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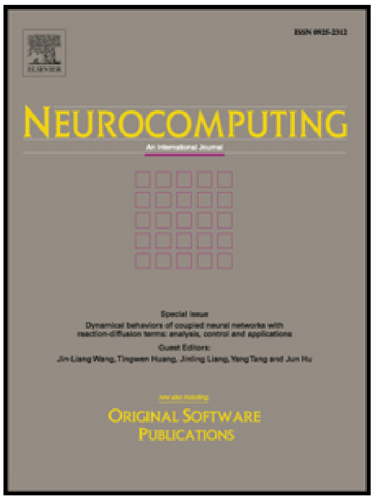

Local Statistical Deformation Models for Deformable Image Registration

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Local Statistical Deformation Models for Deformable Image Registration

Songyuan Tang, Weijian Cong*, Jian Yang, Tianyu Fu, Hong Song, Danni Ai and Yongtian Wang

Abstract—**A fast and robust image registration algorithm for high-dimensional brain Magnetic Resonance images was developed based on the statistical deformation models (SDMs). This model learns deformation fields and achieves fast and robust registration by greatly reducing transformation dimensionality. This model is trained via principal component analysis (PCA), which suffers from large transformation dimensionality and small samples. For the high-dimensional image registration, the dimensions of the deformation fields are huge, the basic functions computed from PCA cannot represent deformation fields well. Therefore, we proposed a local SDM (LSDM) in this paper to solve the aforementioned problems. We divided the images into several small parts, in which the dimensions of the deformation fields are greatly reduced. Then, we trained the LSDM using the deformation fields between sample images and a selected template by applying PCA in each small part. Given that the dimension of eigenvectors of LSDM decreases much more than that of SDM, the orthonormal basis functions of LSDM represent the deformation fields more accurately than those of SDM. We obtained the total deformation fields for warping the image by integrating the deformation fields of all LSDMs. Using the manually labeled MR images of different people, we demonstrated that LSDM could greatly reduce the image registration time while maintaining favorable registration accuracy.**

Index Terms—**Brain MRI, LSDM, Deformable image registration**

I. Introduction

Given its ability to align similar anatomical structures in the same space, the deformable registration of medical images has become an important task in medical image analysis or clinical studies. This method has been widely applied in surgical planning, brain structure segmentation and quantitative evaluation of the anatomical and functional variations among individuals [1-3]. In the deformable image registration, images are warped to a target image by a deformation field. The optimal deformation fields can be estimated by minimizing a cost function. This process involves similarity metrics, which quantifies the degree of alignment between two images and regularization constraints, which smoothen the deformation fields [4, 5]. Monomodal image registration usually utilizes correlation coefficient and sum of squared differences (SSD) [6, 7], while multimodal image registration utilizes mutual information [8, 9]. The regularization constraints are determined by the deformation model selected during the registration. This model may include the elastic model [10, 11] , spline model [12, 13], basis function model [14, 15] etc. . Given that accurate registrations favorably represent those deformation fields that require transformation with high degrees of freedom (DOFs), representing deformation fields requires many parameters. However, optimizing many parameters for optimal deformation fields is an intractable task now. Inter-subject image or atlas registration is even more difficult because the huge differences in the anatomical structures of these images make the cost function optimization an ill-posed problem.

The SDMs have been proposed to obtain optimal deformation fields quickly [16]. These models greatly reduce the dimension of non-rigid transformation by learning from the deformation fields of training sample images, achieve a highly robust registration by constraining the deformation according to the known deformation from the training sample images and well estimate deformation fields even for noisy images that may be mismatched when using standard registration methods. But the SDMs suffer from the large dimensions of the deformation fields and related small samples that compared with the dimensions of the deformation fields. Because SDMs use PCA to reduce the dimensions of deformation fields, and use eigenvectors with large eigenvalues to represent the deformation fields. There are small number of non-zero eigen values with the small number of the samples. The larger images have larger size of the deformation fields. The small number of eigenvectors is not feasible for the large deformation fields.

The origins of SDM can be traced back to active shape models (ASMs) [17] and active appearance models (AAMs) [18]. On the one hand, ASMs capture the variation in the shapes of objects. These models use landmark points to represent the shape of an object and apply PCA to model the displacements in these landmark points. These models only use shape constraints and does not utilize all available information. On the other hand, AAMs train the model parameters by using landmark points and image intensity. Although these models are more robust than ASMs, they extract the landmark correspondence points manually, which poses a challenging

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