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Three-dimensional Fuzzy Kernel Regression framework for registration of medical volume data

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ABSTRACT

In this work a general framework for non-rigid 3D medical image registration is presented. It relies on two pattern recognition techniques: kernel regression and fuzzy c-means clustering. The paper provides theoretic explanation, details the framework, and illustrates its application to implement three registration algorithms for CT/MR volumes as well as single 2D slices. The first two algorithms are landmark-based approaches, while the third one is an area-based technique. The last approach is based on iterative hierarchical volume subdivision, and maximization of mutual information. Moreover, a high performance Nvidia CUDA based implementation of the algorithm is presented.

The framework and its applications were evaluated with a number of tests, which show that the proposed approaches achieve valuable results when compared with state-of-the-art techniques.

Additional assessment was taken by expert radiologists, providing performance feedback from the final user perspective.

1. Introduction

One of the most widely accepted methods of gathering knowledge about tissues, organs and cells, is to integrate information integration coming from volumes/images of such objects that have been acquired with different modalities, different acquisition techniques, and at different times. Volume registration is a mandatory task to achieve information fusion. Registration lets the two volumes to be transformed geometrically so that the best possible spatial correspondence with respect to each other is obtained.

Image and volume registration techniques span a broad class of methods and taxonomies according to either the features used to perform registration or the nature of transformation. Several surveys on the subject are present in the literature [1–5] and this research field is very active as it is reported in [6].

With regard to the features, registration methods can be landmark-based or area-based. Landmark-based approaches rely on the information provided by some corresponding features in the two images, such as points, lines, regions, etc. Area-based techniques use the whole image content to estimate the registration transformation by optimizing some similarity metric. Although several similarity metrics have been proposed in literature, Mutual Information (MI) and its normalized version (Normalized Mutual Information—NMI) has proven to be one of the most effective measures, especially for multi-modality registration tasks [7–10], since it does not assume any functional relationship between the intensity values of the images, taking into account only their statistical correspondence.

With regard to the nature of transformation, many models exist in literature. The simplest ones use global or local mapping by means of rigid, affine, and projective transformations. Other approaches are able to deal with local deformations and use radial basis functions such as thin-plate spline [11] or Wendland's functions [12,13]. A more complex approach is to use parameter-free deformation functions, by considering the volume as a tensile material [14] or a viscous fluid [15] that is deformed by external and internal forces subject to constraints. In this approach, registration is achieved by the iterative minimization of an energy functional.

Another approach called block matching [16], finds local correspondences and then derives the global rigid transformation that best explains them. ANIMAL [17], realizes the registration using a two step registration (a linear and a non-linear part) relying on geometrically invariant spatial features. Polyaffine framework [18] parameterizes deformations with a finite number of rigid or affine components. Lastly, in MIRT [19] a gradient descent method is used hierarchically to iteratively determine optimal B-spline parameters for the transformation.

Using a global method is a practicable choice only when using simple transformation models, where just few parameters are required. When using curved deformations the number of parameters is large, and a direct optimization is not possible due to

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large dimensionality of the search space and the presence of many local optima. A possible solution is to decompose the image domain and operate many local sub-image registrations using simple models. The final global transformation can be recovered by composing local ones, thus obtaining a unique continuous and smooth complex deformation [20,21]. Such idea, and a variety of methods to recover a mapping function using points correspondences have been extensively investigated in [22] and [23].

Recently we proposed some 2D registration systems leveraging onto these concepts [24–26]. However, such image-based approaches were lacking a formal theoretical background. The present work deepens the formal aspects. Additionally, the method proposed in this paper unifies the three approaches to a unique 3D registration framework that relies on using kernel regression and fuzzy c-means clustering for recovering the required volume transformation parameters. We called such framework 3D *Fuzzy Kernel Regression*. Three applications are presented as different instances of the framework where increasing complexity transformations are addressed. The first two are a simple and an improved landmark based technique (*SLB* and *ILB*) while the third one is an automatic area based approach (*AAB*) that addresses several hot problems in the field of registration: it does not require correspondences, achieves a per voxel transformation, and is inherently parallel. The presented techniques are compared to each other to prove the generality of the framework, while the *AAB* algorithm is compared with MIRT, and an overall performance review is provided by a team of radiologists.

The paper is arranged as follows: in Section 2 theoretical background related to kernel regression and fuzzy c-means is reported. The three different framework implementations are illustrated in Section 3, while Section 4 reports the details about the implementation of the framework on the *Compute Unified Device Architecture* (CUDA) for increasing performance using NVidia GPUs to make some of the calculations. In Section 5 the proposed registration methods are tested to evaluate their performances from both qualitative and quantitative perspectives. Finally, in Section 6 final considerations and future works are explained.

2. Theoretical framework

The proposed registration framework relies on two main theoretical concepts: *Kernel Regression* and *Fuzzy c-means*. For this reason, we will provide an explanation of such issues, and how they are used together for the purpose of volume data registration before illustrating the applications of the proposed framework.

