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Measuring sparse temporal-variation for accurate registration of dynamic contrast-enhanced breast MR images

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ABSTRACT

Accurate registration of dynamic contrast-enhanced (DCE) MR breast images is challenging due to the temporal variations of image intensity and the non-rigidity of breast motion. The former can cause the well-known tumor shrinking/expanding problem in registration process while the latter complicates the task by requiring an estimation of non-rigid deformation. In this paper, we treat the intensity's temporal variations as "corruptions" which spatially distribute in a sparse pattern and model them with a L_1 norm and a *Lorentzian* norm. We show that these new image similarity measurements can characterize the non-Gaussian property of the difference between the pre-contrast and post-contrast images and help to resolve the shrinking/expanding problem by forgiving significant image variations. Furthermore, we propose an iteratively re-weighted least squares based method and a linear programming based technique for optimizing the objective functions obtained using these two novel norms. We show that these optimization techniques outperform the traditional gradient-descent approach. Experimental results with sequential DCE-MR images from 28 patients show the superior performances of our algorithms.

1. Introduction

Image registration is a vital process in the dynamic contrast-enhanced (DCE) magnetic resonance (MR) imaging based breast tumor diagnosis. DCE-MR imaging based examinations generally involves multi-times of imaging on the breast volume before and after the administration of contrast agent, yielding the pre-contrast image and a series of post-contrast images. In DCE-MR images, tumor region can have various contrast enhancement patterns due to the agent, leading to significant temporal intensity changes. The analysis on the enhancement curve which describes the temporal changes of intensity of a single pixel or a local region constructs the fundamentals of diagnosis with DCE-MR images. To obtain accurate enhancement curves, image registration plays a critical role by offering spatially aligned images.

However, accurate registration of DCE-MR images is plagued mainly with two challenges: the temporal changes of image intensity, and the non-rigidity of the breast motion in the imaging process. The intensity changes in DCE-MR images can cause volume shrinking/expanding effect of tumor in the process of registration [1], i.e. a tumor area in an image is unexpectedly mapped to a smaller/larger area of another image. This unexpected volume variation in the process of image registration is not consistent with the assumption that the soft tissue is incompressible in the imaging process because of the small deformations involved and the short time imaging durations. As the other challenge, the nonrigid motion of breast makes the registration more complicated in both modeling and estimating the deformations.

To address the above challenges, different mechanisms have been proposed (as to be detailed in Section 2.1). To avoid or alleviate the tumor shrinking/expanding problem, there are various methods using some special regularization terms on the deformation field [1–4] or accounting for the enhancement effect [5,6]. However, most of them need some extra processing like the identification of tumor [1,2], or the estimation of enhancement curve [5] or enhancement field [6], etc. The registration accuracies rely significantly on the results of the extra processing. To achieve more accurate estimation on the nonrigid motion, different registration methods [7–10] have been proposed, which leverage a more efficient similarity measure, a better model of transformation, or a more advanced optimization strategy, etc. However, most

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optimization strategies are gradient descent based, with which only a local minimum can be guaranteed and the results are highly dependent on the initialization. Some other techniques like the simulated annealing can produce a global optimization but require a computational burden. Recently, integer programming was introduced for solving dense image registration [11], which is superior in optimization but incapable of resolving the shrinking/expanding problem.

In this paper, we propose two innovations in order to address the above-mentioned challenges in DCE-MR breast image registration. *First*, as inspired by recent techniques on recovery of sparsely corrupted signals [12–16], we treat the temporal changes of DCE-MR image intensity as structured noise or sparse corruptions and then model them with a L_1 norm and a *Lorentzian* [16]. By assuming the differences between images to be non-Gaussian, these new image similarity measurements are more tolerant of large intensity variations in the process of image registration. This is very different from classical image registration algorithms which assume the two images to be registered have consistent intensities plus a Gaussian noise at the corresponding pixels or have high correlations [17]. With these measurements, the image registration is formulated as minimizing a sparse field of image differences while keeping the smoothness of the deformation field. We show that the proposed measurements are pretty robust and can help to deal with the tumor shrinking/expanding problem in DCE-MR breast image registration without any extra processing. *Second*, we propose two new optimization strategies in order to optimize the parameters of the deformation field when incorporating the L_1 norm or *Lorentzian* into the objective function. They perform as recursively solving a weighted least square or linear programming [18]. For the latter, a global optimum can be attained in each iteration.

