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# Medical Image Registration Framework Using Multiscale Edge Information

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**Abstract**

Efficient multiscale deformable registration frameworks are proposed by combining edge preserving scale space (EPSS) with the free form deformation (FFD) for registration of medical images, where multiscale edge information can be used for optimizing the registration process. EPSS which is derived from the total variation model with the L1 norm (TV-L1) can provide useful spatial edge information for mutual information (MI) based registration. At each scale in registration process, the selected edges and contours are sufficiently strong to drive the deformation using the FFD grid, and then the deformation fields can be gained by a coarse to fine manner. In our deformable registration framework, two ways are proposed for implementing this idea. The experiments on clinical images including PET-CT and CT-CBCT show accuracy and robustness when compared to traditional method for medical imaging system.



*Keywords:* medical image registration; multiscale; edge preserving; medical imaging system.

## 1. Introduction

Image registration is of great importance for clinical medical system, especially in PET-CT and CT-CBCT systems for image guided radiation therapy [1-2]. Multiscale registration strategy can improve the speed without decrease accuracy for medical image registration in medical imaging system, and avoid local extrema during the optimization process, especially for MI based registration [1, 3]. However, traditional multiscale strategy based on Gaussian scale space has limitations in terms of accuracy and robustness. One of the reasons is the isotropic diffusion properties, and the locations of edges and contours which represent the important spatial information at coarse scales are shifted from their true

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location using Gaussian scale space. It is well known that main drawback for MI based registration method is absent of spatial information [4]. In order to provide abundant spatial information for MI based registration, our work presents a new multiscale registration framework based on EPSS.

## 2. Method

### *2.1. Analytical properties of TV-L1:*

Our EPSS is based on the TV-L1 model. Here we give the analytical properties of TV-L1. In the TV-L1 model, the input image $I_0$ is modeled as sum of the image cartoon I and texture V ($V(x)=I_0(x)-I(x)$). The image cartoon contains background hues and important boundaries such as sharp edges and contours. The rest of the image, which is texture, is characterized by small components and noise. Formally, TV-L1 model are always formulated as [5]:

$$\min_I \int_\Omega |\nabla I(x)| + \lambda |I_0(x) - I(x)| dx \tag{1}$$

It has been proved that solving (1) is equivalent to solving the following level set based geometrical problem[5]:

$$\min_I \int_{-\infty}^{+\infty} Per(\{x : I(x) > I\}) + \lambda Vol(\{x : I(x) > I\} \oplus \{x : I_0(x) > I\}) dI \cdot \tag{2}$$

Where *Per*(.) is the perimeter, Vol(.) is the volume, and $S1 \oplus S2 := (S1 \cup S2) - (S1 \cap S2)$. For any set of S1 and S2, using (2), the following geometric properties of the solution to (1) are obtained,

1. Given that $I_0(x) = c_1 1_{B_r(y)}(x)$, an image with the intensity $c_1$ in the disk $B_r(y)$ which is centered at y with radius r , and the intensity 0 anywhere else, then we have

$$I_\lambda(x) = \begin{cases} 0 \ ;(0 \le \lambda \le 2/r) \\ \{s1_{B_r(y)}(x) : 0 \le s \le c_1\};(\lambda = 2/r) \\ c_1 1_{B_r(y)}(x);(\lambda > 2/r) \end{cases}. \tag{3}$$

2. Given that $I_0 = c_1 1_{B_{r_1}(y_1)}(x) + c_2 1_{B_{r_2}(y_2)}(x)$, where $0 < r_2 < r_1$ and $c_1, c_2 > 0$, then we have

$$I_\lambda(x) = \begin{cases} 0 \ ;(0 < \lambda < 2/r_1) \\ c_1 1_{B_{r_1}(y)}(x);(2/r_1 < \lambda < 2/r_2) \\ (c_1 1_{B_{r_1}(y)} + c_2 1_{B_{r2}(y)})(x);(\lambda > 2/r_2) \end{cases}. \tag{4}$$

Based on (3) and (4), TV-L1 model can be used for scale space filtering, and features of different sizes can be extracted from $I$ by applying different values of λ. This λ is in inverse proportion to the geometric size of the different component in images. The images are then decomposed with multiscale manner. Furthermore, geometric properties of TV-L1 developed for 2D images can be extended to 3D images. Organs in clinical medical images are different from each other by different geometric size, and medical image *I* with n different components can be formulated as:

$$I = \sum_{i=1}^{n} C_i \cdot \tag{5}$$

Where the components are classified according to their geometric sizes, and $C_1 < C_2 < C_3 \ldots.. < C_n$. Normally, considering noise existing in medical images, the smallest pattern $C_1$ can be considered as noise in image *I* which can also be removed by TV-L1 scale space filtering. Based on (3-4), TV-L1 scale space is capable of selecting edges and contours of images according to their geometric sizes rather than intensities with the merit of edge preserving property, and features of different sizes in medical images can be extracted from *I* by applying different values of λ. This λ is in inverse proportion to the geometric size of the different component $C_i$ in images.

