

# Virtual Template Registration for DCE-MRI Renography

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**Introduction:** For the non-invasive assessment of renal perfusion and functional parameters it is important to get tissue specific data (e.g. renal cortex, renal medulla). DCE-MRI is usually performed during free breathing because the scan duration is typically in the order of several minutes, providing the basis for renal perfusion. The physiological motion is therefore clearly visible in the dynamic-time-series, leading to marked problem for pixel by pixel analysis [1, 2]. Intensity variations from contrast media uptake are crucial problems in image registration of these dynamic data sets. To overcome the problem of intensity variations (Fig. 1), an image registration procedure was implemented which derives a virtual template image series that keeps the underlying signal time course intact. The applicability of the algorithm and the impact on perfusion analysis was evaluated using a synthetic kidney phantom (Fig. 2) and by in vivo data.



Figure 1: DCE-MRI Renography. 3 images (5, 22 and 100) out of a dynamic-time-series (150 images) are shown. Motion and intensity variations can be seen clearly.

**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 to reduce the influence of noise and fine scale details which are not needed in the template images. **Second**, template images are generated in which motion has been reduced by filtering each pixel over the time domain using a regularized Tikhonov filtering algorithm [4]. 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. The steps above are applied iteratively as follows:

## 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  $\{I_p(x, t)\}$

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

- Compute the registered data set  $\{I_r(x, t)\}$  from  $\{I_p(x, t)\}$  and  $\{I_s(x, t)\}$

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

- Replace  $\{I_r(x, t)\}$  with  $\{I_p(x, t)\}$

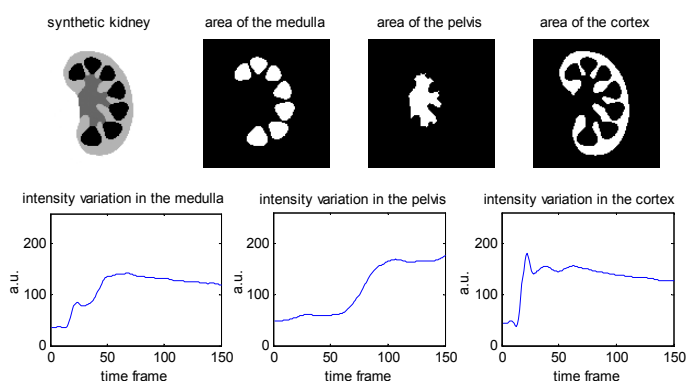


Figure 2: Synthetic kidney phantom containing three individual compartments. Intensity variations are simulated for 150 time frames, representing the uptake of contrast media in the renal medulla, the renal pelvis and the renal cortex.

**Imaging protocol and analysis:** 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/ $\alpha$ =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. The renal blood flow (RBF), was calculated by applying the *Maximum Slope* method [5] using in-house software. The analysis was performed for phantom and in-vivo data prior and after registration.

**Results:** The registration algorithm reduces the motion related shift of the organ from several pixels to approximately  $\pm 1$ . Figure 3 shows the RBF after applying the proposed algorithm to the synthetic kidney phantom and to an in vivo DCE-MRI dataset. It is demonstrated that without registration, artificially high perfusion values and a broadening of the renal cortex occur. After registration can be clearly seen that the cortex and the medulla follows much more the known anatomy and the perfusion values are reduced in more physiological range.

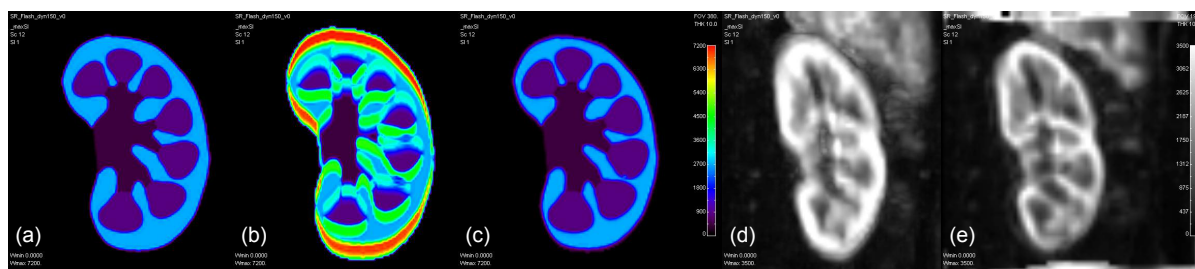


Figure 3: Renal perfusion results before and after registration. (a-c) RBF of the generated synthetic kidney phantom. (d, e) RBF of a real DCE-MRI dataset. (a) RBF without motion artifacts, (b) RBF after applying vertical motion, (c) RBF after registration of the phantom. (d) RBF before registration, (e) RBF after registration of in vivo data.

**Conclusion:** An algorithm for minimizing motion artifacts in DCE-MRI Renography is proposed and evaluated for a synthetic kidney phantom and in vivo DCE-MRI data. The algorithm has been shown to be robust against signal changes due to the uptake of contrast media. Our results indicate that for pixel-by-pixel evaluation of the RBF registration is mandatory.

**References:** [1] Hofer et. al., Proc. ISMRM 18 (2010). [2] Reishofer et. al., Proc. ISMRM 17 (2009). [3] Chambolle, Journal of Mathematical Imaging and Vision 20 (2004). [4] A. N. Tikhonov and V. Y. Arsenin, Wiley (1977). [5] Peters et. al., Nucl. Med. Commun. (1987).

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