Non-rigid 2D-3D Registration Based on Support Vector Regression Estimated Similarity Metric

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Abstract. In this paper, we proposed a novel non-rigid 2D-3D registration framework, which is based on Support Vector Regression (SVR) to compensate the disadvantages of generating large amounts of Digitally Rendered Radiographs (DRRs) in the stage of intra-operation for radiotherapy. It is successfully used to estimate similarity metric distribution from prior sparse target metric values against different featured transforming parameters of non-rigid registration. Through applying the appropriate selected features and kernel of SVR solution to our registration framework, experiments provide a precise registration result efficiently in order to assist radiologists locating the accurate positions of radiation surgery. Meanwhile, a medical diagnosis database is also built up to reduce the therapy cost and accelerate the procedure of radiotherapy in the case of future scheduling of multiple treatments.

Keywords: 2D-3D Registration, Non-rigid, Support Vector Regression, DRR, Registration Framework, Radiotherapy.

1 Introduction

Nowadays, non-rigid registration [1] algorithm is widely employed into many kinds of modern surgery, diagnosis and operation planning in order to combine and enhance the information of two or several different modality data sets at different times. Especially, in the field of radiation surgery [2], most radiologists traditionally diagnose diseases through viewing 2D X-ray film only. It is very hard for a radiologist to imagine the complex 3D shapes of tissue or organ various from different patients and difficult for them to locate the surgical position accurately. To this point, during radiotherapy, we should introduce information of a 3D model reconstructed from pre-operative data obtaining by CT or MRI machine into 2D X-ray image to aid radiologists to diagnose various diseases and locate the surgical position easily and accurately in real time [3]. Because many surgical objects are soft tissues, we have to develop the non-rigid registration to reach the above goal.

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Our target is to utilize an effective 2D-3D registration algorithm [4,5] to decide the physical space position of 3D model for matching the intra-operative 2D X-ray image with deformation as accurately as possible. Scholars had engaged into developing many effective, highly evaluated, deeply proved and widely used cutting-edge non-rigid 2D-3D registration algorithm. Few of them involve the area of matching the intensities between 3D data sets and X-ray images in elasticity deformation by minimizing a similarity measure to reach the goal of registration. On the other hand, Voxel-based registration [4] had been widely used for its simplicity and robustness. As the key technology in this kind of 2D-3D registration, generation of digitally rendered radiographs (DRRs) [7], however, becomes a bottleneck of whole registration routine. Among steps of optimization [1], large amounts of intra- operative 2D DRRs had to be generated from the 3D data sets, which used to be compared with X-Ray image in order to obtain best similarity metric mapping the parameters of transform to match the 3D data sets with 2D X-ray image. Due to the tremendous number of iteration and reduplicated computation during optimization, generation of intra-operative 2D DRRs is very time-consuming, which could not be tolerated by the radiologist during operation. Although lots of accelerated DRR generation method [7] had been rushed out in the past several years, few real-time virtual surgery applications appeared by means of current 2D-3D registration methods.

Aiming at the above two points, we engaged into changing the workflow of traditional registration framework in order to avoid generating intra-operative DRRs and combining with the technology of free-form deformation [1] to realize the non-rigid registration effectively. Among that, a novel intensity based 2D-3D registration method using Support Vector Regression (SVR) [8] was employed into our platform of virtual surgery. It is constructed from the relationship between parameters of non-rigid transformation for 3D volume data sets and sparse offline metric distribution, which evaluates the similarity of X-ray image and pre-operative DRR images of 3D data sets. Because of the characteristics of SVR, it could estimate the real similarity metric during operation and avoid generating intra-operative DRRs during optimization steps. In this way, we could naturally compensate the disadvantage of time-consuming calculation of DRR generation and finally boost up the performance of 2D-3D registration algorithm.

The rest of the paper is organized as follows: in Section 2, the theoretical concept of SVR is briefly reviewed followed by the non-rigid application, based on which a novel registration framework is figured out in section 3, while the merits of the registration algorithm are also demonstrated in this section. Section 4 presents the implementation and some experimental results respectively. Finally, Section 5 summarizes our current work and leads to outlook on further work.

