In Proceedings of the 30th Annual International IEEE EMBS Conference, Vancouver, British Columbia, Canada, August 20-24, p. 5386-5389.

Rangarajan A, Chui H, Bookstein FL, 1997. The softassign procrustes matching algorithm. In Proceedings of the 15th International Conference on Information Processing in Medical Imaging - IPMI 1997, Poultney, Vermont, USA, June 9-13, p. 29-42.

Rao A, Chandrashekara R, Sanchez-Ortiz GI, Mohiaddin R, Aljabar P, Hajnal JV, Puri BK, Rueckert D. 2004. Spatial transformation of motion and deformation fields using nonrigid registration. IEEE Transactions on Medical Imaging 23(9):1065-1076.

Rhode KS, Hill DLG, Edwards PJ, Hipwell J, Rueckert D, Sanchez-Ortiz G, Hegde S, Rahunathan V, Razavi R. 2003. Registration and tracking to integrate X-Ray and MR images in an XMR facility. IEEE Transactions on Medical Imaging 22(11):1369-1378.

Roche A, Malandain G, Pennec X, Ayache N, 1998. The correlation ratio as a new similarity measure for multimodal image registration. In Proceedings of the First International Conference on Medical Image Computing and Computer-Assisted Intervention - MICCAI 1998, Massachusetts Institute of Technology, Cambridge MA, USA, October 11-13, p. 1115-1124.

Roche A, Pennec X, Malandain G, Ayache N. 2001. Rigid registration of 3-D ultrasound with MR images: a new approach combining intensity and gradient information. IEEE Transactions on Medical Imaging 20(10):1038-1049.

Rogelj P, Kovacic S. 2006. Symmetric image registration. Medical Image Analysis 10:484-493.

Rohlfing T, Maurer CR, 2001. Intensity-based nonrigid registration using adaptive multilevel free-form deformation with an incompressibility constraint. In Proceedings of the 4th International Conference on Medical Image Computing and Computer-Assisted Intervention - MICCAI 2001, Utrecht, The Netherlands, October 14-17, p. 111-119.

Rohlfing T, Maurer CR, Bluemke DA, Jacobs MA. 2003. Volume-preserving nonrigid registration of MR breast images using free-form deformation with an incompressibility constraint. IEEE Transactions on Medical Imaging 22(6):730-741.

Rohr K, Stiehl HS, Sprengel R, Buzug TM, Weese J, Kuhn MH. 2001. Landmark-based elastic registration using approximating thin-plate splines. IEEE Transactions on Medical Imaging 20(6):526-534.

