4D DYNAMIC CONTRAST ENHANCED CT DATA REGISTRATION USING OPTICAL FLOW

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Abstract: This paper deals with 4D (3D + time) registration method based on optical flow. The main goal is to obtain the velocity field, which is used to correction of displacement in the thoracic data. The one of the most widely used optical flow method published by Horn and Schunck, is utilized in this paper. The proposed method is based on H-S scheme, which is extended by pyramidal and multi-level approach. This allows estimation a larger displacements and this algorithm is thus more robust. Moreover the optical flow method was extended for three-dimension images that develops in time. The performance of proposed algorithm was applied on POPI model, the public model of lung data, which was deformed by synthetic velocity field.

Keywords: Optical flow, 4D registration, dynamic contrast enhanced

1 INTRODUCTION

The frequent investigative method for obtain dynamic contrast enhanced data is four-dimensional (4D) computed tomography (CT) imaging. The acquire data are images of the same scene, which are scanned at different times. In order to acquire a correct information about the patient's anatomy and physiology, the movement of acquisition scene and contrast changes during scanning must be taken into account. Local motion caused by breathing and heart activity can be corrected by registration methods.

Many registration methods for obtaining 4D deformation field were published. The most widely used methods were summarized in [1] by Zitova and Flusser. The basic transformation model utilized rigid registration, often combined with flexible methods. The certain group of registration models use transform fields, which are fixed at the positions determined by the control points (CPs) in the reference image. For example thin-plate splines (TPS), which are examples of the radial basis functions used in image registration or transformation model based on a free-form B-spline deformation. The estimation of the geometric deformation can be calculated by methods, which are often called elastic registration. Another examples of non-rigid methods are diffusion based registration, level sets registration and optical flow. The first registration model based on optical flow was published by Horn and Schunck [2].

2 METHOD

Majority optical flow registration models is based on Horn-Schunck (H-S) method [2]. These methods are proposed for processing two-dimensional images. In this paper, the H-S method is expanded in the three-dimensional case. The class of optical flow registration covers very large number of methods. The differences between these methods is in a regularization, applied a optimization technique and approximation of partial first and second derivation. Let $E(x,y,z,t)$ be sequence of images with spatial (x, y, z) and temporal (t) coordinates. The brightness constancy assumption states that the pixel intensities, $E(x(t), y(t), y(t), t)$, remain constant over time:

$$\frac{\delta E}{\delta x}u + \frac{\delta E}{\delta y}v + \frac{\delta E}{\delta z}w = 0, \tag{1}$$

where $u = dx/dt$, $v = dy/dt$, $w = dz/dt$ are flow velocity, then it is easy to see that we have a single linear equation with three unknowns u, v and w,

$$E_x u + E_y v + E_z w + E_t = 0, \tag{2}$$

where the additional abbreviation E_x, E_y and E_z for partial derivatives of image brightness are introduced. [2]

In thoracic medical image it is assumed that neighboring points on the objects have similar velocities and the local velocity field in the image varies smoothly. One way to measure the smoothness of the optical flow field is the sum of the squares of the flow Laplacian, which is approximated by local averages of u, v and w. The system of three equations (3-5) with three variables (u, v, w) is acquired by the approximate of Laplacian. It can be solved in iterative manner, such as Gauss-Seidel method. [2]

The new velocity estimates $(u^{n+1}, v^{n+1}, w^{n+1})$ are computed from estimated derivatives and the average of the previous velocity estimates (u^n, v^n, w^n) by

$$u^{n+1} = u^n - E_x \frac{(E_x u^n + E_y v^n + E_z w^n + E_t)}{\alpha^2 + E_x^2 + E_y^2 + E_z^2}, \tag{3}$$

$$v^{n+1} = v^n - E_y \frac{(E_x u^n + E_y v^n + E_z w^n + E_t)}{\alpha^2 + E_x^2 + E_y^2 + E_z^2}, \tag{4}$$

$$w^{n+1} = w^n - E_z \frac{(E_x u^n + E_y v^n + E_z w^n + E_t)}{\alpha^2 + E_x^2 + E_y^2 + E_z^2}, \tag{5}$$

where parameters α defines the rate of convergence [2]. α can be interpreted as the standard deviation of the brightness values in the original images.

