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Mutifractals based multimodal 3D image registration

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ABSTRACT

Multimodal registration is a method to register the volumes of different modalities, for e.g., computed tomography (CT) and magnetic resonance (MR). Mutual information (MI) based methods are widely used for multimodal registration. The MI characterizes the statistical dependence between the voxel intensities of volumes. Robustness of the MI based registration is affected, when there is a low correspondence between the voxel intensities of volumes. This can be improved by integrating the geometric characteristics of volumes like complexity, singularity and irregularity with registration. A novel approach for 3D multimodal image registration based on the multifractal characterization of volumes is being proposed in this paper. The proposed method uses multifractal formalism to incorporate geometric characteristics into registration. Multifractal formalism involves determination of Holder exponent followed by computation of Hausdorff dimension. Holder exponents quantify the local regularity of the volumes and Hausdorff dimensions quantify the global regularity (multifractality) of the volumes. The performance of the proposed algorithm is evaluated using synthetic phantom images for different noise levels and 41 clinical 3D brain images of 7 different patients from a public domain database. The above-mentioned test platforms highlight the efficiency of the proposed method towards improving the robustness and accuracy of registration.

1. Introduction

The spatial alignment of the multimodal 3D images is a key factor to provide a better comprehensive analysis of the underlying anatomy and is widely incorporated in medical applications to improve the diagnostics. Multimodal image registration is very helpful in medical image analysis, as the images of different modalities provide complementary information [1]. It is the process of aligning the volumes of different modalities like CT and MR. The multimodal image registration is used for target delineation and dose distribution, planning of radiotherapy treatment of brain and prostate tumors from CT and MR images [2,3], analyzing gene regulation using chromosome structures in microscopic images of cell nuclei [4], cardiovascular catheterization using hybrid magnetic resonance (MR), X-ray suite (XMR) [5], etc. The axial slice of CT and MR volumes of brain are shown in Fig. 1a and b respectively. The goal of registration is to find the optimal transformation that provides the best alignment between the volumes.

There are two types of techniques commonly used in registration, intensity and feature based methods. In intensity based methods, the idea is to search iteratively for the optimal geometric transformation that maximizes a similarity metric between the reference and moving images. The geometric transformation is applied to the moving image and the voxels are resampled during transformation using an interpolator. The similarity metric is computed from voxel intensities of the fixed and the transformed moving images. The feature based registration is similar to the intensity based registration technique, but the former uses extracted features of the image to compute similarity metric instead of voxel intensities. In general, intensity based methods are more accurate compared to the feature based technique [6].

The Sum of squared difference (SSD), cross-correlation, and MI are some of the similarity measures used for registration [1]. The SSD, cross-correlation and its derivative variants are generally used for monomodal image registration [1]. These measures are pivoted on an assumption that the intensities of the computed volumes are linearly correlated. This assumption for monomodal image reg-

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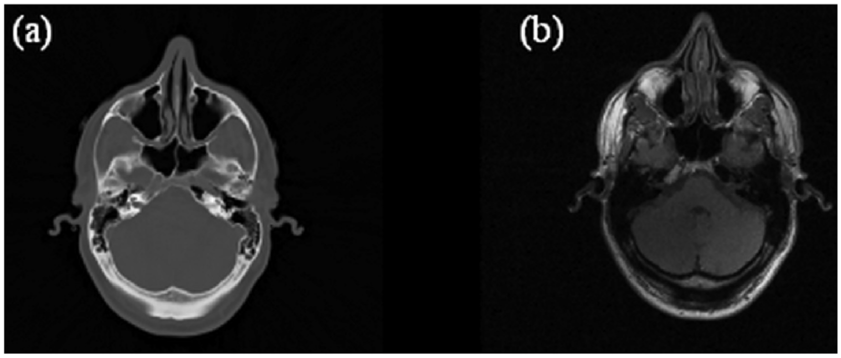

Fig. 1. Multimodal brain images : (a)CT image and (b)MR-T1 image of brain.