2 Support Vector Regression in Non-rigid 2D-3D Registration

2.1 Support Vector Regression

It is well-known that Support Vector Machine (SVM) [9] was developed from statistical learning theory [10]. It could be applied to solve classification problems [11] and had also been extended to solve lots of regression problems [10], named Support Vector Classification (SVC) and Support Vector Regression (SVR) respectively. SVM is very suitable for estimating values based on non-uniform sampling data sets, which would form a sparse distribution in the input space. Furthermore, SVR has advantages to estimate continuously and smoothly from the discrete data distribution through various kinds of kernel function.

As mentioned above, our target is to estimate the similarity metric without generating intra-operative DRRs to approach real metric distribution depending on sparse pre-operative DRRs as accurately as possible. This problem could be demonstrated as follows:

Given a training data set $\{(x_i, y_i)\}_{i=1}^{l}$, minimizes the empirical risk

$$\arg\min_{f \in \mathrm{H}_n} R_{emp}[f] \tag{1}$$

$$R_{emp}[f] = \frac{1}{l}\sum_{i=1}^{l} L(y_i, f(x_i)) \tag{2}$$

Where, H_n is hypothesis space, x_i (feature element) is the parameters of non-rigid transformation in the registration method, y_i is the real similarity value between pre-operative DRR image from 3D data and 2D X-Ray image with the current parameter x_i of transform and f is a non-linear evaluation function to estimate similarity metric. Here, the L is an ε- insensitive loss function. This problem is equivalent to the regression problem using *SVR* method [10]:

$$\min_{w,b,\xi_i,\xi_i^*} \quad \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{l}\xi_i + C\sum_{i=1}^{l}\xi_i^* \tag{3}$$

subject to

$$\begin{aligned} & f(x_i) - y_i \le \varepsilon + \xi_i, \\ & y_i - f(x_i) \le \varepsilon + \xi_i^*, \\ & \xi_i, \xi_i^* \ge 0, i = 1, \ldots, l. \end{aligned} \tag{4}$$

Where ε, C are both customized, ξ_i, ξ_i^* are slack variables, we assumed that *f(x)* is composed of several non-linear basic functions $\{\varphi_j(x)\}$ as follows:

$$f(\mathbf{x}) = \mathbf{w}^T\varphi(\mathbf{x}) \tag{5}$$

After introducing Lagrange function, the above optimization problem could be converted into its dual problem, which is easy to be realized by means of computer programming.

$$\mathbf{w} = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)\varphi(x_i) \tag{6}$$

α_i, α_i^* are Lagrange multiplier. $\boldsymbol{\alpha} = \{\alpha_i\}, \boldsymbol{\alpha}^* = \{\alpha_i^*\}$. And

$$K(x_i, x_j) \equiv \varphi(x_i)^T \varphi(x_j) \tag{7}$$

$K(x_i,x_j)$ is the Kernel function. In our paper, we choose exponential radial basis function to satisfy the special characteristic of similarity metric in 2D-3D registration. Finally, we find appropriate Lagrange multipliers to construct the approximate function, which could estimate the metric value without generating intra-operative DRR image in a reasonable time. The approximate function is like:

$$\sum_{i=1}^{l} (\alpha_i^* - \alpha_i) K(x_i, x) \tag{8}$$

2.2 Non-rigid Registration

Refer to the soft tissues to be registered, our SVR involved registration method ought to be enhanced with a non-rigid resolution. We use free-form deformation (FFD) model [9] to solve the non-rigid deformation part of registration. The basic idea of FFD is to deform an object by manipulating an underlying mesh of control points. The deformation of the inset mesh controls the shape of the object or image that we want to deform to match another object or image.