Rueckert D, Sonoda LI, Hayes C, Hill DLG, Leach MO, Hawkes DJ. 1999. Nonrigid registration using free-form deformations: application to breast MR images. IEEE Transactions on Medical Imaging 18(8):712-721.
Ruijters D, Romeny BMtH, Suetens P. 2009. Vesselness-based 2D–3D registration of the coronary arteries. International Journal of Computer Assisted Radiology and Surgery 4:391-397.
Russakoff DB, Tomasi C, Rohlfing T, Maurer CR, 2004. Image similarity using mutual information of regions. In Proceedings of the 8th European Conference on Computer Vision (ECCV), Prague, Czech Republic, May 11-14, p. 596-607.
Salvi J, Matabosch C, Fofi D, Forest J. 2007. A review of recent range image registration methods with accuracy evaluation. Image and Vision Computing 25(5):578-596.
Schnabel JA, Rueckert D, Quist M, Blackall JM, Castellano-Smith AD, Hartkens T, Penney GP, Hall WA, Liu H, Truwit CL, Gerritsen FA, Hill DLG, Hawkes DJ, 2001. A generic framework for non-rigid registration based on non-uniform multi-level free-form deformations. In Proceedings of the 4th International Conference on Medical Image Computing and Computer-Assisted Intervention - MICCAI 2001, Utrecht, The Netherlands, October 14-17, p. 573-581.
Schnabel JA, Tanner C, Castellano-Smith AD, Degenhard A, Martin O. Leach, Hose DR, Hill DLG, Hawkes DJ. 2003. Validation of nonrigid image registration using finite-element methods: application to breast MR images. IEEE Transactions on Medical Imaging 22(2):238-247.
Serifovic-Trbalic A, Demirovic D, Prljaca N, Szekely G, Cattin PC. 2008. Intensity-based elastic registration incorporating anisotropic landmark errors and rotational information. International Journal of Computer Assisted Radiology and Surgery 4:463-468.
Shekhar R, Walimbe V, Raja S, Zagrodsky V, Kanvinde M, Wu G, Bybel B. 2005. Automated 3-dimensional elastic registration of whole-body PET and CT from separate or combined scanners. Journal of Nuclear Medicine 46(9):1488-1496.
Shekhar R, Zagrodsky V. 2002. Mutual information-based rigid and nonrigid registration of ultrasound volumes. IEEE Transactions on Medical Imaging 21(1):9-22.
Shekhar R, Zagrodsky V, Garcia MJ, Thomas JD. 2004. Registration of real-time 3-D ultrasound images of the heart for novel 3-D stress echocardiography. IEEE Transactions on Medical Imaging 23(9):1141-1149.
Shen D, 2004. Image registration by hierarchical matching of local spatial intensity histograms. In Proceedings of the 7th International Conference on Medical Image Computing and Computer Assisted Intervention – MICCAI 2004, Rennes, Saint-Malo, France, 26-30 September, p. 582-590.
Shen D. 2007. Image registration by local histogram matching. Pattern Recognition 40:1161-1172.
Shen D, Davatzikos C. 2002. HAMMER: hierarchical attribute matching mechanism for elastic registration. IEEE Transactions on Medical Imaging 21(11):1421-1439.
Slomka PJ, Baum RP. 2009. Multimodality image registration with software: state-of-the-art. European Journal of Nuclear Medicine and Molecular Imaging 36(Suppl 1):44-55.
Staring M, Heide UAvd, Klein S, Viergever MA, Pluim JPW. 2009. Registration of cervical MRI using multifeature mutual information. IEEE Transactions on Medical Imaging 28(9):1412-1421.
Stewart CV, Tsai C-L, Roysam B. 2003. The dual-bootstrap iterative closest point algorithm with application to retinal image registration. IEEE Transactions on Medical Imaging 22(11):1379-1394.

Studholme C, Constable RT, Duncan JS. 2000. Accurate alignment of functional EPI data to anatomical MRI using a physics-based distortion model. IEEE Transactions on Medical Imaging 19(11):1115-1127.
Studholme C, Drapaca C, Iordanova B, Cardenas V. 2006. Deformation-based mapping of volume change from serial brain MRI in the presence of local tissue contrast change IEEE Transactions on Medical Imaging 25(5):626-639.
Studholme C, Hill DLG, Hawkes DJ. 1997. Automated three-dimensional registration of magnetic resonance and positron emission tomography brain images by multiresolution optimization of voxel similarity measures. Medical Physics 24(1):25-35.
Studholme C, Hill DLG, Hawkes DJ. 1999. An overlap invariant entropy measure of 3D medical image alignment. Pattern Recognition 32(1):71-86.
Sun S, Zhang L, Guo C. 2007. Medical image registration by minimizing divergence measure based on Tsallis entropy. International Journal of Biological and Medical Sciences 2(2):75-80.
Tang L, Hamarneh G, Celler A, 2006. Co-registration of bone CT and SPECT images using mutual information. In Proceedings of the 2006 IEEE International Symposium on Signal Processing and Information Technology, Vancouver, BC, p. 116-121.
Tarel J-P, Boujemaa N. 1999. A coarse to fine 3D registration method based on robust fuzzy clustering. Computer Vision and Image Understanding 73(1):14-28.
Thévenaz P, Blu T, Unser M. 2000. Interpolation revisited. IEEE Transactions on Medical Imaging 19(7):739-758.
Thévenaz P, Ruttimann UE, Unser M. 1998. A pyramid approach to subpixel registration based on intensity. IEEE Transactions on Image Processing 7(1):27-41.
Thévenaz P, Unser M. 2000. Optimization of mutual information for multiresolution image registration. IEEE Transactions on Image Processing 9(12):2083-2099.
Thirion J-P. 1998. Image matching as a diffusion process: an analogy with Maxwell's demons. Medical Image Analysis 2(3):243-260.
Tomazevic D, Likar B, Slivnik T, Pernus F. 2003. 3-D/2-D registration of CT and MR to X-Ray images. IEEE Transactions on Medical Imaging 22(22):1407-1416.
Tosun D, Prince JL. 2008. A geometry-driven optical flow warping for spatial normalization of cortical surfaces. IEEE Transactions on Medical Imaging 27(12):1739-1753.
Tsai C-L, Li C-Y, Yang G, Lin K-S. 2010. The edge-driven dual-bootstrap iterative closest point algorithm for registration of multimodal fluorescein angiogram sequence. IEEE Transactions on Medical Imaging 29(3):636-649.
Tsallis C. 1988. Possible generalization of Boltzmann-Gibbs statistics. Journal of Statistical Physics 52(1-2):479-487.
Tsao J. 2003. Interpolation artifacts in multimodality image registration based on maximization of mutual information. IEEE Transactions on Medical Imaging 22(7):854-864.
Vercauteren T, Pennec X, Perchant A, Ayache N, 2007. Non-parametric diffeomorphic image registration with the demons algorithm. In Proceedings of the 10th International Conference on Medical Image Computing and Computer Assisted Intervention - MICCAI 2007, Brisbane, Australia, October 29 - November 2, p. 319-326.
Vercauteren T, Pennec X, Perchant A, Ayache N. 2009. Diffeomorphic demons: efficient non-parametric image registration. NeuroImage 45(1):S61-72.
Viola PA, Wells WM, 1995. Alignment by maximization of mutual information. In Proceedings of the 5th International Conference on Computer Vision (ICCV 95), Cambridge, MA, USA, p. 16-23.

