Respiratory Motion Modelling using cGANs

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Background & Contribution

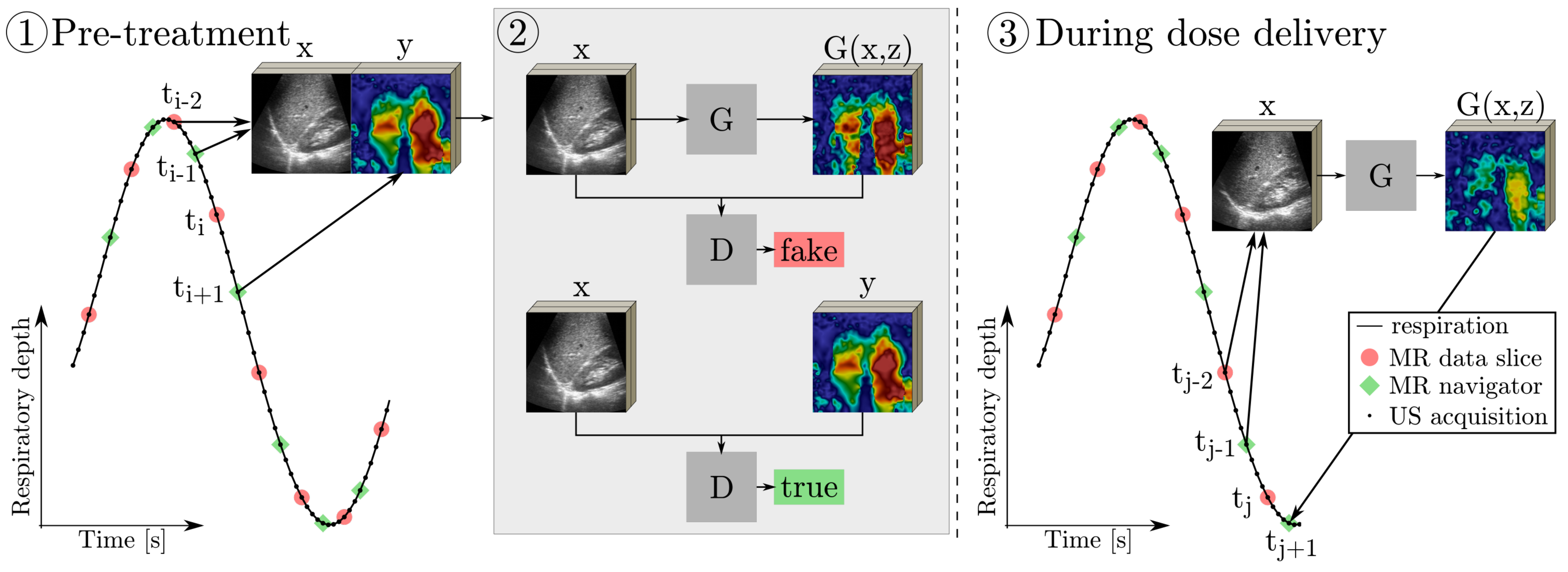

Fig. 1: Schematics of the motion modelling pipeline.

Respiratory motion models in radiotherapy are considered as one possible approach for **tracking mobile tumours** with the goal of ensuring the best combination of target coverage and dose conformation. We present a motion modelling framework which is:

- **patient-specific**,
- relying on 2D abdominal ultrasound (US) images as surrogates, and hence on **internal motion data**,
- capable of predicting **dense volume information** within reasonable computation time.

Method

Goal For every time t_j we aim to predict a complete MR volume given temporally corresponding abdominal 2D US images.

① **Data acquisition and image registration** Simultaneous US/MR imaging is performed based on an interleaved MR acquisition scheme [1] where data and navigator slices were acquired alternatingly. Using deformable image registration [2], 2D deformation fields of the navigator slices are extracted.

② **Training of the neural network** We train a conditional generative adversarial network (cGAN) as proposed in [3] where

- generator $G : \{x, z\} \mapsto y$ learns the mapping from US images x and a random noise vector z to the deformation field y, and
- discriminator D aims to classify real and synthesised image pairs.

We introduce gradient information by feeding two consective US images as inputs to the cGAN: given the US images at times t_{i-2} and t_{i-1}, we aim to predict the deformation field at t_{i+1}.

③ **Real-time prediction during dose delivery** At time t_{j-1}, online US images are fed to the trained cGAN generating the deformation field for t_{j+1}. Following the slice stacking approach in [1], MR data slices acquired in step ① are grouped into a complete volume predicting the state of the thorax at t_j.

