Interpolation of Temporal Image Sequences by Optical Flow based Registration

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Abstract. Modern tomographic imaging devices enable the acquisition of temporal image sequences. In our project, we study cine MRI sequences of patients with myocardial infarction. Because the sequences are acquired with different temporal resolutions, a temporal interpolation is necessary to compare images at predefined phases of the cardiac cycle.
This paper presents an interpolation method for temporal image sequences. We derive our interpolation scheme from the optical flow equation. The spatiotemporal velocity field between the images is determined using an optical flow based registration method. Here, an iterative algorithm is applied, using the spatial and temporal image derivatives and a spatiotemporal smoothing step. Afterwards, the calculated velocity field is used to generate an interpolated image at the desired time by averaging intensities between corresponding points.
The behavior and capability of the algorithm is demonstrated on synthetic image examples. Furthermore, quantitative measures are calculated to compare this optical flow based interpolation method to linear interpolation and shape–based interpolation in 5 cine MRI data sets. Results indicate that the presented method statistically significantly outperforms both linear and shape–based interpolation.

1 Introduction

The study of organ motion becomes more and more important, e.g. in cardiac imaging or in radiotherapy treatment planning. But in general, the spatial and temporal resolution of imaging devices is limited and a compromise between spatial resolution, temporal resolution, acquisition time and signal–to–noise ratio must be found. Therefore, in a number of image processing tasks a spatial and temporal interpolation of data sets is necessary to calculate dense motion models for instance. In our project, we compare cardiac cine MRI sequences of different patients, acquired with different temporal resolutions. A temporal interpolation of the image data is necessary to generate images at predefined phases of the cardiac cycle.

This paper describes an optical flow based interpolation method for temporal image sequences. Five cine MRI data sets were used to perform a quantitative analysis. Statistical measures were calculated to compare our interpolation algorithm to linear and shape–based interpolation.

2 Method

The theoretical motivation of our interpolation method is the optical flow equation. Other registration–based interpolation methods for 3D image volumes were presented for example in [1] and [2]. But no theoretical background was provided and the methods are limited to consecutive slices. In contrast, the optical flow equation makes the use of more than two consecutive slices for the calculation of the velocity field possible.

Determining the optical flow. The initial hypothesis of optical flow based methods is that the pixel intensities of time varying image regions remain constant: $dI(\boldsymbol{x}(t),t)/dt = 0$. From the optical flow equation we obtain

$$\boldsymbol{v} = -\nabla I \frac{\partial_t I}{||\nabla I||^2}, \tag{1}$$

where $\boldsymbol{v}$ is the spatiotemporal velocity field and ∇I the spatial image gradient. Equation (1) is ill–posed and additional constrains are necessary [3]. In our implementation the regularization is done by a spatiotemporal Gaussian smoothing of the velocity field. The temporal derivative $\partial_t I$ can be simply computed by finite differences or by a convolution with a Gaussian derivative in time direction to take more than two consecutive slices into account.

Optical flow based interpolation. From the intensity conservation assumption follows for the image $I(\boldsymbol{x},t)$ at time $t = t_0 + \delta t$:

$$I(\boldsymbol{x}(t),t) \approx I(\boldsymbol{x}(t) - \delta t \cdot \boldsymbol{v}, t_0). \tag{2}$$

Thus, if the velocity field $\boldsymbol{v}$ is known, we can interpolate the image at time t from an image at time t_0. But in general the intensity conservation assumption might not be fulfilled and structures may appear or disappear between two time steps. Therefore, we use a weighted average between corresponding voxels in the adjacent time frames $I(\boldsymbol{x},t_i)$ and $I(\boldsymbol{x},t_{i+1})$:

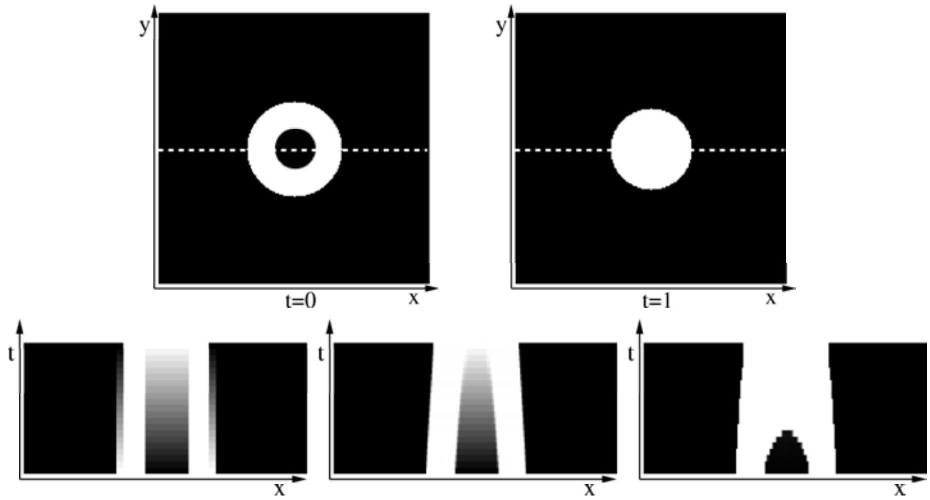
$$I(\boldsymbol{x}(t),t) = (1-\delta t) \cdot I\left(\boldsymbol{x}(t) - \delta t \boldsymbol{v}, t_i\right) + \delta t \cdot I\left(\boldsymbol{x}(t) - (1-\delta t)\boldsymbol{v}^{-1}, t_{i+1}\right), \tag{3}$$

with $t_i < t < t_{i+1}$, $\delta t = t - t_i$ and a normalized time step $t_{i+1} - t_i = 1$. In general, the inverse velocity field $\boldsymbol{v}^{-1}$ can't be computed directly. In our interpolation scheme an iterative Newton–Raphson method is used to calculate the inverse velocity for each grid point [4].

Evaluation methods. Our interpolation method relies on two assumptions: the intensity conservation assumption and that the algorithm is capable to calculate the correct velocity field $\boldsymbol{v}$.

In a first evaluation we generated a synthetic phantom (see fig. 1). For this image sequence the intensity conservation assumption is violated. The aim was to evaluate the behavior of the algorithm in this case.

Fig. 1. Top row: Two slices of the phantom. Bottom row: Interpolations between the phantom slices with varying time step. Each row shows one line in the interpolated image for a given time step. The position of the line is indicated by the dotted line in the top images. Bottom left: linear interpolation, bottom middle: optical flow based interpolation and bottom right: shape–based interpolation.

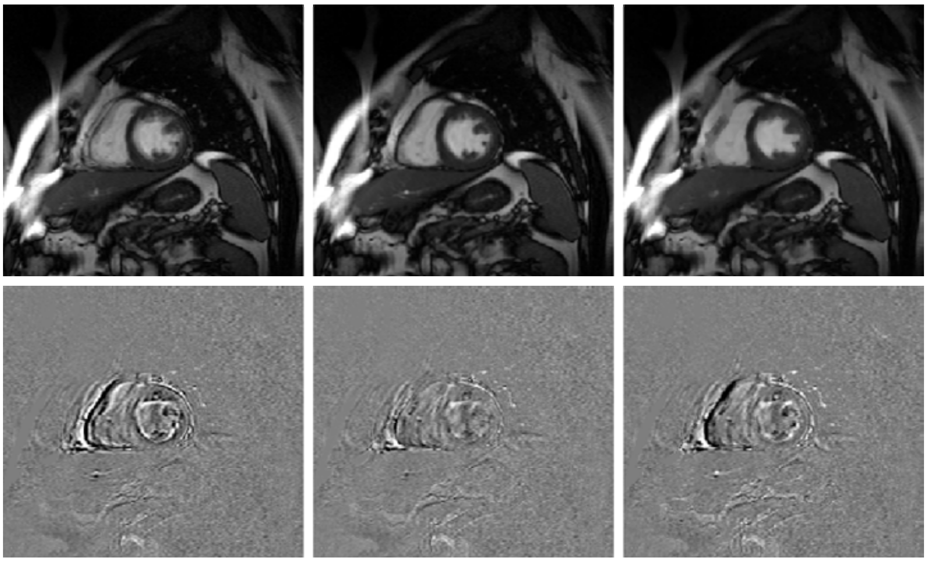


In a second evaluation procedure we calculated quantitative measures to compare our interpolation method with two other methods: linear and shape–based interpolation [5]. Linear interpolation is the most frequently used interpolation technique and was chosen as a baseline reference. The shape–based interpolation algorithm was chosen since it was shown to have the best performance in a comparison of interpolation methods [6].