Given an image with resolution ρ and spacing Δ, the control mesh with resolution σ, we can get the spacing of control grid:

$$\delta = \Delta/(\sigma - 1) \tag{9}$$

The deformation at any position X of the image is interpolated using a cubic B-spline convolution kernel:

$$D(X) = \sum_{i=-1}^{2} \beta^{(3)}((X - \phi_{i+n})/\delta) \tag{10}$$

Where, $n = \lfloor X/\delta \rfloor$, ϕ_j denotes the displacement of the *jth* control point of the mesh, $\beta^{(3)}(X)$ is a differentiable convolution kernel given by the product of B-spline kernel function in each dimension.

In FFD deformation, each control point presents three deformation coefficients for 3D data set, which scanned before operation during routine check. Furthermore, these coefficients should be treated as the features vector of the training data set for SVR method. The high resolution of control mesh can offer more flexible local deformations while also introduce a larger number of coefficients, which makes the optimization procedure much more time-consuming. Fortunately, the above procedure and training process are both implemented before in-line operation. And we only choose those active control points deform the control mesh while those passive ones not. Through which, this method can speed up the algorithm while contain the same deformations that we concern.

3 Novel Non-rigid 2D-3D Registration Framework

3.1 Novel Non-rigid 2D-3D Registration Framework Using SVR

As mentioned above, we introduce SVR method to estimate similarity metric between 3D data sets and 2D X-Ray image without the help of generating intra-operative DRR images in every optimization step for non-rigid registration. We could utilize the promising empirical performance of SVR to predict the similarity metric value by means of sparse training data sets. To this point, the SVR separate the traditional calculation of similarity metric into two parts. One is the offline sparse similarity distribution in real condition, the other one is the online estimated continuous similarity distribution. The latter could be calculated out by the promising empirical performance of SVR method without generating any DRRs. Theoretically speaking, it could boost up the efficiency of the process of registration in the aspect of the intra-operative operation.

The framework of our effective non-rigid 2D-3D registration algorithm is depicted as the following figure:

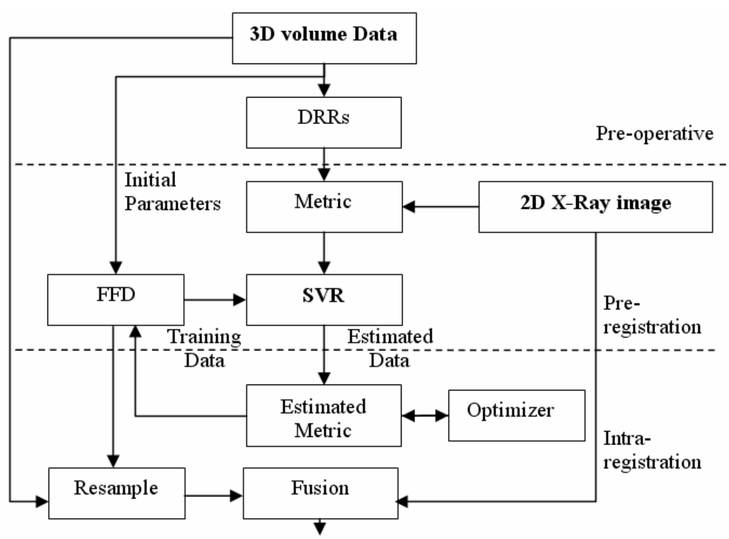


Fig. 1. Novel 2D-3D Registration Framework using SVR

Through which we could build up an evaluation metric function of similarity for optimizer in registration method to find the optimal parameters of transformation to match 3D data sets with 2D X-Ray perfectly. Note that the feature vector of the training data of SVR method is carefully selected from the parameters of control points of FFD transformation in the non-rigid transformation. Furthermore, the kernel function of SVR method is also the most suitable function for the non-rigid registration after various experiments.

We could also figure out that the above flow chart illustrate that our novel 2D-3D registration has three indispensable stages including pre-operative, pre-registration and intra-registration, which comes from the SVR method.