Wachowiak MP, Smolíková R, Peters TM, 2003. Multiresolution biomedical image registration using generalized information measures. In Proceedings of the 6th International Conference on Medical Image Computing and Computer Assisted Intervention - MICCAI 2003, Montréal, Canada, November 15-18, p. 846-853.

Wang H, Dong L, O'Daniel J, Mohan R, Garden AS, Ang KK, Kuban DA, Bonnen M, Chang JY, Cheung R. 2005. Validation of an accelerated 'demons' algorithm for deformable image registration in radiation therapy. Physics in Medicine and Biology 50:2887-2905.

Wang SY, Lim KM, Khoo BC, Wang MY. 2007. A geometric deformation constrained level set method for structural shape and topology optimization. Computer Modeling in Engineering & Sciences 18(3):155-181.

Wang SY, Wang MY. 2006. Structural shape and topology optimization using an implicit free boundary parametrization method. Computer Modeling in Engineering & Sciences 12(2):119-147.

Washington CW, Miga MI. 2004. Modality independent elastography (MIE): a new approach to elasticity imaging. IEEE Transactions on Medical Imaging 23(9):1117-1128.

Wellner P, (1993) 'Adaptive thresholding for the digital desk', in *Technical Report EPC-1993-110* (Cambridge: Rank Xerox).

Wells WM, Viola PA, Atsumid H, Nakajimae S, Kikinise R. 1996. Multi-modal volume registration by maximization of mutual information. Medical Image Analysis 1(1):35-51.

West J, Fitzpatrick JM, Wang MY, Dawant BM, Maurer CR, Kessler RM, Maciunas RJ. 1999. Retrospective intermodality registration techniques for images of the head: surface-based versus volume-based. IEEE Transactions on Medical Imaging 18(2):144-150.

West J, Fitzpatrick JM, Wang MY, Dawant BM, Maurer CR, Kessler RM, Maciunas RJ, Barillot C, Lemoine D, Collignon A, Maes F, Suetens P, Vandermeulen D, Elsen PAvd, Napel S, Sumanaweera TS, Harkness B, Hemler PF, Hill DLG, Hawkes DJ, Studholme C, Maintz JBA, Viergever MA, Malandain G, Pennec X, Noz ME, Maguire GQ, Pollack M, Pelizzari CA, Robb RA, Hanson D, Woods RP. 1997. Comparison and evaluation of retrospective intermodality brain image registration techniques. Journal of Computer Assisted Tomography 21(4):554-566.

Wiles AD, Likholyot A, Frantz DD, Peters TM. 2008. A statistical model for point-based target registration error with anisotropic fiducial localizer error. IEEE Transactions on Medical Imaging 27(3):378-390.

Wong A, Bishop W, Orchard J, 2006. Efficient multi-modal least-squares alignment of medical images using quasi-orientation maps. In Proceedings of the International Conference on Image Processing, Computer Vision, & Pattern Recognition (IPCV 2006), Las Vegas, Nevada, USA, June 26-29, p. 74-80.

Wong A, Orchard J, 2006. Efficient and robust non-rigid least-squares rectification of medical images. In Proceedings of the International Conference on Image Processing, Computer Vision, & Pattern Recognition (IPCV 2006), Las Vegas, Nevada, USA, June 26-29, p. 67-73.