For the quantitative evaluation five cardiac MRI datasets (ECG-triggered true FISP sequences, between 13 and 21 time frames, 224×256 pixels) were used. For evaluation each slice of the temporal image sequence (apart from the first and the last slice) was removed one at a time and the three interpolation methods were used to interpolate the missing slice. Finally, the interpolated slices were compared to the original removed slices. In conformity with the paradigm proposed by Grevera and Udupa three error measures were used: the *mean difference (MD)*, the *number of sites of disagreement (NSD)* and the *largest difference per slice (LDS)* (see [6] for an exact definition). To compare two interpolation methods a measure called *statistical relevance* was used. This measure expresses the degree of importance of the observed difference between the methods, e.g. the statistical relevance between the linear MD and the optical flow based MD is given by:

$$r^{MD}_{flow/lin} = \begin{cases} +100 \cdot (1 - MD_{flow}/MD_{lin}) \,, \text{if } MD_{lin} > MD_{flow} \\ -100 \cdot (1 - MD_{flow}/MD_{lin}) \,, \text{otherwise} \end{cases} . \qquad (4)$$

Fig. 2. Top row: A sample slice estimated by linear (left) optical flow based (middle) and shape–based (right) interpolation. Bottom row: Corresponding difference image $I^{int}(\boldsymbol{x}) - I^{orig}(\boldsymbol{x})$ between the interpolated and original slice.



3 Results

In the first qualitative evaluation we interpolated 20 slices between the images of the phantom at varying time steps $\delta t \in [0, 1]$. The bottom row of fig. 1 gives a comprehensive sketch of the behavior of the different interpolation methods. Each row of the images show one line of the interpolated image for a given time step. Although the intensity constrain is violated the optical flow based method produced satisfactory results. In this case a compromise between intensity–based and shape–based interpolation was found.

In a second evaluation five cardiac MRI datasets were used. Table 1 shows the statistical relevance of the error measures MD and NSD and the mean statistical relevance of LSD (averaged over the slices) to compare the interpolation methods. Positive values indicate that the optical flow based method performed better.

The results in table 1 show that the optical flow based interpolation outperformed linear and shape–based interpolation in most cases significantly. In contrast to NSD and LDS only a slight improvement of the mean difference (MD) is indicated. Since a large part of the displayed structures doesn't change over the cardiac cycle the mean difference is strongly influenced by noise.

If the image structures change considerably between adjacent slices, the most noticeable improvements by our method were observed. In fig. 2 sample slices estimated by the three interpolation methods and corresponding difference images

Table 1. Statistical relevance values of *mean difference (MD)*, *number of sites of disagreement (NSD)* and *largest difference per slice (LDS)* to compare the optical flow based with linear and shape–based interpolation. Positive values indicate the optical flow method performed better. A dash in the table indicates that the difference between the two methods was not statistically significant (paired student's t–test, $p \leq 0.05$).

data set	statistical relevance					
	flow/lin			flow/shape		
	r^{MD}	r^{NSD}	$\overline{r^{LDS}}$	r^{MD}	r^{NSD}	$\overline{r^{LDS}}$
MRI 01	3.35	12.11	14.46	3.4	19.91	20.72
MRI 02	–	13.33	21.95	1.47	24.65	26.3
MRI 03	5.49	9.35	9.97	3.05	8.19	16.07
MRI 04	3.69	8.63	–	2.84	9.18	17.68
MRI 05	–	3.07	7.12	3.02	14.24	12.75

were shown. The linear interpolated image appears blurred and large differences can be observed. The shape-based interpolation conserves edges of image structures but small details are lost. The optical flow based interpolation performs more accurately and only few differences are shown in the difference image.

4 Conclusion

The quantitative results show that the optical flow based method clearly outperforms the linear and shape–based interpolation. Furthermore, in our experiments the optical flow based method was computational less expensive than the shape–based interpolation. But our interpolation method relies on two assumptions: the intensity conservation assumption and that the algorithm described is capable to calculate the correct velocity field. Therefore, further evaluation is necessary to study the robustness of the algorithm.

References

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