



Neural Machine Registration for Motion Correction in Breast DCE-MRI

Federica Aprea, Stefano Marrone, and Carlo Sansone

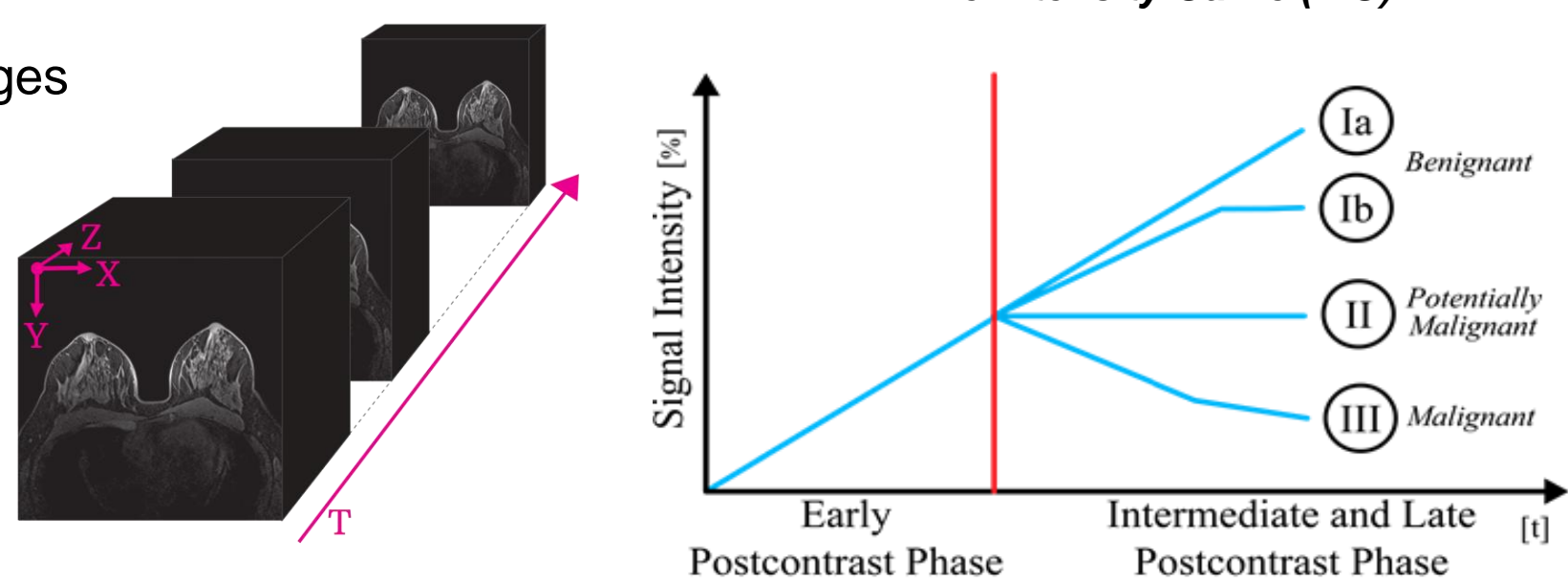


1. Background & Motivation

Dynamic Contrast Enhanced-Magnetic Resonance Imaging (**DCE-MRI**):

- ✓ Important complementary diagnostic methodology able to visualize 3D images
- ✓ Minimal invasiveness (uses a paramagnetic contrast agent CA)
- ✓ Produces 4D volumes (3 spatial + 1 temporal)

- ✗ Long acquisition time that can cause claustrophobia
- ✗ Huge amount of data to analyze
- ✗ **Involuntary patient movements can cause mispredictions¹**



It is possible to perform an assessment of the lesion malignancy by analysing its Time Intensity Curve (TIC)

2. Materials

The investigation was performed on:

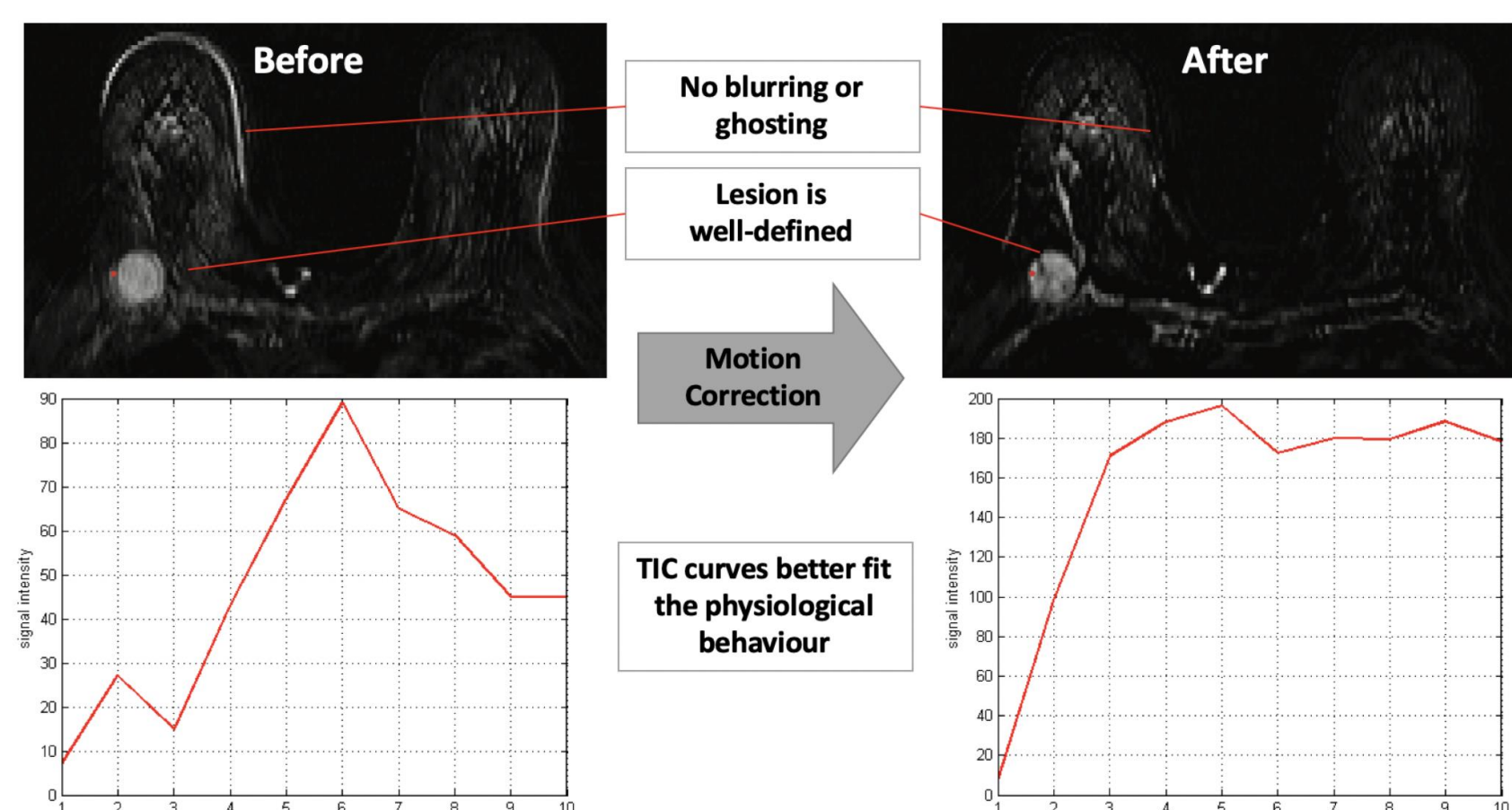
- 33 women breast DCE-MRI 4D data
- 13 benign lesions, 20 malignant lesions
- Contrast agent: gadolinium (0.1 mmol/kg)
- 10 time series

Gold Standard

Each lesion was manually segmented while malignancy had been histopathologically proven

