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A Survey on Image Registration using Machine Learning Algorithms

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Abstract:

Image registration is the process of transforming different sets of data into one coordinate system. Data may be multiple photographs, data from different sensors, times, depths, or viewpoints. Image registration or image alignment algorithms can be classified into intensity-based and feature-based. In linear registration, it is generally difficult to optimize the large deformations between images with large anatomical differences. This is further complicated if images of two different imaging modalities with large appearance differences need to be registered. Second, with the advent of cutting-edge imaging technology, the scale and diversity of imaging data has increased significantly, posing significant challenges to registration. Modern registration methods need to be sufficiently versatile to deal with diverse imaging data with high efficiency, accuracy, and robustness. Fortunately, machine learning techniques applied to image registration tasks can help address the aforementioned issues. Specifically, different machine learning techniques can be employed to learn from prior registration results to improve the registration performance in some challenging tasks. This paper will be dedicated to summarize state-of-the-art learning-based Regis- ration algorithms, particularly methods for deformable registration. Methods for linear registration will also be discussed where necessary

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I. INTRODUCTION

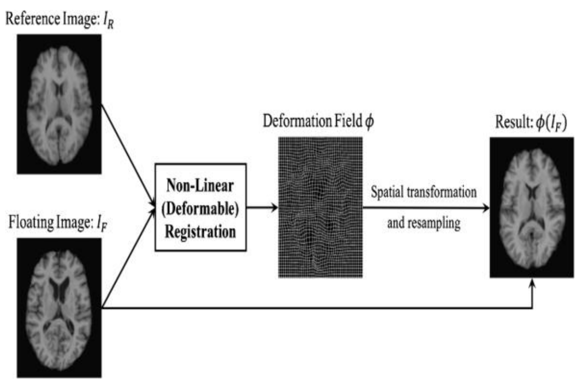

Image registration is a crucial and fundamental procedure in medical image analysis. The aim of registration algorithm is to obtain a spatial transformation that can align a floating image to a reference image. The resulting anatomical correspondences allow image comparison for applications such as population analyses, longitudinal studies, and image-guided interventions.

II. MACHINE LEARNING

In this section, we introduce the machine-learning-based image registration methods. Shows two registration cases that are challenging for traditional registration methods. As shown in Fig., the infant brain MR images at different time points exhibit large appearance differences.It is a comparison between the normal brain MRI and the brain MRI with Alzheimer's disease (AD), where the brain image with AD has significant atrophy. Conventional registration methods cannot solve these challenging tasks well. To solve them, machine learning can be applied to learn prior registration knowledge based on a training dataset, in order to simplify these challenging registration tasks. Basically, based on the learning objective, the learned model can be classified into the following three categories: (1) learning the initialized deformation field to simplify the complicated optimization, (2) learning intermediate

Image that provides a bridge/link between the to-be-registered floating and reference images, and (3) learning the image appearance changes to eliminate the appearance difference.

III. Learning initialized deformation field

One registration problem is to align images with large anatomical differences, this is difficult to solve using traditional registration methods since the complex optimization process often falls into the local minima when the large deformations need to be estimated, which yields inaccurate registration result. Learning- based-registration method can elevate this problem by providing a good initialized deformation, which can transform the floating image close to the reference image. Then, the subsequent registration is simplified to estimate the remaining deformations, which are usually small and can be effectively optimized. To date, many machine learning approaches, such as support vector regression, random forest, and sparse learning, have been proposed to learn a model from a training dataset for predicting an initialized deformation.

Representative studies for machine learning based registration methods.

Generally, for the learning-based registration in this category, machine learning technologies can be used to provide a good initialization model for the difficult registration tasks, which can accelerate the convergence in the registration optimization process,

Initialized deformation field	Regression forest Support vector regression Sparse learning	Elderly brain MRI Adult brain MRI Adult brain MRI
	PCA	Adult brain MRI
	Sparse learning	Adult brain MRI Elderly brain MRI Infance brain MRI
Image appearance	Logistic intensity model Random forest	Monkey brain MRI Infant brain MRI

thus improving the registration performance in terms of efficiency, accuracy and also robustness.

IV Learning intermediate image

Instead of generating intermediate images, machine learning techniques can also be used for selecting intermediate images from an available training set. For example, in- stead of simply choosing only one intermediate image for bridging the floating image and the reference image, Wang et al. Proposed to utilize the patch-scale guidance from the intermediate images for improving the registration accuracy of brain MR images. They assumed that if points in the floating and the intermediate images share similar local appearance, they may share the common correspondence to the common reference image. Thus, instead of locating only one correspondence for each certain subject point in the intermediate image, the authors proposed a method to locate several candidate points in the intermediate images for each certain subject point by using sparse learning techniques. Then, the selected intermediate candidates can bridge the correspondence from the floating point to the template space, yielding the transformation associated with the floating point at the confidence level that relates to the learned sparse coefficients. After predicting the transformation fields on the key points, the dense transformation field that covers the entire image space can then be recon- structed immediately. In another study, Dong et al. proposed a joint segmentation and registration method for iteratively refining the registration of infant brain images at different time points by using spatial–temporal trajectories learned from a large number of training subjects with complete longitudinal data. In this work, the preregistered atlas images at different time points act as intermediate images bridging the time gap between the two new images under registration. By using a multi-atlas-based label fusion method, which was incorporated with additional label fusion priors borrowed from the reference time domain, both segmentation and registration performance can be progressively improved.