The rest of this paper is organized as follows. A brief review of techniques of image registration and recent applications of the sparsity prior is given in Section 2. In Section 3, we present the details of our new image registration methods, including the image transformation model in Section 3.1, the energy function in Section 3.2, the new measurements on sparse image variations in Section 3.3 and the new optimization technique in Section 3.4. Experimental results with real DCE-MR scans are included in Section 4. We finally close in Section 5 with conclusions and future directions.

2. Previous work

2.1. Image registration

Extensive investigations have been carried out on image registration due to its importance in a wide variety of practical tasks. There are a huge number of related publications and the existing methods can be basically classified into two categories: pixel-based and feature-based. Detailed review to all these methods is beyond the scope of this paper and we refer the reader to papers [17,19,20] for a general survey. In this paper, we only provide a brief review to methods of dealing with the tumor shrinking/expanding problem caused by temporal changes of image intensities in the breast tumor area between the pre-contrast DCE-MR image and a pot-contrast one.

To resolve the tumor shrinking/expanding problem, different methods have been proposed through incorporating a rigid structure of tumor in the nonrigid deformation modeling [1,2], enforcing tissue incompressibility constraint during registration by constraining the local Jacobian determinant to be close to unity everywhere in the image [3] or enforcing the orthogonality condition on the local Jacobian matrix [4], predicting the enhancement by modeling the enhancement curve [5], or by estimating and removing the enhancement field [6], etc. However, most of them require an extra processing and the final registration accuracy highly depend on the accuracy of this extra procedure. For example, methods in [1,2] need the identification of the tumor region in advance. Method in [3] enforces the incompressibility on the whole volume, which is not always true in practice. Methods in [5,6] need to model the enhancement curve or enhancement field, for which deformation estimation depends the selected model of enhance and registration can be biased towards model fits that are neither appropriate nor accurate. In contrast, we deal with the tumor shrinking/expanding problem by manipulating the image similarity measurement and therefore no extra processing is needed.

Existing image similarity measures used in image registration [7] include the sum of squared differences (SSD) [21], Mutual information, normalized mutual information and local correlation, etc. In contrast, the measurements proposed in this paper are based on the sparse distribution pattern of intensity's temporal changes in DCE-MR images and characterized with an L_1 norm or a *Lorentzian*.

In a wide range of optimization techniques for image registration, local searching is one important class, which starts from an initial guess and tries to find a minimum within a local area. It includes techniques of gradient descent [3,4,22], conjugate gradient descent, Newton Raphson, Levenberg-Marquardt optimization, etc. These methods need a lower computational burden, however, their solution depends significantly on the initialization. The other class is global optimization, which is usually more robust than the local searching methods. It includes the simulated annealing, and generic algorithm, etc. The simulated annealing generally spends a lot of time to get an optimal solution especially when the number of unknowns is huge. The generic algorithm has a tendency to converge towards local optima or even arbitrary points rather than the global optimum of the problem. In contrast, we treat the nonlinear registration problem as recursively solving a weighted least square or a linear programming [18]. For the latter, a global optimum can be attained for each iteration.

2.2. Sparsity prior

Image/signal was demonstrated to be sparse in the sense that they can be reconstructed from a smaller number of linear measurements relative to the dimension of the image/signal space [23,24]. In other words, a vector/matrix representing an image/signal is mostly composed of zeros. Taking image for example, this prior comes from the fact that colors/intensities are largely the same in areas of a natural/medical image. This important property has been widely used in the communities of medical imaging, computer vision, multimedia and signal processing. It has been successfully applied to practical applications of shape modelling [25], image segmentation [26–28], image reconstruction [29,30], motion analysis [31], bias correction [32,33], image registration [34], image retrieval [35,36] and deconvolution [37,38] in the fields of medial imaging and medical image analysis. In addition, it has also been used in a large variety of applications in the field of computer vision, including face recognition [39], image restoration [40], image denoising, deblurring, superresolution and object recognition [41–48].

Sparse-signal recovery techniques can be basically classified into three categories in sense of the assumption on the source used for performing the recovery: measurements free from noise, measurements with unstructured Gaussian noise and measurements with structured noise (also called outliers) [13]. There are various algorithms designed for accomplishing sparse-signal recovery for the former two cases. Recently, the structured noise has attracted a lot of research interests [12–16] and is usually treated as sparse and modeled in a similar way to the sparse signal to be