This capability is illustrated in row 1 of Fig.1 and row 1 of Fig.2 comparing the Gaussian scale space in row 2 of Fig.1 and row 2 of Fig.2.

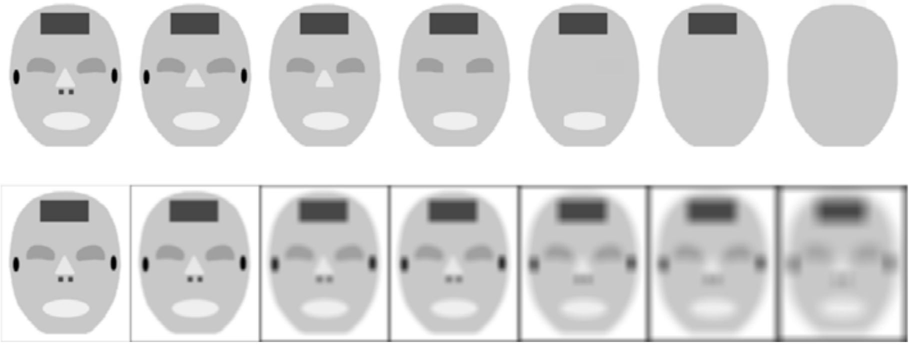

Fig.1 Multiscale decomposition for synthetical image
The first row is using TV-L1 scale space with λ =0.26, 0.17, 0.1, 0.08, 0.06, 0.04
The second row is using Gaussian scale space with standard deviation σ =2, 4, 8, 16, 32, 64, 80

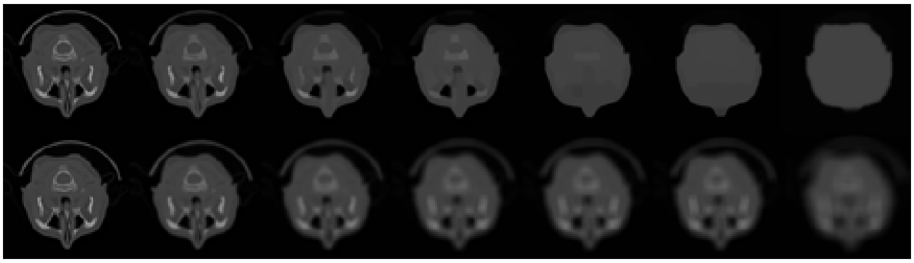

Fig.2 Multiscale decomposition for clinical CT image
The first row is using TV-L1 scale space with λ = 0.7, 0.45, 0.3, 0.2, 0.15, 0.12
The second row is using Gaussian scale space with standard deviation σ = 2, 4, 8, 16, 32, 64, 80

### *2.2. Proposed multiscale deformable Registration via EPSS:*

The registration framework can be divided into two stages just as illustrated in Fig.3. In the first stage, the reference and the floating images are decomposed with TV-L1 multiscale representation. In the second stage, coarse scale images containing less detail are firstly to register, and the results are set as the initial values for registration of fine images. This way can accelerate the process of fine image registration containing rich details.

Furthermore, choosing a proper deformation model for registration is a vital task. Because B-spline based FFD has the advantage that the control points act as parameters of the B-spline deformation model, and the freedom degree of deformation field depends on the resolution of the mesh of FFD control points. A coarse spacing of control points can model global deformation, while a fine spacing of control points can model local deformations [6]. So in our work, coarse to fine FFD girds will be in conjunction with our TV-L1 multiscale decomposition perfectly, where multiscale FFD grids of control points were chosen automatically.

Although image details are expressed in coarse to fine manner using multiscale space, sizes for these family images are same. Conventional methods using a pyramid structure improves this process [7]. In our work, two ways are used for implementation of the TV-L1 pyramid framework. The first way is that TV-L1 scale space filtering is preceded by equidistant subsampling to reduce the image size (Way1), and the second way is that equidistant subsampling is preceded by TV-L1 scale space filtering (Way2). Because time needed for TV-L1 filtering is much longer than time for subsampling, Way2 is more saving time comparing Way1 when implementing in medical imaging systems.