Woods RP, Grafton ST, Holmes CJ, Cherry SR, Mazziotta JC. 1998. Automated image registration: I. general methods and intrasubject, intramodality validation. Journal of Computer Assisted Tomography 22(1):139-152.

Woods RP, Grafton ST, Watson JDG, Sicotte NL, Mazziotta JC. 1998. Automated image registration: II. intersubject validation of linear and nonlinear models. Journal of Computer Assisted Tomography 22(1):153-165.

Wu C, Murtha PE, Jaramaz B. 2009. Femur statistical atlas construction based on two-level 3D non-rigid registration. Computer Aided Surgery 14(4):83-89.
Wu G, Qi F, Shen D, 2006a. A general learning framework for non-rigid image registration. In Proceedings of the Medical Imaging and Augmented Reality, MIAR 2006, Third International Workshop, Shanghai, China, August 17-18, p. 219-227.
Wu G, Qi F, Shen D. 2006b. Learning-based deformable registration of MR brain images. IEEE Transactions on Medical Imaging 25(9):1145-1157.
Wyawahare MV, Patil PM, Abhyankar HK. 2009. Image registration techniques: an overview. International Journal of Signal Processing, Image Processing and Pattern Recognition 2(3):11-27.
Xie Z, Farin GE. 2004. Image registration using hierarchical B-splines. IEEE Transactions on Visualization and Computer Graphics 10(1):85-94.
Xu C, Prince JL. 1998. Snakes, shapes, and gradient vector flow. IEEE Transactions on Image Processing 7(3):359-369.
Xu Q, Anderson AW, Gore JC, Ding Z. 2009. Unified bundling and registration of brain white matter fibers. IEEE Transactions on Medical Imaging 28(9):1399-1411.
Xu R, Chen Y-W. 2007. Wavelet-based multiresolution medical image registration strategy combining mutual information with spatial information. International Journal of Innovative Computing, Information and Control 3(2):285-296.
Yamazaki T, Watanabe T, Nakajima Y, Sugamoto K, Tomita T, Yoshikawa H, Tamura S. 2004. Improvement of depth position in 2-D/3-D registration of knee implants using single-plane fluoroscopy. IEEE Transactions on Medical Imaging 23(5):602-612.
Yassa MA, Stark CEL. 2009. A quantitative evaluation of cross-participant registration techniques for MRI studies of the medial temporal lobe. NeuroImage 44:319-327.
Yeo BTT, Sabuncu MR, Vercauteren T, Ayache N, Fischl B, Golland P. 2010a. Spherical demons: fast diffeomorphic landmark-free surface registration. IEEE Transactions on Medical Imaging 29(3):650-668.
Yeo BTT, Sabuncu MR, Vercauteren T, Holt DJ, Amunts K, Zilles K, Golland P, Fischl B. 2010b. Learning task-optimal registration cost functions for localizing cytoarchitecture and function in the cerebral cortex. IEEE Transactions on Medical Imaging 29(7):1424-1441.
Yeo BTT, Vercauteren T, Fillard P, Peyrat J-M, Pennec X, Golland P, Ayache N, Clatz O. 2009. DT-REFinD: diffusion tensor registration with exact finite-strain differential. IEEE Transactions on Medical Imaging 28(12):1914-1928.
Zagorchev L, Goshtasby A. 2006. A comparative study of transformation functions for nonrigid image registration. IEEE Transactions on Image Processing 15(3):529-538.
Zhang D, Lu G. 2004. Review of shape representation and description techniques. Pattern Recognition 37:1-19.
Zhang YJ, 2001. A review of recent evaluation methods for image segmentation. In Proceedings of the Sixth International Symposium on Signal Processing and its Applications (ISSPA), Kuala Lumpur, Malaysia, p. 148-151.
Zhang Z, Zhang S, Zhang C-X, Chen Y-Z, 2005. Multi-modality medical image registration using support vector machines. In Proceedings of the 27th Annual International Conference of the Engineering in Medicine and Biology Society, IEEE-EMBS, Shanghai, China, September 1-4, p.
Zhilkin P, Alexander ME. 2000. 3D image registration using a fast noniterative algorithm. Magnetic Resonance Imaging 18:1143-1150.
Zhilkin P, Alexander ME. 2004. Affine registration: a comparison of several programs. Magnetic Resonance Imaging 22(1):55-66.

