

Neural Machine Registration for Motion Correction in Breast DCE-MRI

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Breast DCE-MRI

Dynamic Contrast Enhanced-Magnetic Resonance Imaging

- Makes use of electromagnetic fields (non-ionizing)
- Provides functional information (produces a 4D volume) by using a contrast agent (often gadolinium)

Time Intensity Curve (TIC)

- Fourth dimension of DCE- MRI volume
- Represents the contrast agent absorption in the tissue
- Its course allows to discriminate the lesions' malignancy



Motion Correction in DCE-MRI

Motion Artefacts

- Patient movements leads to motion artefacts
- Removing all the artefacts is very important for a proper evaluation
- Motion Correction (MC) is the procedure intended to fix motion artefacts
- There are several algorithms for MC, most of which adapted for the natural image domain



Real breast DCE-MRI before (left) and after (right) the use of a motion correction technique

Applying Motion Correction

Many different Motion Correction Techniques (MCTs)

- It is very hard to detect the MCT best suited for a given patient and study
- Traditional images similarity indices are unable to take into account for the contrast agent concentration time-course
- However, in a previous work¹ we showed that It is possible to leverage Physiologically Based PharmacoKinetic (PBPK) modelling to rank MCTs effectiveness
- Can we exploit the same idea to develop a new MCT for breast DCE-MRI based on PBPK modelling?





Top: a breast DCE-MRI
 Bottom: deformation introduced by an improper MCT

1S. Marrone, G. Piantadosi, R. Fusco, A. Petrillo, M. Sansone, and C. Sansone, "A Novel Model-Based Measure for Quality Evaluation of Image Registration Techniques in DCE-MRI" in IEEE 27th CBMS (2014)

Pharmacokinetic Modelling in Breast DCE-MRI

- TIC can be modelled by many **Physiologically Based PharmacoKinetic** (PBPK) models
- The most used in breast DCE-MRI is the Extended Tofts-Kermode (ETK) combined with the Arterial Input Function (AIF) proposed by Parker et al. (from now on ETK-P)

$$C_{v}(t) = K^{\text{trans}} \int_{0}^{t} e^{-\frac{K^{\text{trans}}}{v_{e}}(t-s)} \cdot C_{p}(s) \, ds + v_{p}C_{p}(t)$$
$$C_{p}(t) = \sum_{i=1}^{2} \frac{A_{i}}{\sigma_{i}\sqrt{2\pi}} e^{\frac{-(t-T_{i})^{2}}{2\sigma_{i}^{2}}} + \alpha \frac{e^{-\beta t}}{1+e^{-s(t-\tau)}}$$

- *K^{trans}* → tissue permeability
 v_p → blood/plasma volume fraction
- $v_e \rightarrow \text{tissues volume ratio}$ ● $C_p(t) \rightarrow \text{AIF}$



Neural Registration Network

- The proposed Neural Registration Network (NRN) relies on
 - a Spatial Transformer (ST) to learn how to perform an effective affine motion correction slice-by-slice
 - a task specific loss to enforce a physiologically suited transformation



Experimental Setup

We compared our approach against some state-of-the art MCTs

- The Rueckert algorithm (RKT) using a hierarchical model of registration that works both on global and local movements
- Iterative slice-by-slice intensity-based procedures by MATLAB that can be executed both in a mono-modal (MoMM) and in a multimodal (MuMM) fashion
- Enhanced Correlation Coefficient (ECC) Maximization algorithm based on a similarity measure invariant to photometric distortion of contrast and brightness (from OpenCV)
- Non-Rigid, multi-resolution iterative approaches provided by Elastix (ELX)
- Using a median filter, considering a 3D window of 3x3x3 pixels (MED)
- The dataset consists of 33 patients (13 with benign lesions and 20 with malignant lesions) from Istituto Nazionale Tumori "Fondazione Pascale" in Naples

Sequence	FLASH 3D - Coronal
TR	9.8 ms
TE	4.76 ms
FA	25 deg
FoV	370x185 mm2
Matrix	256x128
Thickness	2 mm
Acquisition Time	56 s
Dose	0.1 mmol/kg
Injection flow rate	2 ml/s

Results

Pat.	NRN	RKT	MoMM	MuMM	ECC	ELX	MED
p01	1	3	7	5	6	4	2
p02	1	2	4	7	5	3	6
p03	1	2	5	6	3	4	7
p04	1	5	3	4	2	6	7
p05	1	2	5	3	4	7	6
p06	1	2	3	5	6	7	4
p07	1	4	3	6	2	5	7
p08	1	2	6	4	5	3	7
p09	1	3	2	7	4	5	6
p10	1	2	7	5	3	4	6
p11	1	2	3	7	5	4	6
p12	1	2	4	3	5	7	6
p13	1	6	5	2	7	4	3
p14	1	5	6	7	4	3	2
p15	1	2	4	7	5	6	3
p16	1	2	6	3	4	7	5
p17	1	7	4	2	6	5	3
p18	1	2	6	7	5	3	4
p19	1	2	6	7	3	5	4
p20	1	7	2	5	6	4	3
p21	1	2	5	7	3	6	4
p22	1	3	4	7	2	5	6
p23	1	2	4	7	3	6	5
p24	1	2	6	4	7	3	5
p25	1	4	3	7	5	6	2
n76	1	2	7	5	1	າ	6
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MCTs ranked on the bases of a PBPK QI



 Boxplots for the patients' QI values distributions evaluated after using our NRN approach (first boxplot) and the second-ranked MCR (second column)

Results



Fitting (in magenta) of the measured contrast agent concentration (in blu) before the registration (top left) and after the motion correction obtained by using the proposed Neural Registration Network (top right), ECC (lower left) and Elastix (lower right) on a patient with a benign lesion (LEFT) and on a patient with a malignant lesion (RIGHT)

Discussion

- This work aimed to introduce a new Motion Correction Technique (MCT) for breast DCE-MRI leveraging Physiologically Based PharmacoKinetic (PBPK) modelling and Artificial Neural Networks (ANN) to determine the most suitable physiologically-compliant transformation
- The idea was to realise a technique able to take into account the brightness variation due to contrast agent flowing while re-aligning voxels belonging to the same tissues
- Despite this work must be considered as a proof-of-concept, results show the effectiveness of the proposed approach even when compared against other motion correction techniques designed to take into account for brightness variations
- Future works will focus on the use of the proposed architecture in an end-to-end training for classification and segmentation tasks

THANKS!

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