3. The Effects of Motion Correction

- 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



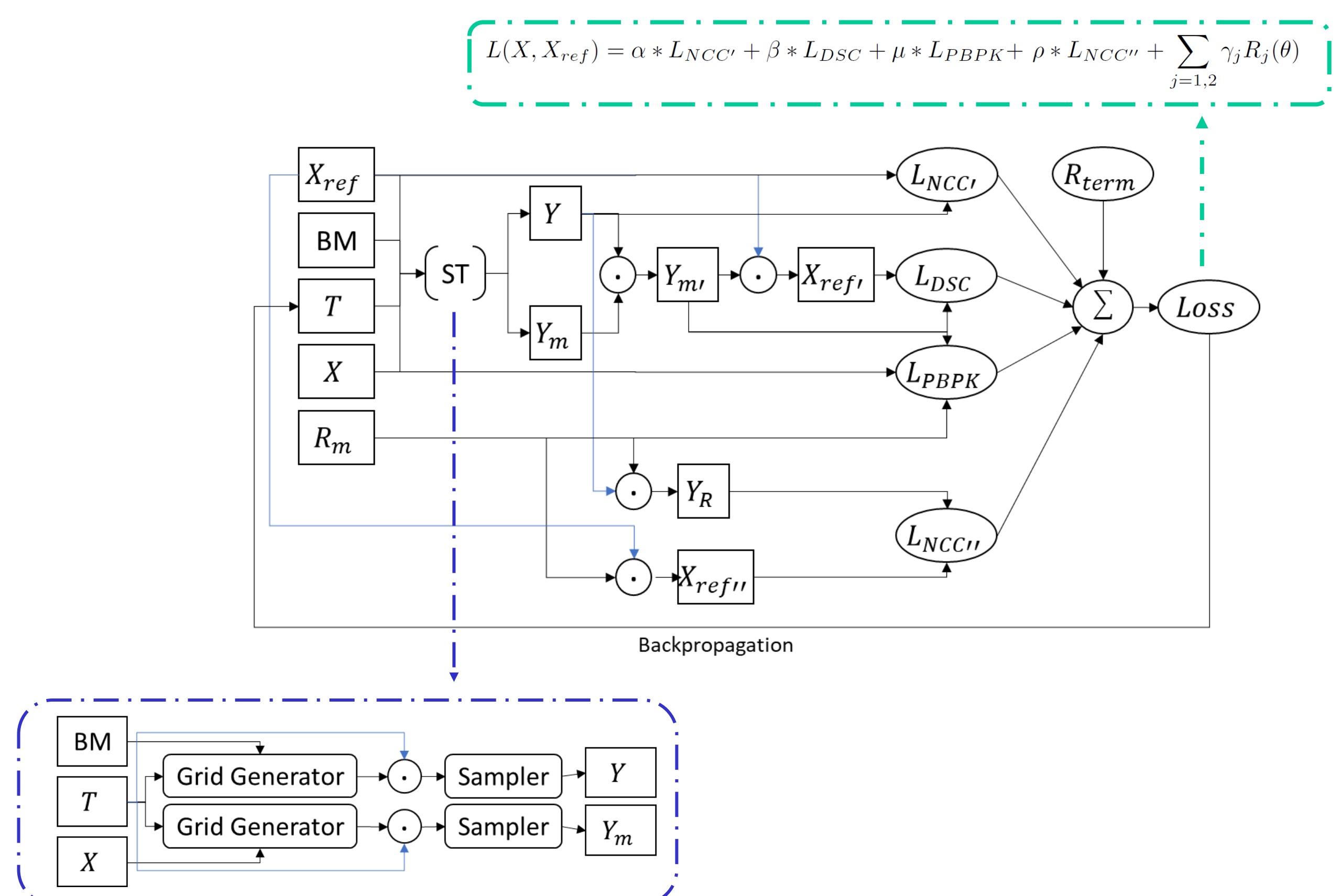
Example of **motion artefacts** in a DCE-MRI Breast slice (upper images) and the TIC associated to the marked region (down images), before (left column) and after (right column) the application of a motion correction technique

- 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 work³ 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?

4. Neural Registration Network

The proposed Neural Registration Network (NRN) relies on

- a Spatial Transformer (ST) to learn how to perform an affine motion correction
 - X and X_{ref} are the input and reference slice respectively
 - BM is the slice Breast Mask (used to exclude non-breast tissues)
 - R_m is the ROI mask (used to delimit the lesion boundaries)
 - T are the affine transformation parameters
 - Y and Y_m are the transformed version of X and of BM
 - Y_R and Y_m are Y with respectively R_m and Y_m applied on it
 - $X_{ref'}$ and $X_{ref''}$ are the X_{ref} with respectively Y_m and R_m applied on it
- a task specific loss to enforce a physiologically suited transformation
 - L_{NCC} evaluates the dissimilarity between $X_{ref'}$ and Y using the Normalized Cross Correlation (NCC)
 - L_{DSC} evaluates the dissimilarity between $X_{ref'}$ and $X_{ref''}$ using the Dice Similarity Coefficient (DSC)
 - $L_{NCC''}$ evaluates the dissimilarity between Y_R and $X_{ref''}$ using the Normalized Cross Correlation (NCC)
 - L_{PBPK} leverages a PBPK model to enforce a physiologically suited transformation
 - R_{term} are Regularization terms used to penalize undesirable transformations