Zhu Y-M, Cochoff SM. 2002. Influence of implementation parameters on registration of MR and SPECT brain images by maximization of mutual information. The Journal of Nuclear Medicine 43(2):160-166.

Zhuang X, Rhode KS, Razavi RS, Hawkes DJ, Ourselin S. 2010. A registration-based propagation framework for automatic whole heart segmentation of cardiac MRI. IEEE Transactions on Medical Imaging 29(9):1612-1625.

Zitová B, Flusser J. 2003. Image registration methods: a survey. Image and Vision Computing 21:977-1000.

Zvitia O, Mayer A, Shadmi R, Miron S, Greenspan HK. 2010. Co-registration of white matter tractographies by adaptive-mean-shift and gaussian mixture modeling. IEEE Transactions on Medical Imaging 29(1):132-145.

FIGURE CAPTIONS

Figure 1. Diagram of the typical algorithms used in the intensity based registration methodologies.

Figure 2. Diagram of a typical feature based registration algorithm.

Figure 3. Registration sequence of two CT volumes of the heads of two subjects. At the top, eight slices built on a checker format (by alternating square sub-images from both original images) before registration; in the middle, the checker slices built after an affine registration; at the bottom, the checker slices built after a free form registration using cubic B-splines.

Figure 4. Matching and registration of two brain slices. At the top, fixed image overlapped by the contour segmented from the corpus callosum, moving image overlapped by the contour segmented from the corpus callosum, and the illustration of the matching established. At the bottom, input images overlapped before the registration, the same images overlapped after the registration, and the difference between the input images after the registration.

TABLE CAPTIONS

Table 1: Medical image registration classification criteria proposed by Maintz and Viergever (Maintz and Viergever, 1998).