In detail, in the *pre-operative* stage, a 3D model reconstructed from CT or MRI machine when doing the routine check of patient. We just generate a little number of pre-operative DRR images on the key position of each degree of freedom separately as training data according to the 3D model. The second stage called *pre-registration* is responsible for generating the training data constructed from the information of DRR images and the intra-operative X-Ray images. The features of training data for SVR method are the parameters of active control points of FFD transformation. The outputs of training data for SVR method are the real sparse similarity metric value between the pre-operative DRR images and the intra-operative X-Ray images. The third stage called *intra-registration* is responsible for searching the optimal parameters in the estimated space built up in the previous stage. There is no need to generate the DRR image comparing with the intra-operative fluoroscopic X-Ray image. Finally optimal multi-parameters could be obtained until the convergence of optimizer. With the help of these optimal parameters, complicated information of pre-operation 3D data could be fused into intra-operative 2D X-Ray image to assist radiologists in making surgery plan and diagnosing disease.

3.2 Merits of SVR in Novel 2D-3D Registration Framework

In the aspect of efficiency, due to the SVR method, we could directly estimate the similarity metric distribution in the intra-operative stage without generating large number of intra-operative DRR images. As we mentioned above, many accelerated DRR generation algorithm are proposed in order to overwhelm the obstacles of conventional method. However, they are all based on the traditional registration framework, which could not avoid the bottleneck of computation during registration even accelerating DRR generation algorithm. To this point of view, in the stage of intra-operation for radiotherapy, our novel framework is another valuable way to speed up the therapy procedure. On the other hand, due to the characteristic of SVR method, optimizer could smoothly and quickly find optimal parameters of transformation to help the process of intra-registration reaching the real-time.

Regarding to its robustness, it could be successfully integrated into many clinical cases including the brain, thorax and other virtual surgery platform. Once the original data are normalized and pre-processed, training data set for SVR method would be kept stable, which would be insensitive to noise of source data. We could also find that optimizer on the estimated similarity metric between the pre-operative DRR images and 2D image data would be free of local minima, which could increase the robustness and result in good convergence.

The expansibility of our new registration framework is very obvious. We utilize the feature of the training data of SVR method to realize the non-rigid registration. That is to say, the pre-operative DRR images could be generated according the adjustment of different parameters of transforms. There is no need to replace or re-design the other part of our framework. And it could also build up the database classified by each different patient, which services for the future multi-treatments.

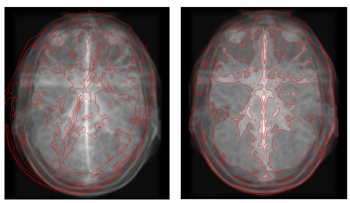
4 Experimental Results

We evaluated our non-rigid 2D-3D registration methods with preoperative 3D volume data sets and intra-operative fluoroscopic X-Ray image. In order to test the robustness and universality of our novel registration framework, our source data cover different modalities and different typical thorax area in the human body. The experiments are performed on a PC with Core-T2400 1.83GHz, 1GB RAM.

A Brain Case

Once most suitable SVR is decided and the estimated searching space is acquired, we could adopt our optimizer to search the space finding the optimal parameters. At first, an experimental result of registration for 3D MRI Brain data set and 2D X-Ray image is illustrated in Fig. 2. The format of 3D T1-MRI data is 181×217×181, slice thickness is 1mm. 2D X-Ray image is simulated by 3D MRI using DRR method, its size is 220×250.

In order to evaluate the results of our proposed registration method, Table.1 summarized some attributes in order to compare our proposed registration method with the conventional one, which uses Mutual Information [12] as similarity metric and calculates large number of intra-operative DRRs at each optimization step for searching the optimal parameters of free form transformation.



a) b)

Fig. 2. Registration between 3D MRI data and simulated X-Ray image. (Brain Case) a) 2D X-Ray image with contours (wire frames) of DRR image from initial 3D volume data. The initial position of 3D volume data is minus ten degree rotated against Z axis with some deformation. b) 2D X-Ray image with contours of DRR image from registered 3D volume data by our proposed registration method.