The other way solving of the system of equations is using the minimization by Euler-Lagrange equations. These equations are nonlinear, therefore the first order Taylor expansion is used to linearize them. The obtained linear system of equations is solved using a iterative method of successive overrelaxation (SOR). [3]

$$u^{n,r+1} = (1-\beta)\, u^{n,r} - \beta\, \frac{E_1 - E_2 + E_{2x} u^{n,r} - E_{2y}(v^{n,r} - v^n) - E_{2z}(w^{n,r} - w^n) + \alpha^2 A(u^{n,r})}{\alpha^2 + E_{2x}^2} \tag{6}$$

$$v^{n,r+1} = (1-\beta)\, v^{n,r} - \beta\, \frac{E_1 - E_2 + E_{2y} v^{n,r} - E_{2x}(u^{n,r} - u^n) - E_{2z}(w^{n,r} - w^n) + \alpha^2 A(v^{n,r})}{\alpha^2 + E_{2y}^2} \tag{7}$$

$$w^{n,r+1} = (1-\beta)\, w^{n,r} - \beta\, \frac{E_1 - E_2 + E_{2z} w^{n,r} - E_{2x}(u^{n,r} - u^n) - E_{2y}(v^{n,r} - v^n) + \alpha^2 A(w^{n,r})}{\alpha^2 + E_{2z}^2} \tag{8}$$

The optical flow fields u, v, w are iteratively modified by equations 6-8 [3], where parameter β is the relaxation parameter of SOR method, with $0 < \beta < 2$. The regularization member (increment) is computed from original images E_1 and E_2, where the subscript determines a point in time, further variable E_{2x} defines the partial derivation in x plane of image in second time point. The value of $A(u)$ is computed from the neighbors of u as

$$A(u_{i,j}) = \frac{1}{6}(u_{i-1,j} + u_{i+1,j} + u_{i,j-1} + u_{i,j+1}) + \frac{1}{12}(u_{i-1,j-1} + u_{i-1,j+1} + u_{i+1,j-1} + u_{i+1,j+1}). \tag{9}$$

The equation 9 in [3] can be realized using 3D convolution of the optical flow field with the mask defined by equation 9. This mask modifies the point of velocity field depending on value of neighbors without the influence of itself.

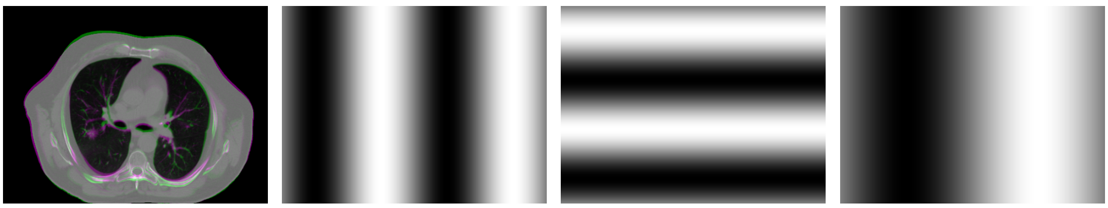
The classic algorithm of Horn-Schunck schema is able only to estimate small displacements (within one voxel). In order to estimate large displacements, the multi-scale strategy must be used. The image is reducing N_{sampl} times by a factor $\gamma \in (0,1)$ with use of an anti-aliasing filter. The Gaussian kernel with a standard deviation, with depends on γ is used to avoid aliasing. This approach is based on estimate of the flow field in each scale. The obtained velocity field at the coarsest level is upsampled by liner interpolation. Moreover the multi-level approach is used within same pyramidal level. If the velocity field within level is obtained, the image warping is performed. The velocity field is computed again from deformed image. It repeats N_{warp} times in each pyramidal level. The structure of algorithm is:

1. downsampling the refer and moving image to the pyramidal level,
2. iteratively estimate optical flow field,
3. warping the moving image by the linear interpolation,
4. repeat N_{warp} times steps 2 and 3 (multi-level strategy),
5. sum of velocity fields (step 4) of is upsampled to higher pyramidal level,
6. warping the moving image by linear geometrical transformation, like in step 3,
7. repeat N_{sampl} times 1-6 steps, every intermediate solution is used as the initialization in the following scale.

The multi-level strategy is used to the increase robustness of the algorithm. In parts of the image, where the brightness gradient is zero, the velocity estimates are simply computed from the neighboring velocity estimates. This is achieved by application of averaging filter with the size of mask based on the parameter γ.

