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Scatter to volume registration for model-free respiratory motion estimation from dynamic MRIs

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ABSTRACT

Respiratory motion is one major complicating factor in many image acquisition applications and image-guided interventions. Existing respiratory motion estimation and compensation methods typically rely on breathing motion models learned from certain training data, and therefore may not be able to effectively handle intra-subject and/or inter-subject variations of respiratory motion. In this paper, we propose a respiratory motion compensation framework that directly recovers motion fields from sparsely spaced and efficiently acquired dynamic 2-D MRIs without using a learned respiratory motion model. We present a scatter-to-volume deformable registration algorithm to register dynamic 2-D MRIs with a static 3-D MRI to recover dense deformation fields. Practical considerations and approximations are provided to solve the scatter-to-volume registration problem efficiently. The performance of the proposed method was investigated on both synthetic and real MRI datasets, and the results showed significant improvements over the state-of-art respiratory motion modeling methods. We also demonstrated a potential application of the proposed method on MRI-based motion corrected PET imaging using hybrid PET/MRI.

1. Introduction

Geometric uncertainties caused by respiratory motion remain a significant source of errors in a wide range of image acquisition applications and image-guided interventions. For example, in radiotherapy treatments in the thorax and upper abdomen, respiration complicates the precision of tumor localization and causes healthy tissues to be radiated. In 3-D imaging with a long acquisition time (such as Positron Emission Tomography (PET)), respiratory motion degrades the image quality and cause motion artifacts. Therefore, respiratory motion estimation has been an active research topic, and various motion modeling techniques have been investigated [1].

Many existing respiratory motion estimation methods are based on motion models, which take some "surrogate" data as the input and produce a motion estimate as the output. To form a respiratory motion model, a number of motion measurements from various breathing states need to be made available from certain imaging data. The surrogate data needs to be acquired simultaneously with the imaging data, or can be extracted from the imaging data, in order to generate correspondence between the surrogate data and motion measurements. To apply the motion model, only the surrogate data is acquired and fed into the model, which produces the corresponding motion estimate.

A common assumption made by previous respiratory motion modeling methods is that the respiratory motion is "repeatable", and different assumptions on the repeatability have been made by various methods [1]. The strongest assumption is that the motion during expiration is the same as the motion during inspiration (i.e., intra-cycle repeatability) and the motion paths are the same from one breathing cycle to the next (i.e., inter-cycle repeatability). Motion models based on this assumption can use a scalar to uniquely represent a motion state [2], and therefore can be driven by 1-D surrogate data (e.g., from Magnetic Resonance (MR) navigator, respiratory bellows, spirometer and chest/abdomen displacement etc.). As the intra-cycle variation of respiratory motion became widely recognized, many proposals modeled the inspiration and expiration separately, and hence only assumed inter-cycle repeatability [3]. However, it was also shown that the inter-cycle repeatability assumption is also not always valid, and significant variations in breathing motion paths have been reported [4].

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Several attempts have been reported to address the inter-cycle variation. Low et al. [5] and Yang et al. [6] proposed motion models with 5 degrees of freedom (DoF) to capture breathing variability. Multiple groups [7–9] have proposed to construct Principal Component Analysis (PCA) or Kernel PCA (K-PCA) model to determine the statistical modes of variation of respiratory motions. Although these methods could capture inter-cycle variation in theory, they all require 4-D Computed tomography (CT) images to construct the motion model, which are acquired using respiratory-gated imaging and by themselves assume the inter-cycle repeatability of the respiratory motion. Specifically, in respiratory-gated imaging, data acquired at the same breathing phase across multiple breathing cycles are combined to reconstruct a motion-free 3-D image, with an assumption that the underlying motions at the same phase in different cycles are the same.

Only a few methods dealt with inter-cycle variation in both the motion modeling and data acquisition stages. King et al. introduced a PCA model for respiratory motion, formed using dynamic 3-D MR Image (MRI) data acquired from the same subject [10,11]. While this method does not assume repeatable respiration in either the PCA modeling nor the dynamic MR imaging, there is an implicit assumption that the PCA model learned from the training data can cover the variations presented during model application. However, for a long imaging or treatment session, the respiratory pattern could change significantly [12]. For example, it is common that a patient breathes shallower at the beginning of the session because of anxiety and deeper as he/she becomes more relaxed. In this case, the PCA model learned from a portion of the session may not be able to provide sufficient motion variation coverage. To ensure sufficient coverage, in [10], the subjects are instructed to perform different breathing patterns during the acquisition of the training data. In addition, a model applicability test is conducted after every model application to check if the model is applicable to the observed data. If the model is not applicable, more 3-D MRI data will be acquired to update the model. In general, this image acquisition strategy is cumbersome in clinical environments and may not be practical for patients suffering from painful diseases.