Table 1. Evaluation of our proposed method compared with conventional method. (Brain Case)

Features	Our Proposed Method	Conventional Method
DRR generation times	218(pre-operative)	435 (intra-operative)
Time consuming (s)	376.7	930.1
Squared Sum Difference	0.1713	0.2033

B Thorax Cases

Four thorax cases of volunteers had been experimented to validate the effective and robustness of our registration framework. Here, the direction of DRR image is along the Y axis. The format of 3D T1-MRI data is listed in Table 2 and the size of intra-operative 2D X-Ray image is 500×500. The control points of FFD for non-rigid transformation, the total consuming time and accuracy of registration results are also illustrated in Table 2.

Table 2. Evaluation of our proposed method under four thorax data sets

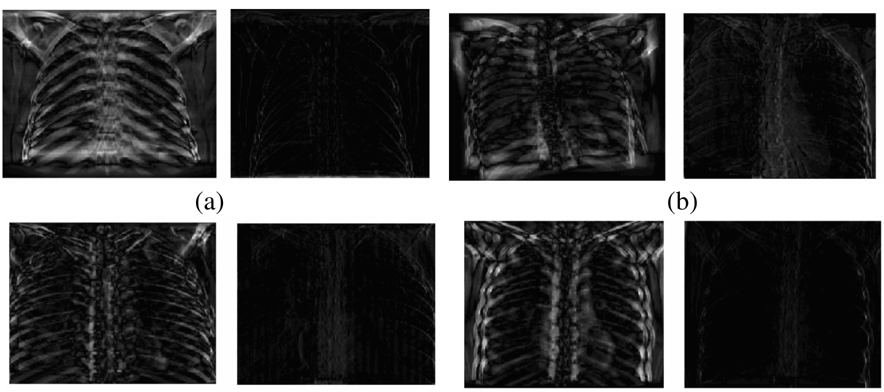
Our Proposed Method	3D Volume Size	Control points	Time consuming (s)	Squared Sum Difference (SSD)
Data #1	233×233×138	18×18×11	2928.5	0.1056
Data #2	482×482×128	12×12×10	3197.1	0.1641
Data #3	522×522×138	13×13×11	2778.1	0.0189
Data #4	600×600×128	15×15×10	3289.7	0.0718

In order to evaluate the results of our proposed registration method, Table.3 gives the comparison results between our proposed method and conventional method, which had been mentioned in Table.1. The data provided here are the average results of all the thorax cases.

Table 3. Evaluation of our proposed method compared with conventional method. (Thorax Cases)

Features	Our Proposed Method	Conventional Method
DRR generation times	313 (pre-operative)	473 (intra-operative)
Squared Sum Difference (SSD)	0.1951	0.2118
Offline Calculation Time (s)	3374.7	--
Online Calculation Time (s)	0.60	3048.5
Total Time consuming (s)	3375.3	3048.5

Experimental result of registration for 3D MRI thorax data sets and 2D X-Ray image is illustrated in Fig.3.



(a) (b) (c) (d)

Fig. 3. Registration between 3D MRI data and simulated X-Ray image. (Four Thorax Cases (a-d)). First Column of each case shows the difference image of 2D X-Ray image and DRR image of 3D volume at an initial position. Second Column of each case shows the difference image of 2D X-Ray image and DRR image of 3D volume at a final position by our proposed registration method. (a) is the registration between 2D X-Ray image and 3D volume data with ten degree rotated against X axis with some deformation. In (b), the initial position of 3D volume data is minus ten degree rotated against Y axis with some deformation. Similarly, ten degree rotated against Z axis with deformation in (c) and twenty mm offset against Z axis with deformation in (d).

5 Conclusion

This paper proposed a novel non-rigid 2D-3D registration framework using Support Vector Regression with free form deformation. We estimated the similarity metric efficiently and avoid generating time-consumed intra-operative DRR images successfully. The experiments also reveal that our method has a satisfying performance comparing with the conventional registration method.

Our future work will be focus on the multi-resolution non-rigid registration. It would be promoted to apply for the large scale data sets. The selection of feature vector of training set should be changeable during registration. The main challenges are efficiency and accuracy.

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