5. Results & Findings

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

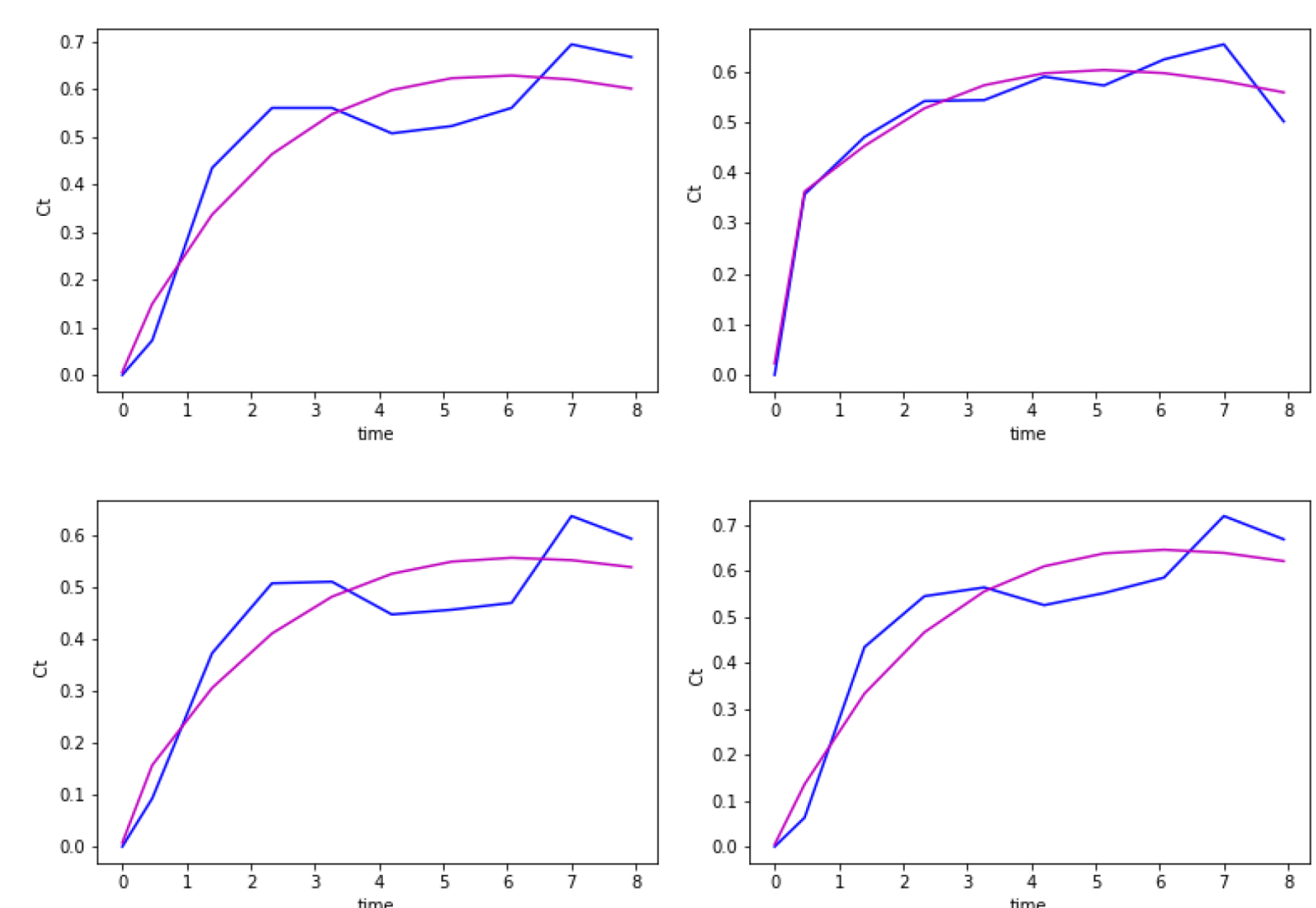
- The Rueckert algorithm (RKT) using a hierarchical model of registration that works both on global and local movements
- Iterative slice-by-slice intensity-based procedures by MATLAB that can be executed both in a mono-modal (MoMM) and in a multimodal (MuMM) fashion
- Enhanced Correlation Coefficient (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)

Results are ranked on the bases of a PBPK QI³

- 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

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
p26	1	3	7	5	4	2	6
p27	1	5	7	3	4	6	2
p28	1	2	5	4	7	6	3
p29	1	2	4	3	5	6	7
p30	1	5	4	6	3	7	2
p31	1	2	3	4	5	6	7
p32	1	4	4	7	6	5	2
p33	1	7	4	3	6	2	2

MCTs ranked based on a PBPK QI



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

6. References

1. Piantadosi et al. "Data-driven selection of motion correction techniques in breast DCE-MRI" in proceedings of IEEE MeMeA (2015)
2. Degani et al. "Mapping pathophysiological features of breast tumors by MRI at high spatial resolution" in Nature medicine (1997)
3. Marrone et al. "A novel model-based measure for quality evaluation of image registration techniques in DCE-MRI." in proceedings of IEEE CBMS (2014)

7. Contacts

Federica Aprea¹, Stefano Marrone², and Carlo Sansone²

1. CORE Reply S.r.l., Via Robert Koch 1/4, 20152 Milano (Italy)
Email: f.aprea@reply.it
2. DIETI - University of Naples Federico II, Via Claudio 21, 80125 Napoli (Italy)
Email: first.last@unina.it