3 RESULTS

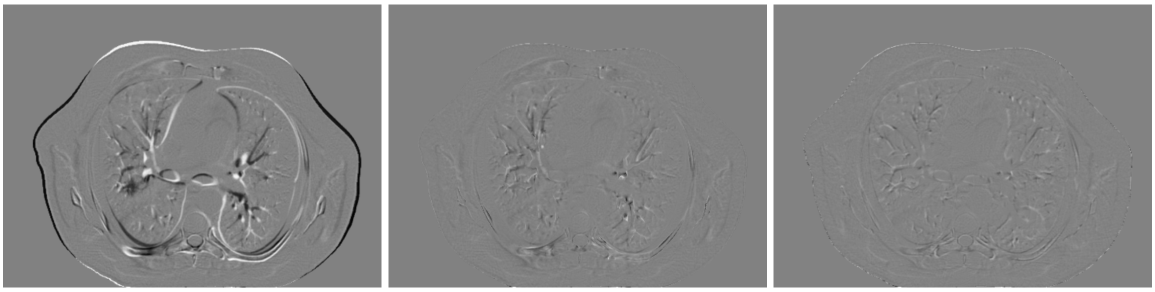
The proposed algorithm is tested on the medical image of thorax, which is deformed by the synthetic velocity field. These disparities are formed by sine waveform with different amplitude and spatial frequency, which are shown in Figure 1(b-d). The synthetic data of size $360 \times 482 \times 141 \times 2$ is created by linear interpolation.



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

Figure 1: a) The synthetic data are represented by interlacing of color layers RGB, images in Figure 1 b-d shows synthetic transformation functions, which defines image deformation (ground truth) in x, y, and z plane.

The basic Horn-Schunck method was extended for a three-dimensional data and implemented in Matlab® for comparison with the proposed extended method. The pyramidal and multi-level strategies were used in H-S method, as well as in the proposed algorithm. The algorithm with changes of optimization approach and using Taylor's extension gives better results, which are shows in Figure 2. The number of pyramidal and registration levels is equal during both methods. The parameter α takes value of global image standard deviation [3]. The ε is stopping criterion threshold of iteration cycle and takes of average Euclidean distance between two iteration.



(a) **(b)** **(c)**

Figure 2: a) The image shows the subtraction of original data. Figures 2(b-c) shows subtraction of images after registration by basic H-S (b) and extended method (c). $\varepsilon = 0.01$, $N_{sampl} = 3$ with factor $\gamma = 0.65$ and $N_{warp} = 5$.

