DCE-MRI Non-Rigid Kidney Registration

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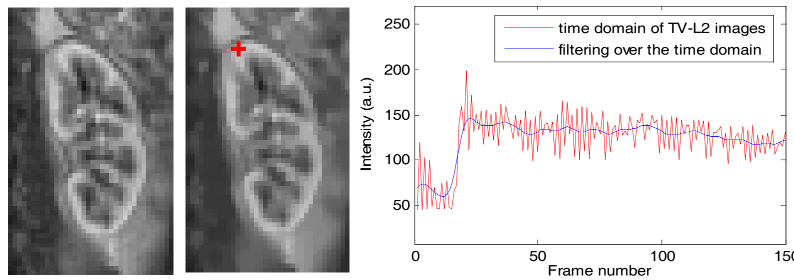
Introduction: Dynamic contrast enhanced magnetic resonance imaging (DCE-MRI) is a very promising method for noninvasive assessment of renal function such as renal perfusion or glomular filtration rate. The acquisition of DCE-MRI for that purpose is usually performed during free breathing because the scan duration, necessary for data analysis, is typically in the order of several minutes. The physiological motion is therefore clearly visible in the time series data, measured with a snapshot technique. For a pixel-by-pixel analysis (e.g. perfusion map) or small ROI's (cortex), the data suffer from severe noise like artifacts (see Fig. 1a). Furthermore, the motion leads to a blurring and a bias of derived parameters of the individual compartments. Image registration is therefore a very important preprocessing step for the analysis of DCE-MRI data from moving organs. However, image registration is a challenging task due to the signal enhancement induced by contrast media [1, 2]. To overcome that problem, an image registration procedure was implemented which derives a template image series with the underlying signal time course. The original dynamic time series (source images) is registered by elastic registration to this virtual template. It is demonstrated that the algorithm is able to reduce motion artifacts to a high extend and allows a more differentiated analysis of several kidney tissue types such as renal cortex and renal medulla.

Methods: The proposed method consists of three parts.
First – preprocessing of the original images (source images) is performed by applying a TV-L2 (ROF) based smoothing algorithm [3] onto all images of the DCE time series to reduce the influence of noise and fine scale details which are not needed in the template images (see Fig. 1a, 1b).
Second – template images are generated in which motion has been reduced by filtering each pixel over the time domain (see Fig. 1c) using a regularized Tikhonov filtering algorithm [4, 5]. This results in a second dynamic time series where each image is used as a template image for the non-rigid registration algorithm.
Third – image registration is performed by using a non-rigid (elastic) registration algorithm [6]. Other registration methods, e.g., with similarity measures based on edges, with regularization requiring less smoothness, lead to inaccurate results. Each source image is registered to its appropriately generated template image. The steps above are applied iteratively as follows:



(a) (b) (c)

Figure 1: *Preprocessing and template generation: Denoised images (a) before and (b) after TV-L2 smoothing. (c) Result after filtering the red marked pixel in (b) over the time domain.*

Algorithm:

- *Given set of input images $\{I(x, t)\}$*
- *Denoise the input images to obtain $\{I_p(x, t)\}$*
- *Continue until changes in $\{I_p(x, t)\}$ are less than a given tolerance:*
  - *Compute the temporally smoothed data set $\{I_s(x, t)\}$ from $\{I_p(x, t)\}$ according to (1)*
  - *Compute the registered data set $\{I_r(x, t)\}$ from $\{I_p(x, t)\}$ and $\{I_s(x, t)\}$ according to (2)*
  - *Replace $\{I_r(x, t)\}$ with $\{I_p(x, t)\}$*

$$J_x(I) = \int_0^T \left[\ \left|I_p(x,t) - I(x,t)\right|^2 + \alpha(t)\left|\partial_t I(x,t)\right|^2\ \right] dt = \min \qquad (1)$$

$$J_t(u) = S_{ssd}(I_p(x,t) \circ (1+u), I_s(x,t)) + R_{elas}(u) = \min \qquad (2)$$

where

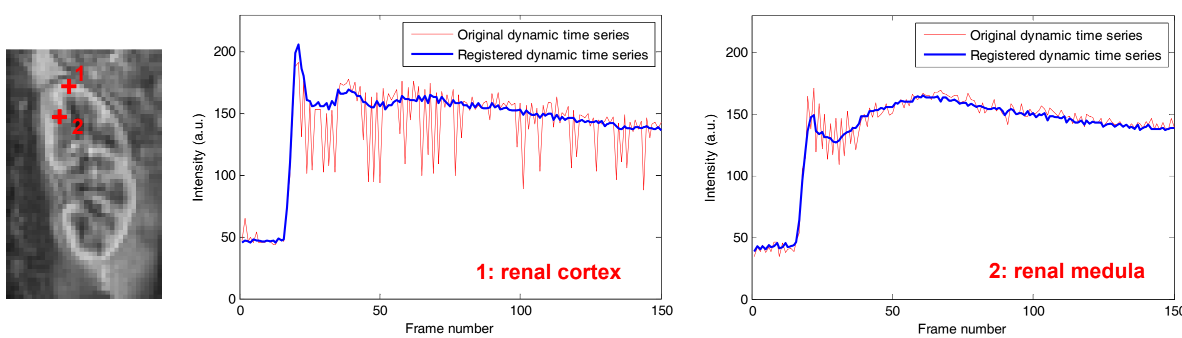
$$R_{elas}(u) = \int_\Omega \left[\ \lambda\left|\nabla \cdot u(x)\right|^2 + \frac{1}{2}\mu\left|\nabla u(x)^T + \nabla u(x)\right|^2\ \right] dx \qquad (3)$$

$$S_{ssd}(I_0 \circ (1+u), I_1) = \int_\Omega \left|I_0(x+u(x)) - I_1(x)\right|^2 dx \qquad (4)$$

Imaging Protocoll: In-vivo DCE-MRI data were obtained from routine examinations on a 1.5T MRI scanner (Siemens Symphony). A 2D FLASH sequence was used (FOV/TR/TE/α=380mm/480ms/1.38ms/12°), image matrix of 128x128, slice thickness of 10.0mm and a temporal resolution of 2.4s for 5 slices and 150 time points.

Results: Figure 2 shows the displacement of the kidney for the unregistered and the registered dynamic time series. Movement artifacts due to breathing are obviously decreased in the time course for two different tissue types. The average pixel displacement in the vertical direction between two consecutive frames could be decreased in the renal cortex from 18.7 to 4.3 pixels (-77%) and in the renal medulla from 6.4 to 2.2 pixels (-66%). These findings suggest that our method allows a better differentiation of perfusion in renal tissue types.

Figure 2: *Result after registration of the whole DCE-MRI series (10 iterations). The registered dynamic time series is compared to the original dynamic time series at the locations of the renal cortex (1) and the renal medulla (2).*



Conclusion: A novel registration approach for minimizing motion artifacts in DCE-MRI time series is proposed. The method of registering the original dynamic time series with a filtered template time series makes this process independent from signal changes due to contrast media uptake. In combination with an iterative elastic registration procedure, the algorithm successfully reduces motion artifacts due to breathing. A comparison between pre and post registration, underlines the importance of image registration in DCE-MRI examinations. Future studies will be performed to evaluate the impact of the proposed method on the evaluation of different parameters.

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