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Robust 3D registration of CBCT images aggregating multiple estimates through random sampling

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ABSTRACT

In this work, we propose a novel 3D rigid registration technique, by applying the Conventional Mutual Information based 3D Registration (*CMIR*) repeatedly in sampled data sets. Using the statistical distribution in the parameter space, we have considered mean, median, and mode of the distribution, and found that the median and mode provide reasonably good estimates. We call the method Robust Rigid Registration by Multiples Estimates in Sampled data points (R^3MES). It provides higher accuracy than the *CMIR* technique. When the number of iterations of multiple estimates is kept low, the R^3MES technique requires less computation, as it works in the sampled data set. The performance of the R^3MES technique is better when the sampling rate is greater than 3%. We present a theoretical validation of this observation, considering uniform sampling with replacement. We also demonstrate its application for registering 3D *CBCT* image volumes of a *colo-rectal* cancer patient captured on different days. To demonstrate its general applicability, we present its performance on registering a pair of 3D *brain MRI* image volumes.

1. Introduction

In the areas of medical imaging diagnosis and treatment planning, image registration or geometric alignment of 2D and/or 3D image data is becoming necessary now-a-days [5]. Image registration may be used to monitor subtle changes between the source and target. Conformal Radiotherapy (*RT*) can shape the radiation beams around the area of the cancer [4]. The process of preparation of radiation beams considering the daily variation in shape and spread of the tumor from Cone Beam CT (*CBCT*) image data of a patient is termed as *Treatment planning*. In the process of preparation of treatment planning, oncologists diagnose the patient for a series of consecutive days by observing his/her 3D *CBCT* image volumes of cancer affected organs. The positioning of the patient inside the *CBCT* scanner may vary slightly from day-to-day, in spite of special care being taken to place the patient with reference to a few markers. External beam *RT* is a treatment given to the cancer patients by focusing prescribed dose of radiation externally. With the help of the 3D *CBCT* image volumes, oncologists determine the relative shift and rotation of the target zones with respect to a reference position, set on the inaugural day of *RT*. However, applying *RT* on patients without registration of these images may result in harming healthy tissues, not considered before.

Mandal et al. [8] reported, by studying the *CBCT* image volumes of colo-rectal cancer patients, that the positioning of patients significantly vary from day to day. This happens as the 3D image volumes are not aligned or registered with respect to any reference image volume. Signal intensity based 3D image registration techniques are the most used techniques for registration. In such methods, normalized cross correlation is used as the metric for registration [16]. Highly dependent nature and higher computational complexity of the cross correlation on the signal intensity is its main drawback. The mutual information (*MI*) is one of the significant measures for image registration. In [16], it is mentioned that *MI* based methods are effective for 3D MR/PET and MR/CT multimodal registration. In the work done by Holia and Thakar [6], an algorithm was proposed for recovering translational parameters, where the 2D cross-sections of *MRI* or *CT* scan brain images were subjected to translation, rotation and scaling. This algorithm tries to maximize the mutual information by finding the joint histogram of both the source and target. For multimodal medical image registration, an algorithm is proposed by Ying et al. [15], which computes similarity between two contours using *MI*. By modelling

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two point sets as two mixtures of Gaussians, mean shift algorithm is proposed by Arellano and Dahyot [1] for robust registration. *MI* is affected in two ways depending on the size of overlapping part of the images. By reducing the overlap, the statistical power of the probability distribution gets reduced. This in turn decreases the number of samples. In the works done by Studholme [12] and Studholme et al. [13], it is mentioned that with reduction of the overlap, *MI* measure may actually increase. Studholme et al. [13] proposed a normalized measure of *MI*, which is less sensitive to changes in the overlap.

The Conventional Mutual Information based 3D registration (*CMIR*) technique [14] registers the source image volume onto the target image volume maximizing the *MI* of both the volumes. We propose a novel 3D rigid registration technique, by applying the *CMIR* technique repeatedly in sampled data sets. We call the method Robust Rigid Registration by Multiples Estimates in Sampled data points (R^3MES). It provides higher accuracy than the *CMIR* technique. It may be noted that a part of this work is briefly presented in [7]. Our main contributions in this work include:

- We propose a robust method of registering two images by using statistical distribution of multiple estimates of the parameters through random sampling of points in images.
- Though the proposed method is generic, we primarily experimented with 3D *CBCT* image volumes of *colo-rectal* cancer patients. We have also demonstrated its application to register a pair of 3D *brain MRI* image volumes.
- Experimentation for choosing suitable sampling rate and the number of iterations has been carried out. A theoretical justification on the sampling rate is also provided.
- As this algorithm has been developed targeting processing of *CBCT* image volumes of *colo-rectal* cancer patients, we demonstrate its application for registering 3D *CBCT* image volumes of a patient captured on different days during *RT*.