2.1. Kernel regression

Consider a target volume T, an input volume I and a set of known displacements $\mathbf{t}_n$ for some given pairs of corresponding points $\mathbf{c}_n^T$ and $\mathbf{c}_n^I$. In what follows, boldface notation will indicate 3D vectors and/or points. The registration problem can be stated as recovering the values for reconstructing the whole deformation function $g(\mathbf{x})$ which brings I to the best spatial correspondence with T. In our work this was accomplished using kernel regression. Kernel regression is a *memory-based* pattern recognition method, i.e. it uses data points both in the training and in the prediction phase. It consists in predicting the function value for given input points by means of linear combinations of a *kernel function* evaluated at the training data points. Kernels depending only on the magnitude of the distance between their argument and the training points, are known as *homogeneous* kernels or *radial basis functions*. In our work we used the derivation of kernel regression from the scheme known as the Nadaraya–Watson model [27]. Starting from the training set made by N couples $\langle \mathbf{c}_n, \mathbf{t}_n \rangle, i=1,\dots,N$, the joint distribution $p\ (\mathbf{x}, \mathbf{t})$ can be modeled using a Parzen density estimator

$$p(\mathbf{x},\mathbf{t}) = \frac{1}{N}\sum_{n=1}^{N} f(\mathbf{x}-\mathbf{c}_n, \mathbf{t}-\mathbf{t}_n) \quad (1)$$

where $f(\mathbf{x},\mathbf{t})$ is the component density function. There is an instance of $f(\cdot)$ centered in each sub-image. The regression function $y(\mathbf{x})$, corresponding to the conditional average of the target variable depending on the input, is given by

$$y(\mathbf{t}) = E[\mathbf{t}|\mathbf{x}] = \int_{-\infty}^{+\infty} \mathbf{t}p(\mathbf{t}|\mathbf{x})\, d\mathbf{t} = \frac{\int \mathbf{t}p(\mathbf{x},\mathbf{t})\, d\mathbf{t}}{\int p(\mathbf{x},\mathbf{t})\, d\mathbf{t}} = \frac{\sum_n \int \mathbf{t}f(\mathbf{x}-\mathbf{c}_n, \mathbf{t}-\mathbf{t}_n)\, d\mathbf{t}}{\sum_m \int f(\mathbf{x}-\mathbf{c}_m, \mathbf{t}-\mathbf{t}_m)\, d\mathbf{t}}. \quad (2)$$

Assuming that the component density functions have zero mean so that

$$\int_{-\infty}^{+\infty} f(\mathbf{x},\mathbf{t})\mathbf{t}\, d\mathbf{t} = 0 \quad (3)$$

for all values of $\mathbf{x}$, we can operate a variable substitution, and we get

$$y(\mathbf{x}) = \frac{\sum_n g(\mathbf{x}-\mathbf{c}_n)\mathbf{t}_n}{\sum_m g(\mathbf{x}-\mathbf{c}_m)\mathbf{t}_m} = \sum_n k(\mathbf{x},\mathbf{c}_n)\mathbf{t}_n, \quad (4)$$

where the kernel function $k(\mathbf{x}, \mathbf{c}_n)$ is defined as

$$k(\mathbf{x},\mathbf{c}_n) = \frac{g(\mathbf{x}-\mathbf{c}_n)}{\sum_m g(\mathbf{x}-\mathbf{c}_m)} \quad (5)$$

and

$$g(\mathbf{x}) = \int_{-\infty}^{+\infty} f(\mathbf{x},\mathbf{t})\, d\mathbf{t}. \quad (6)$$

This form is known as the *Nadaraya–Watson* model or *kernel regression* [27], [28]. In case of localized kernel functions, it has the property of weighting more the data points $\mathbf{c}_n$ close to $\mathbf{x}$ than the others. The kernel (5) satisfies the summation constraint

$$\sum_{n=1}^{N} k(\mathbf{x},\mathbf{c}_n) = 1. \quad (7)$$

2.2. Fuzzy c-means clustering

In order to use the kernel regression model we need to choose a suitable equivalent kernel which satisfies (7). Several functions can be chosen for this purpose, such as Gaussians, multiquadric, polyharmonic, Thin-plate splines [11], etc. In our framework we introduce fuzzy membership maps as equivalent kernels. Such functions are designed using fuzzy c-means (FCM) clustering algorithm [29]. Given a training set of feature vectors $\{\mathbf{x}_i,\ i=1,\dots,k\}$ that defines a feature space Ω, FCM finds analytically the position of the cluster centroid vectors $\{\mathbf{c}_j,\ j=1,\dots,m\}$ in such a space. This is accomplished by minimizing the following functional:

$$J_s = \sum_{j=1}^{m}\sum_{i=1}^{k} (u_{ij})^s\, d(\mathbf{x}_i,\mathbf{c}_j)^2, \quad 1 \le s < \infty, \quad (8)$$

where $d(\mathbf{x}_i,\mathbf{c}_j)$ is a distance function between each observation vector $\mathbf{x}_i$ and the cluster centroid $\mathbf{c}_j$, m is the number of clusters, which should be chosen a priori, k is the number of observations, u_{ij} is the membership degree of the sample $\mathbf{x}_i$ belonging to the j-th cluster and $s \geq 1$ is a parameter which defines the amount of clustering fuzziness, i.e. the form of the membership function. For common tasks this value ranges generally in an interval around 2. An additional constraint is that the membership degrees should be