FIGURES

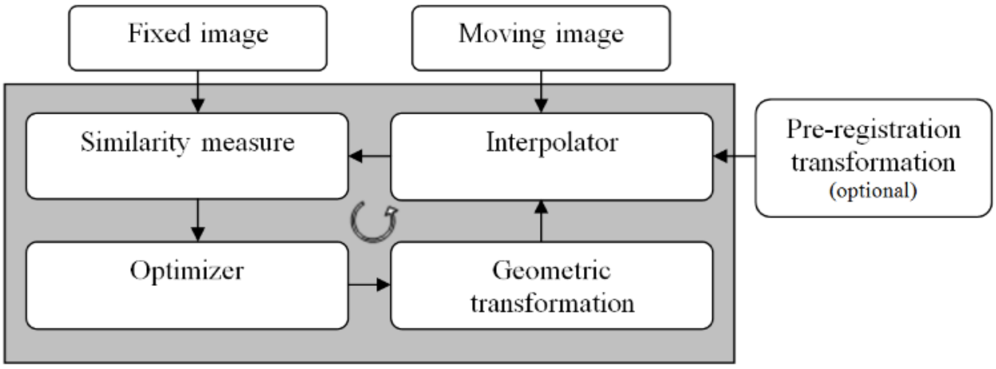

Figure 1

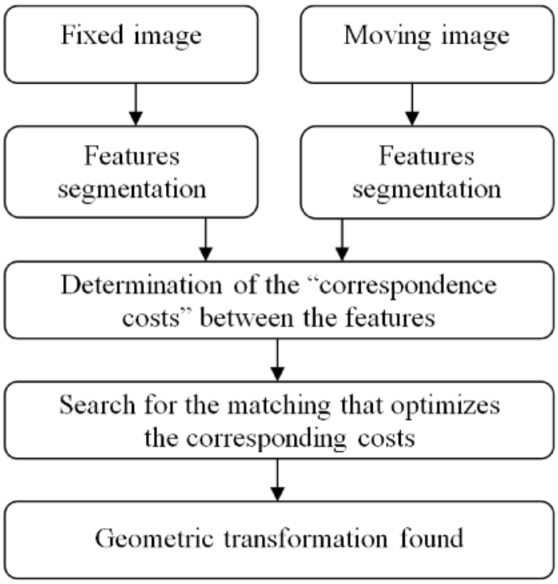

Figure 2

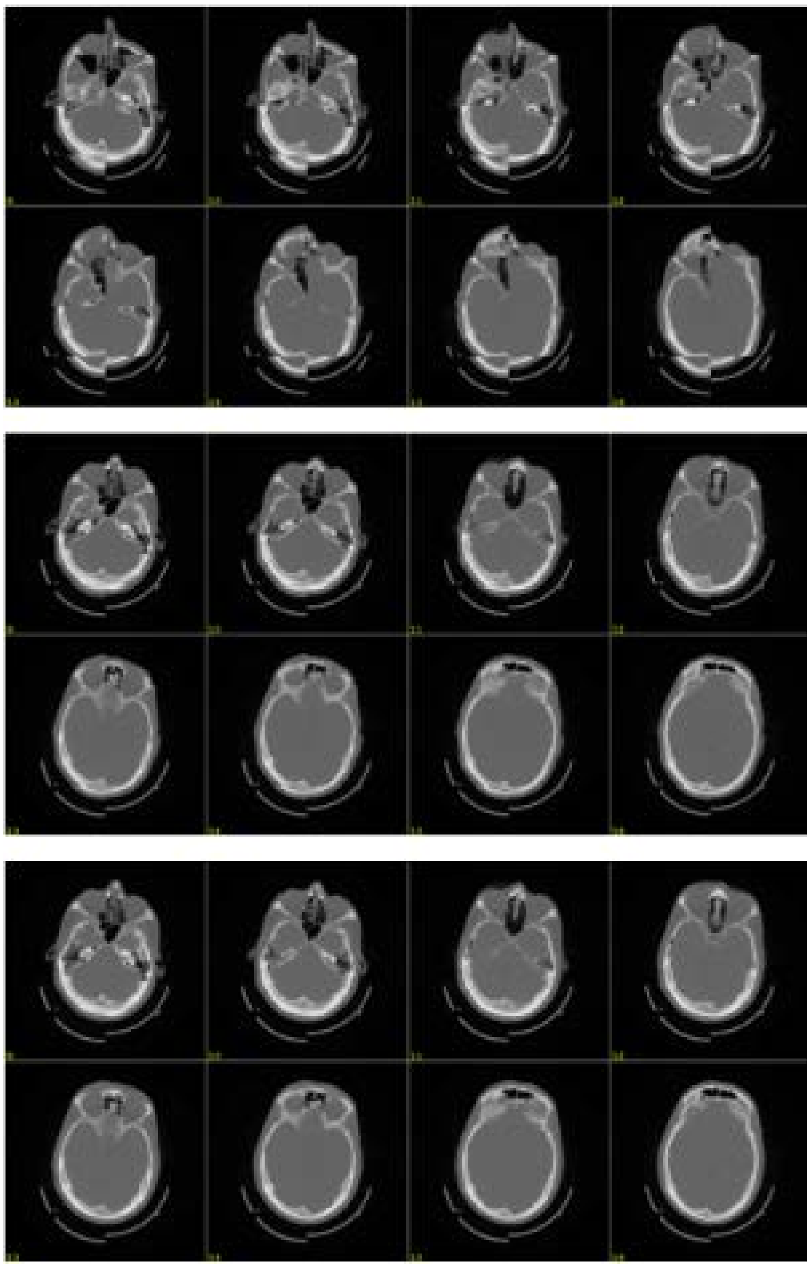

Figure 3

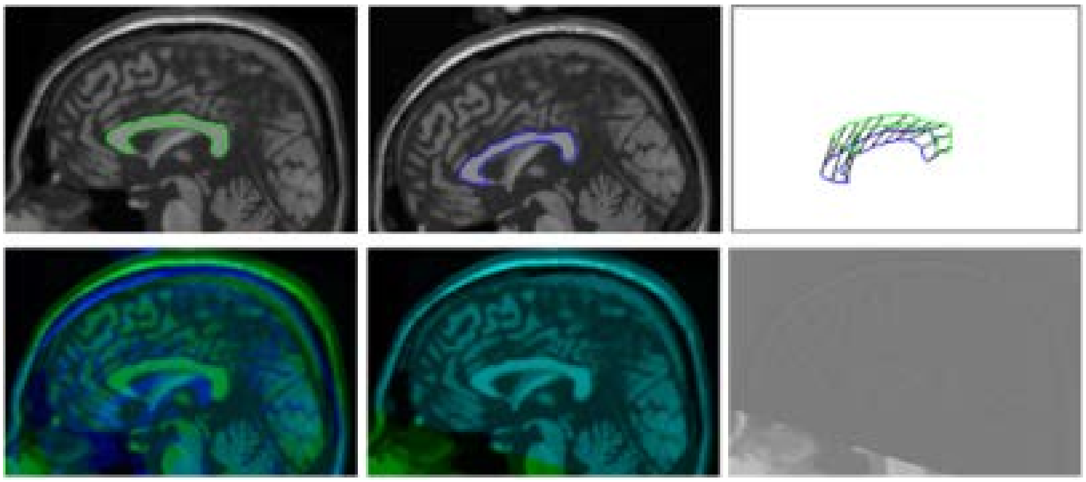

Figure 4

TABLES

Table 1

<table>
<tr><th>Classification criteria</th><th colspan="3">Subdivision</th></tr>
<tr><td rowspan="2">Dimensionality</td><td colspan="3">Spatial dimension: 2D/2D, 2D/3D, 3D/3D</td></tr>
<tr><td colspan="3">Temporal series</td></tr>
<tr><td rowspan="11">Nature of the registration basis</td><td rowspan="4">Extrinsic (based on foreign objects introduced into the imaged space)</td><td rowspan="2">Invasive</td><td>Stereotactic frame</td></tr>
<tr><td>Fiducials (screw markers)</td></tr>
<tr><td rowspan="2">Non-invasive</td><td>Mould, frame, dental adapter, etc.</td></tr>
<tr><td>Fiducials (skin markers)</td></tr>
<tr><td rowspan="6">Intrinsic (based on patient)</td><td rowspan="2">Landmark based</td><td>Anatomical</td></tr>
<tr><td>Geometrical</td></tr>
<tr><td rowspan="2">Segmentation based</td><td>Rigid models (points, curves, surfaces, volumes)</td></tr>
<tr><td>Deformable models (snakes, nets)</td></tr>
<tr><td rowspan="2">Voxel property based</td><td>Reduction to scalars/vectors (moments, principal axes)</td></tr>
<tr><td>Using full image content</td></tr>
<tr><td colspan="3">Non-image based (calibrated coordinate systems)</td></tr>
<tr><td rowspan="4">Nature of transformation</td><td colspan="3">Rigid (only rotation and translations)</td></tr>
<tr><td colspan="3">Affine (translation, rotation, scaling and shearing)</td></tr>
<tr><td colspan="3">Projective</td></tr>
<tr><td colspan="3">Curved</td></tr>