So far we have obtained two multiscale deformable registration frameworks by using TV-L1 pyramid both of Way1 and Way2 in conjunction with coarse to fine FFD grids, and the deformation fields between the reference image and the floating image are estimated by coarse to fine manner which can improving speed, accuracy and robustness hopefully for medical image registration.

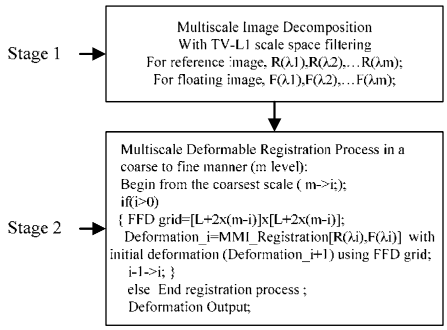


Fig.3 Diagram for Multiscale deformable registration framework, in the experiment, we set L=5 and M=3 for balancing the accuracy and speed for efficiency.

## 3. Experiments results and discussion

Both of mono-modality and multi-modality medical images from PET-CT and CT-CBCT systems are tested for validating the efficiency of our proposed framework. For quantitatively evaluating the performance, three known deformation vectors (KDV_1<KDV_2<KDV_3, from small to large) are implemented on the floating images within the well registered pairs from Shandong Cancer Hospital. We computer the deformation difference (DD) with the sum of mean absolute difference between the vector deformation calculated by proposed method and the known define vector deformation.

The results are illustrated in Table 1. Three methods are compared with each other, where FFD grid and other setting are in the same manner, and each number in Table 1 is the average results of 10 patients. From the Table 1, DD results obtained by Way1 and Way2 are smaller than GFFD (Gaussian scale space combined with coarse to fine FFD grid) and the DD results for Way 2 is the smallest both for mono-modal and multi-modal medical image registration, which indicate that Way1 and Way2 are more accurate than GFFD, and Way2 is the most accurate method. Furthermore, benefiting from the edge preserving property, Way1 and Way2 can find registration results in coarser scale more accurately, which can make the registration process faster. In our experiment, under the same computer machine and same data, Way1 and Way2 can save 9%-15% time comparing with GFFD. Image pairs with larger deformation can save little more time, although registered pairs with larger deformation needs more time to resume the deformation field comparing with the pairs with small deformation. Because time needed for TV-L1 filtering is much longer than time for subsampling, Way2 is more saving time than Way1 when clinical implementing.

Finally, we do applications for image guided radiation therapy with the proposed deformable registration method, including adaptive deformable re-contouring and re-dosing for improving the treatment in PET-CT and CT-CBCT system, where tumors and ORs (organs at risk) are delineated by the oncologist using the treatment planning system for CT in two systems. Here we used the method which is the same as the method in [8], where the deformation field provides voxel to voxel mapping between the reference image and the moving image. After statistic analysis by the radiation oncologists, the overlap between the automatically generated contours and the contours delineated by the oncologist using the planning system is on an average 90%-95%, while the dose distribution overlap is also on an average 90%-97%. The radiation oncologists conclude that the results from re-contouring and re-dosing are helpful for clinical re-planning using daily CBCT.

Table 1 DD comparisons for the registration results

| | CT-CT | PET-PET | PET-CT | CT-CBCT | Methods |
|---|---|---|---|---|---|
| KDV_1 | 0.472 | 0.475 | 0.527 | 0.519 | GFFD |
| | 0.458 | 0.461 | 0.514 | 0.505 | Way1 |
| | 0.447 | 0.453 | 0.506 | 0.501 | Way2 |
| KDV_2 | 0.543 | 0.551 | 0.638 | 0.632 | GFFD |
| | 0.527 | 0.537 | 0.619 | 0.626 | Way1 |
| | 0.522 | 0.529 | 0.613 | 0.615 | Way2 |
| KDV_3 | 0.584 | 0.595 | 0.649 | 0.642 | GFFD |
| | 0.572 | 0.587 | 0.637 | 0.629 | Way1 |
| | 0.563 | 0.579 | 0.632 | 0.627 | Way2 |

## 4. Conlusions

Proposed multiscale registration framework can be easily customized to various medical image registration problems automatically. This framework can increase the efficiency of registration process, and improve the application for image guided radiation therapy with current medical system.

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