istration becomes obsolete for multimodal images as the images have different intensity distributions. Therefore, the MI [10,11] is an alternate technique preferred for multimodal image registration [1,8]. The MI is very robust [7] and reliable [8,9] metric for multimodal image registration. It measures the statistical dependence between the voxel intensities of images to be registered and gets maximized, when the images are aligned. It can also be used for monomodal registration. Since, the MI based registration technique mainly depends upon the statistical dependence among the voxels, the local intensity variations in the images affect the performance of the registration method. In order to overcome this limitation, multiple methodologies were proposed previously such as, incorporating a Harris operator [6,12] in registration, using voxel intensity gradients [7] for computing the similarity measure and a spatial MI based similarity measure [13] for 3-D brain images. Similarly, another technique proposed [14], combines the MI with the magnitude and orientation gradients computed from voxels to clear the technical offsets in MI. However, these methods do not consider the geometric characteristics like singularity, irregularity and complexity of the given image data. Further, the above-mentioned techniques cannot differentiate between different types of singularities, for instance, differentiation between edge points and isolated points [15]. The proposed algorithm to register the multimodal images, facilitates the characterization of multifractality of volumes using Hausdorff dimension [15], which helps in discrimination of singularities during registration. Holder exponents are used in [16] to compute descriptor for photographic image registration. Holder exponents quantify the local regularity [16] of the structure, but in this work, Hausdorff dimensions are used to quantify the global regularity based on the distribution of Holder exponents. The original contributions of this work are the following:

1 the use of multifractal characterization applied to multimodal 3D image registration.
2 comparative analysis of outputs generated using different multifractal measures to determine the measure that provides better extraction of details and fewer noise compared to other measures.
3 the analysis of multifractal spectra of images to infer the accuracy of proposed registration method for those images.
4 results for simulated images and public image database to showcase the performance of the proposed method.

The rest of the paper is organized as follows. The proposed multifractals based registration method based on a novel multifractal image processing technique is explained in Section 2. Section 3 describes various components of the MI registration. Section 4 presents simulation and experimental results along with discussion on the performance of the proposed registration method in comparison to the other techniques. It is followed by concluding remarks in Section 5, which summarizes the technical contributions of the proposed method.

2. Proposed method

2.1. Multifractals based multimodal image registration

In this work, a novel technique is proposed to measure the similarity, by computing the MI from the Hausdorff dimensions of voxels. The MI is based on statistical dependence between the voxel intensities, whereas the proposed method is based on statistical dependence between the voxel singularities. This helps in finding similarity between the singular structures of the volumes and makes the registration robust to variation in the intensity distributions of the volumes.

The flowchart of the proposed method is shown in Fig. 2. Fixed and moving 3D images are input data to the registration process. Fixed image is the image that remains unchanged and moving image is the image that is transformed using the fixed image as reference. Let $I_T(X)$ be a moving image that must be aligned to a fixed image $I_R(X)$. $O_T(X)$ and $O_R(X)$ are the fractal image processing outputs for inputs $I_T(X)$ and $I_R(X)$ respectively. The values of $O_T(X)$ and $O_R(X)$ are defined within the bounded domain of V_T and V_R, respectively for $V_T,\ V_R \in \mathbb{R}^3$. $X = [x,\ y,\ z]$ is the voxel location in the volume. Multifractal image processing involves determination of Holder exponents followed by computation of Hausdorff dimensions based on the distribution of Holder exponents. After multifractal image processing, registration is done between the resulting images using the MI similarity measure as shown in Fig. 2. Let $w(X; \mu 1, \mu 2, ..)$ be some geometric transformation with associated parameters $\mu = (\mu 1,\ \mu 2,\ \ldots)$. Registration is the problem of finding the transformation $w(X|\mu)$ that spatially aligns $I_T(w(X|\ \mu))$ to $I_R(X)$. It is an optimization problem in which similarity measure is maximized iteratively with respect to transformations. A coarse to fine pyramidal approach is adopted for both the volumes. In pyramidal approach, the images are smoothed and down sampled by a factor of 2 at each level. When the optimum parameters are found at one level, they are used to initialize the next level of the pyramid. This increases speed and robustness of registration. At every iteration, the moving image pyramid is transformed using w, then the MI similarity measure between the fixed image pyramid and the transformed moving image pyramid is determined. Interpolation is used to determine values at non-voxel positions during the transformation. All the voxels are not necessary for registration, a subset of voxels is sufficient [19]. The subset of voxels is randomly selected in the sampling step and then the MI similarity measure is computed using the sampled voxels as shown in Fig. 2. Maximum number of iterations or gradient magnitude tolerance is used to stop the optimization process. If the value of the gradient is smaller than the gradient magnitude tolerance or if the optimizer