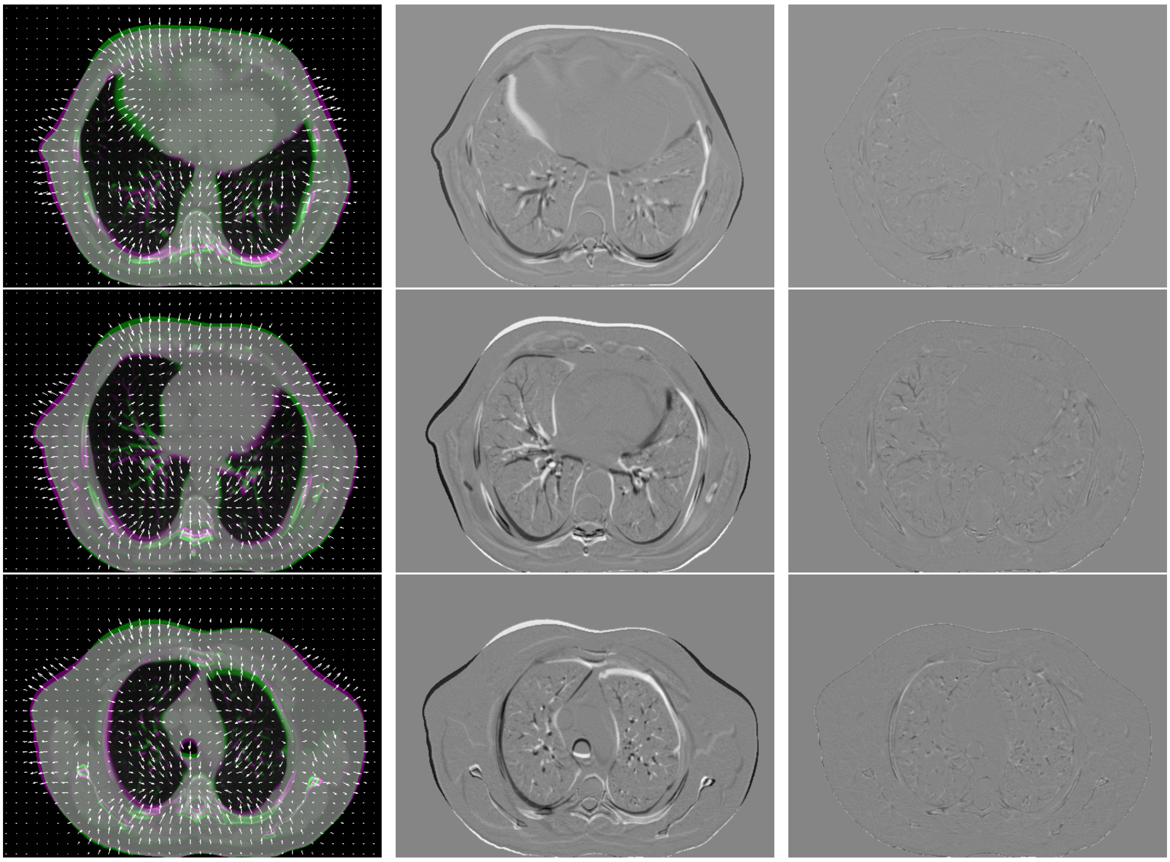


Figure 3: Results of velocity field estimate and registration of images. In the first column the original data are shown, which are represented by interlacing of color RGB layers with estimated velocity fields in horizontal and vertical plane displayed. The second column display the fusion of original images by subtractions with respect to sign. The subtractions after registration is shown in third column. In rows the individual slices of one patient are shown.

As can be seen in Figure 2 that proposed method estimates the velocity field more accurately and the correction of local deformations achieves better subjective results. Some local deformations are not eliminated, because the derivative estimate provides small values. This is caused by a low contrast in the region with a small thoracic structures.

Quality of synthetic images registration is tested only by proposed algorithm. The data used for the registration are created by 4D synthetic velocity field and are geometrically transformed by linear interpolation. Then this synthetic deformation field is estimated by proposed method and the image warping is performed. For display of registration results subtraction with to respect sign before differences is used.

Registration results of one patient visualized by subtractions are displayed in Fig. 3. First, the original data are shown by interlacing of color RGB layers, where the moving image is represented by green component of the RGB space. Finally, it can be seen in subtracted images, that the local deformations are correctly eliminated by registration method.

The displacements are detected only in parts of image, where nonzero gradient is. This algorithm can not estimate disparities in region with homogeneous intensities. These disparities are interpolated from neighboring values, which affect ability to estimate more local displacements. The noise robustness and convergence rate is influenced by the parameter α.

4 CONCLUSION

In this paper, the robust 4D registration of thoracic data by optical flow was proposed and realized in *Matlab*® environment. The Horn-Schunck method was used and extend for three-dimension data. Due to the implemented pyramidal and multi-level strategies are possible to estimate also large displacements.

This algorithm was tested on data from single patient and reaches, according to subjective assessment, very similar result as other novel registration methods. The main advantage of the proposed algorithm is low computational complexity enabled by using fast algorithms, such as the 3D convolution in spectral domain and fast discrete Fourier transform.

Nevertheless, the proposed algorithm is not suitable for registration of pre-contrast and post-contrast images. The optical flow estimates correct velocity fields assuming that pixel intensities do not change over time. This constraint will be eliminated in future work and the algorithm will be suitable for fast 4D registration of contrast enhanced lung CT.

REFERENCES

[1] Zitová, B., Flusser, J. (2003). Image registration methods: A survey. Image and Vision Computing, 21(11), 977–1000.

[2] Horn, B. K. P., Schunck, B. G. (1981). Determining optical flow. Artificial Intelligence, 17(1-3), 185–203. doi:10.1016/0004-3702(81)90024-2.

[3] Meinhardt-Llopis, E., Sánchez Pérez, J., Kondermann, D. (2013). Horn-Schunck Optical Flow with a Multi-Scale Strategy. Image Processing On Line, 2013, 151–172. doi: 10.5201/ipol.2013.20