<tr><td rowspan="2">Domain of transformation</td><td colspan="3">Local</td></tr>
<tr><td colspan="3">Global</td></tr>
<tr><td rowspan="6">Interaction</td><td rowspan="2">Interactive</td><td colspan="2">Initialization supplied</td></tr>
<tr><td colspan="2">No initialization supplied</td></tr>
<tr><td rowspan="3">Semi-automatic</td><td colspan="2">User initializing</td></tr>
<tr><td colspan="2">User steering/correcting</td></tr>
<tr><td colspan="2">Both</td></tr>
<tr><td colspan="3">Automatic</td></tr>
<tr><td rowspan="2">Optimization procedure</td><td colspan="3">Parameters computed (the transformation parameters are computed directly)</td></tr>
<tr><td colspan="3">Parameters searched for (the transformation parameters are computed using optimization algorithms)</td></tr>
<tr><td rowspan="4">Modalities involved in the registration</td><td colspan="3">Monomodal (CT-CT, MRI-MRI, PET-PET, CTA, etc.)</td></tr>
<tr><td colspan="3">Multimodal (CT-MRI, CT-PET, CT-SPECT, PET-MRI, MRI-US, etc.)</td></tr>
<tr><td colspan="3">Modality to model</td></tr>
<tr><td colspan="3">Patient to modality (register the patient with the coordinate system of the imaging equipment)</td></tr>
<tr><td rowspan="3">Subject</td><td colspan="3">Intrasubject (same subject)</td></tr>
<tr><td colspan="3">Intersubject (different subjects)</td></tr>
<tr><td colspan="3">Atlas</td></tr>
<tr><td rowspan="6">Object</td><td colspan="3">Head (brain, eye, dental, etc)</td></tr>
<tr><td colspan="3">Thorax (entire, cardiac, breast, etc)</td></tr>
<tr><td colspan="3">Abdomen (general, kidney, liver, etc)</td></tr>
<tr><td colspan="3">Limbs</td></tr>
<tr><td colspan="3">Pelvis and perineum</td></tr>
<tr><td colspan="3">Spine and vertebrae</td></tr>
</table>