The above-mentioned learning-based registration method is also suitable for registering images with large anatomical variations. By using the intermediate image(s), the floating and the reference image space, which are far away on the image manifold, can be effectively bridged to make the registration more efficient and accurate.

V. Learning image appearance

The image appearance mapping model can be built via different machine learning methods. Csapo et al. Proposed a logistical model to adjust the image intensity change between two time points. Then, instead of registering the image pair with both image intensity and morphological changes, the authors eliminated the image

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intensity change by using the image adjustment model, and decoupled the problem into the traditional registration between the two intensity-adjusted images. Other studies

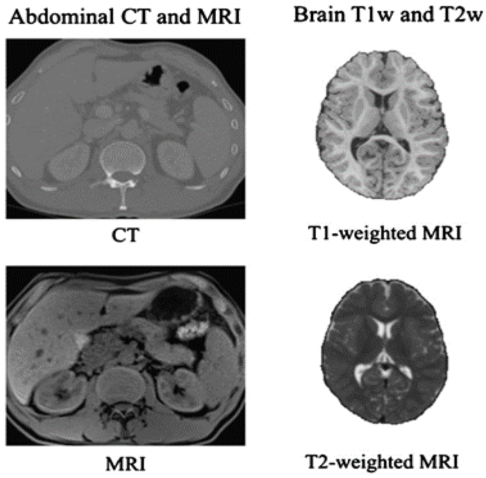
Proposed to use random forest for predicting both the image appearance change and anatomical variations. In the training stage, Hu et al. used random forest to train two models for predicting both the initialized deformation and appearance changes, where one model was trained for learning the relationship between the image appearance and its displacement to a template image, and another model was trained for learning the appearance change between the two images at different time points. In a later work, Wei et al. Proposed to use a random forest regression coupled with an auto context model to further improve the registration performance. In the application stage, the registration between the two infant images at different time points is composed of two phases: (1) the learned model is used to predict the initialized deformation field and image appearance changes; (2) a traditional image registration method is then applied to get the final registration result.

In summary, the learning-based registration methods are favorable to solve various image registration problems that pose different difficulties. By learning different kinds of prior knowledge based on the training dataset, the robustness, accuracy, and efficiency are significantly improved compared with traditional registration methods.

image appearance changes in infant brain longitudinal studies during the first year of life.

VI. Machine-learning-based multimodal registration

Multimodal registration aims to relate clinically relevant and often complementary information from different imaging scans. It is a fundamental step to conduct the multi- modal information fusion and facilitate the clinical diagnosis and treatment subsequently. It can compensate the deformations for the patient motion caused by different positioning or breathing level, and pathological changes between different imaging scans. Following Fig. shows two typical multimodal images that need to be registered in clinical applications. The first one is the abdominal CT and MRI used for pancreas or other organs related diagnosis and treatment, and the second one is the brain T1w and T2w MRI used for brain related quantification and analysis.



In addition to the geometric distortion caused by patient motion, multimodal registration also needs to deal with the large appearance difference across modalities. Usually, the appearance relationship between different modalities is highly complex and nonlinear. In contrast to the mono modal registration, where many similarity metrics (e.g., NCC, SSD, etc.) can be leveraged, it is difficult to define an effective similarity metric to measure the anatomical correspondence across different modalities. Thus, deformable registration of multimodal images remains a challenging task in medical image analysis. Machine learning techniques applied in multimodal registration can

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help address the above issues and solve this challenging registration problem. It can be Used to learn (1) an effective similarity metric, (2) a common feature representation, or (3) an appearance mapping model, in order to make the registration method more effective and feasible to deal with the large appearance difference. Under

Similarity metric	Joint Intensity Distribution(Maximum Likelihood)	Brain CT and MRI Brain PET and MRI
		Brain T1w and T2w DSA and MRA
		Brain T1w and T2w Thorax SPECT and CTThorax PET and CT
		Brain CT and MRI
	Joint Intensity Distribution (Bhattacharyya Divergence)	Brain CT and MRI
	Joint Intensity Distribution (Jensen–Renyi Divergence)	Brain T1w, T2w and PD Brain PET and MRI
	Max-margin Structured Learning	Brain CT and MRI Brain PET and MRI
	Boosting	Brain CT and MRI Brain PET and MRI
	Neural Network	Brain CT and MRI
	Canonical Correlation Analysis (CCA)	Pelvic CT and MRI
	Manifold Learning	Brain T1w, T2w and PD
	Polynomial Fitting	Brain MRI and ultrasound
	Fully Convolutional Network	Brain CT and MRI
	Random Forest	Pelvic CT and MRI

these three categories, the current learning-based multimodal registration methods are summarized in above Table.