2. Conventional Mutual Information based 3D Registration (*CMIR*)

The *CMIR* technique is a 2D/3D registration technique maximizing *MI* among the source and target, thereby providing required transformation parameters. Let us consider the alignment of the source image *U*, onto the target image *V*. This technique considers all the 3D image voxels of *U* and *V* to evaluate the joint probability distribution, which helps in finding *MI* of *U* and *V* [14]. An estimate of the transformation $\vec{T}^*$ that aligns *U* to *V* by maximizing the *MI* over all possible transformations $\vec{T}$ is,

$$\vec{T}^* = \mathbf{arg}max_{\vec{T}} I(U(\vec{T}), V). \tag{1}$$

where the mutual information is given by

$$I(U(\vec{T}), V) = H(U(\vec{T})) + H(V) - H(U(\vec{T}), V). \tag{2}$$

In Eq. (2), $U(\vec{T})$ denotes the transformed *U* with the parameter vector $\vec{T}$. $\vec{T}$ represents the transformation parameter as a multidimensional vector. H(.) is the entropy of a random variable *x*, and is defined as

$$H(x) = -\sum_{x} p(x) log(p(x)). \tag{3}$$

whereas the joint entropy of two random variables *x* and *y* is defined as

$$H(x, y) = -\sum_{x,y} p(x, y) log(p(x, y)). \tag{4}$$

The *MI* and the joint entropy are sensitive to the size and contents of the overlap. $H(U(\vec{T}))$ and $H(V)$ yield low values when the overlapping parts of the images contain only background, and become high when the corresponding volumes contain anatomical structures [11]. This shows that they decrease the chance of misregistration by maximizing *MI*, only when the overlapped regions of $U(\vec{T})$ and *V* have anatomical information. The measure of *MI* may increase even if the overlap reduces. When the relative areas of the object and the background in an image are equal, $H(U(\vec{T}))$ and $H(V)$ increase faster than $H(U(\vec{T}), V)$. This gives rise to higher *MI*, which may result in misregistration. We have used the measure of *Normalized MI* (*NMI*) which is less sensitive to changes in the overlap of $U(\vec{T})$ with *V* [13], and is given as

$$NMI(U(\vec{T}), V) = \frac{H(U(\vec{T})) + H(V)}{H(U(\vec{T}), V)}. \tag{5}$$

In this work, the rigid transformation $\vec{T}$ that is applied for registering images, includes only translations and rotations, which is sufficient to register images of rigid objects like bones. For finding the optimal transformation parameters, this technique goes on overlapping $U(\vec{T})$ with *V* till it converges to maximum *MI*. It uses an optimization method proposed by Nelder and Mead [9] to choose the transformation parameters that are to be applied over *U*. These parameters are chosen based on *MI* evaluated in the previous overlap of $U(\vec{T})$ with *V*. A sequence of steps explaining the *CMIR* technique, is presented in Algorithm 1.

Algorithm 1: Conventional Mutual Information based 3D Registration (*CMIR*).

```
Input: Source U, target V, number of iterations E.
Output: Parameter vector T* for registering U on V.
while (T* not found) or (iteration (β) < E) do
    Perform β^th iteration of the Nelder Mead optimization
    step in search of maximum MI.
        Let T_β be the transformation obtained by the
        optimization step.
        Compute the Joint Entropy between U(T_β) and V in
        the overlap region.
        Compute NMI using Eq. 5.
    if NMI is found to increase then
        T* = T_β
The transformation vector, T* for registering U on V is
obtained.
```

3. Robust rigid registration by multiples estimates in sampled data points (R^3MES)

The R^3MES technique is obtained by modifying the *CMIR* technique for obtaining better 3D registration. It considers sampling the voxel space (Ω) of *U* and *V* for registration, thereby reducing the computational time of the registration. For robust estimation, the R^3MES technique iteratively performs the *CMIR* technique (say *F* times) over the sampled voxel space (Ω_s) for obtaining a set of *F* parameter tuples. On this set, we apply various statistical estimates like mean, median and mode to find the transformation required to align *U* onto *V*. The product of the sampling rate (in fraction) and the number of iterations indicates the amount of computations required. So long this product remains less than 1, the method is computationally efficient than the *CMIR* technique. A step wise description of the computation is provided in Algorithm 2. For computing the mode, we have used mean shift algorithm [2]. For estimating the median, we have computed the vector median of translational parameters and the scalar median of the rotational parameters, independently.

4. Data set and simulation

The data set that we have considered, in this work, is the 3D *CBCT* image volumes of colo-rectal cancer patients. Each of them is