Some groups also applied physical driven biomechanical modeling to address intra- and inter-cycle variations of respiratory motion, e.g., using Finite Element Method (FEM) to model lung and/or liver during respirations [13–15]. Due to the high computational cost of FEM, these methods typically use simple anatomical models. For example, in [15], the patient's thorax and abdomen are modeled as four components, i.e., left and right lungs, the thorax and the sub-diaphragm area. While such simplified and general anatomical models may be able to represent breathing patterns of normal and healthy subjects, they are typically not applicable to patients with diseases in thorax and/or abdomen, which can create unique tissue properties (e.g., lesions) that cannot be represented by the general anatomical model.

In this paper, to truly address both inter-cycle and intra-cycle variations of respiratory motion, we present a method to estimate the respiratory motion from dynamic 2-D MRIs without employing any motion model. The applications of particular interest for the proposed method include motion corrected PET imaging in hybrid PET-MRI systems and motion compensation (MoCo) in the MRI-guided radiation therapy, where MRI data can be acquired dynamically and used for motion estimation. In the proposed method, dynamic 2-D MRIs in sparsely-spaced sagittal and coronal planes are acquired in real-time and registered to a reference 3-D MRI to extract dynamic 3-D motion fields. As the pixels in sparsely-spaced 2-D MRIs can be regarded as scattered 3-D data, we propose a scatter to volume registration algorithm to register the 2-D MRIs and the reference 3-D MRI. Compared with the existing methods, the contributions of the proposed method are two-fold: (1) It estimates the patient's motion directly from dynamic 2-D MRI data, and thus is robust to breathing pattern variabilities; (2) It does not rely on any motion model, and therefore can be straightforwardly extended to estimate other types of motions.

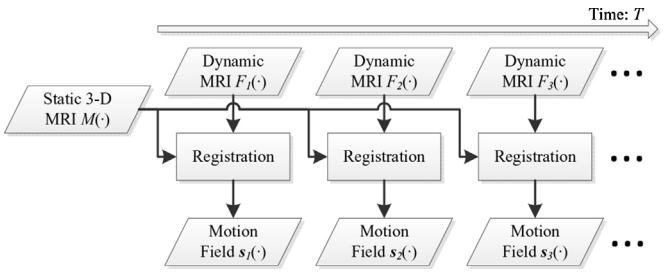

Fig. 1. Flowchart of the proposed MRI-based motion estimation system.

The rest of this paper is structured as follows. Section 2 introduces the problem formulation for MRI-based motion estimation. Section 3 provides a numerical solution for the proposed problem formulation. Section 4 describes the simulation and experiment methods. Section 5 reports the results and compares the proposed method with the state-of-art methods. Section 6 discusses the strengths and potential limitations of the proposed method, as well as future works. Section 7 concludes this paper.

2. Problem formulation

2.1. MRI-based motion estimation system

The proposed MRI-based motion estimation system consists of two parts: (1) acquisition strategy of static 3-D and dynamic 2-D MRIs; (2) motion estimation via image registration. A flowchart of the proposed system is shown in Fig. 1. It first takes a static motion-free 3-D MRI as input, denoted as $M : \Omega \mapsto \mathbb{R}$, where $\Omega \subseteq \mathbb{R}^3$ is the imaging domain, typically covering the patient's thoracic and/or abdomen. The static motion-free 3-D MRI provides image information at the reference state for motion estimation, and can be acquired with breath holding. During the period that motion estimation needs to be performed, dynamic 2-D MRIs are continuously acquired from multiple sagittal and coronal slices to provide real-time image information. The dynamic 2-D MRIs acquired at a time point i (referred to as a *Dynamic 2-D MRI Set*) are denoted as $F_i : \Phi \mapsto \mathbb{R}$, where $\Phi \subseteq \mathbb{R}^3$ is the dynamic imaging domain formed by the union of 3-D coordinates of pixels from the dynamic 2-D MRIs.

The dynamic 2-D MRI sets need to be acquired at a reasonably fast rate in order to capture the motion. We propose acquiring a dynamic 2-D MRI set every 0.5 s, which consists of 2-D MRIs in both sagittal and coronal slices. For respiratory motion estimation, we heuristically choose to use 4 sagittal slices and 2 coronal slices to capture motion in all directions. Such dynamic 2-D MRI can be acquired within 72 ms per slice using a product MR pulse sequence that is widely available on Siemens MR systems. Details of the MR pulse sequence and example images can be found in Section 4.5.

With a static 3-D MRI $M(\cdot)$ and a series of dynamic 2-D MRI sets $F_i(\cdot)$, a motion field $\boldsymbol{s}_i : \Omega \mapsto \mathbb{R}^3$ is estimated for each time point i by registering $M(\cdot)$ and $F_i(\cdot)$ using the proposed scatter to volume registration method. The dynamic 2-D MRI sets can be regarded as scattered 3-D data, meaning that the MRI intensity information is only observed at scattered locations. Therefore, the proposed image registration method is referred to as a scatter to volume registration.