VI. Learning similarity metric

It can be implemented in two different ways: (1) learning an expected intensity distribution of multimodal images to make the existing metrics easy to distinguish the similarity between the new to-be-registered images, or (2) directly learning a metric that can measure the similarity across modalities. In the first category, a pre aligned multimodal image dataset is needed to learn an expected intensity distribution, which acts as a domain-specific model or a priori knowledge. Then, the registration method employs a metric with the expected intensity distribution to evaluate the similarity between the reference and floating images.

Although it does not directly learn a new metric, it makes the existing metrics more effective and powerful to measure the anatomical difference of multimodal images.

The second category of learning-based multimodal registration methods can directly learn an effective similarity metric in a discriminative manner, and under the learned similarity metric, the reference image and correctly aligned floating image receive high similarity values. Intuitively, a training dataset is also needed with pre aligned multimodal images, to train a distinctive similarity metric in a supervised manner. However, using supervised learning to learn a similarity metric is challenging. Unlike the traditional classification problem that can judge whether the images (or local patches) are similar or not, an effective similarity metric for registration task should provide a continuous similarity score, i.e., a similarity degree. Yet, the learning objective is not easy to clearly define in the training stage. Several approaches have been proposed to deal with this challenging task.

VII. Learning common feature representation

Since the hand-engineered image features cannot directly work well for multimodal registration task due to the large appearance/intensity gap across modalities, some learning-based methods have been developed to learn a common feature representation for imaging data from different modalities.

In common feature representation was learned by projecting the two native feature spaces (derived from the two image modalities) to a common space. In this common space, the correlation between the corresponding anatomies or corresponding features are maximized. Since the appearance information of multimodal medical images can be completely different and statistically uncorrelated, the kernel canonical correlation analysis (KCCA) was applied in this work to reveal such nonlinear feature mappings. Then, the multimodal registration can take advantage of the learned common features to effectively establish the reliable correspondences for conducting the local matching. The experiments were performed on pelvic CT–MR images and the longitudinal infant brain MR images. The deformable multimodal registration results demonstrated the improved registration accuracy, compared with the conventional multimodal registration methods. Additionally, there are still some other methods that learn the common feature representations across multiple imaging modalities. Although these methods are not designed for multimodal registration purpose, they have the potentials to further improve/investigate the multimodal registration problem.

VIII Learning appearance mapping

The multimodal registration is more challenging compared with the mono-modal registration, since the large appearance difference across modalities makes it difficult to use the existing similarity metrics. To eliminate the appearance difference, some machine learning techniques have been applied to learn an image synthesis model between two modalities. Afterwards, the multimodal registration can be simplified as a mono modal registration problem, then, many effective similarity metrics can be applied. For ex- ample, Roche et al. Synthesized an ultrasound image and then estimated rigid registration between the ultrasound and MR images. Zhao et al. Simulated CT image from MRI to realize the brain CT and MRI registration. However, in these

Approaches, the image synthesis is often performed in single direction, and the synthetic direction is from the image modality with rich anatomical information to that with limited anatomical information, e.g., synthesizing ultrasound/CT from MRI.

To further improve the accuracy of multi-modal registration, a bi-directional image synthesis based multimodal registration algorithms were proposed to nonlinearly register the pelvic CT and MR images. In these works, a structured random forest was applied to learn the image synthesis model in both directions, i.e., not only synthesizing CT from MRI, but also synthesizing MRI from CT. One novelty in this study is that the MR image is synthesized from a single CT modality, which is a “simple-to-complex” image synthesis problem, since the anatomical information of MRI is more complex than that in CT image. Fig. Shows an example of the bi-directional image synthesis results in this study. Afterwards, a dual-core steered multimodal registration method was proposed by using the complementary anatomical information from bot modalities, to more accurately steer the deformable registration. Experimental results demonstrated that, the bi-directional image synthesis can help significantly improve the multimodal registration performance. Based on the learning-based bi-directional image synthesis framework, a region-adaptive multimodal registration method was further proposed to solve the pelvic CT and MRI registration problem.

IX SUMMARY

In summary, machine learning algorithms can be applied in learning the prior knowledge in different aspects, to help solve or simplify the challenging multimodal registration problem. This includes learning the similarity metric, the common feature representation, and the appearance mapping model. By leveraging machine learning, many multimodal registration problems can be effectively resolved. Based on more pre- cise multimodal information fusion achieved by accurate registration, various clinical applications can be facilitated accordingly.

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