Conclusion

A first proof-of-concept study demonstrated the feasibility of the proposed approach. Future work will be devoted towards the development of effective data augmentation strategies and must include a thorough investigation of the robustness of cGANs within the context of motion modelling.

References & Acknowledgements

[1] von Siebenthal et al., “4D MR imaging of respiratory organ motion and its variability.” *Physics in Medicine and Biology*, 2007.

[2] Sandkühler et al., “Adaptive Graph Diffusion Regularisation for Discontinuity Preserving Image Registration.” *8th International Workshop on Biomedical Image Registration*, 2018.

[3] Isola et al., “Image-to-Image Translation with Conditional Adversarial Networks.” *CVPR*, 2017.

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Results

The proposed approach is demonstrated based on 3 hybrid US/MR datasets of 2 healthy volunteers (acquisition duration: 9.5 min each).

Training details The datasets were split into $N_{train} = 480$ training images and $N_{test} = \{224, 100, 110\}$ test images for datasets $\{1, 2, 3\}$, respectively. We applied the U-Net based generator architecture and the convolutional PatchGAN classifier as discriminator.

Validation For each consecutive navigator pair of the test set a complete MR volume was reconstructed using the data slices of the training set as possible candidates.

RDF **R**eference stacking method using the **d**eformation **f**ields computed on the actually recorded MR navigator slices

GDF Proposed approach based on **g**enerated **d**eformation **f**ields

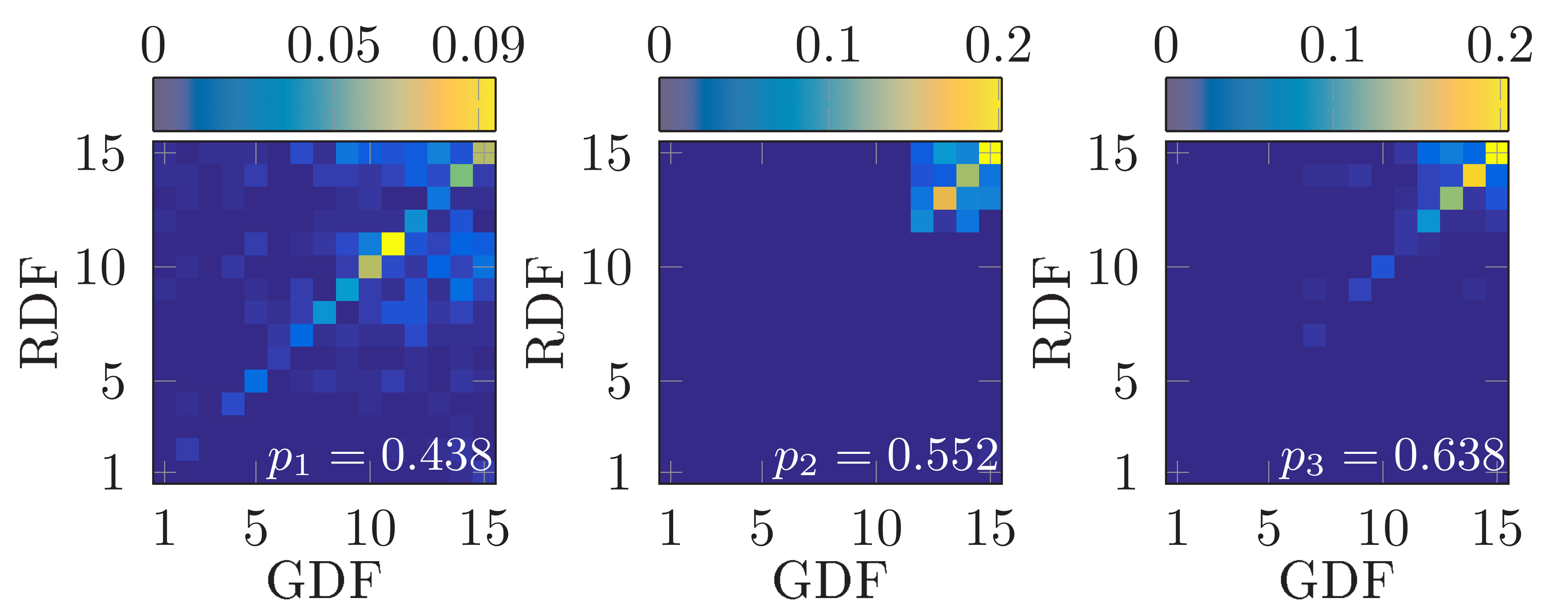

Fig. 2: Slice selection illustrated as joint histogram for reference and generated deformation fields, respectively. Left to right: datasets 1 to 3.

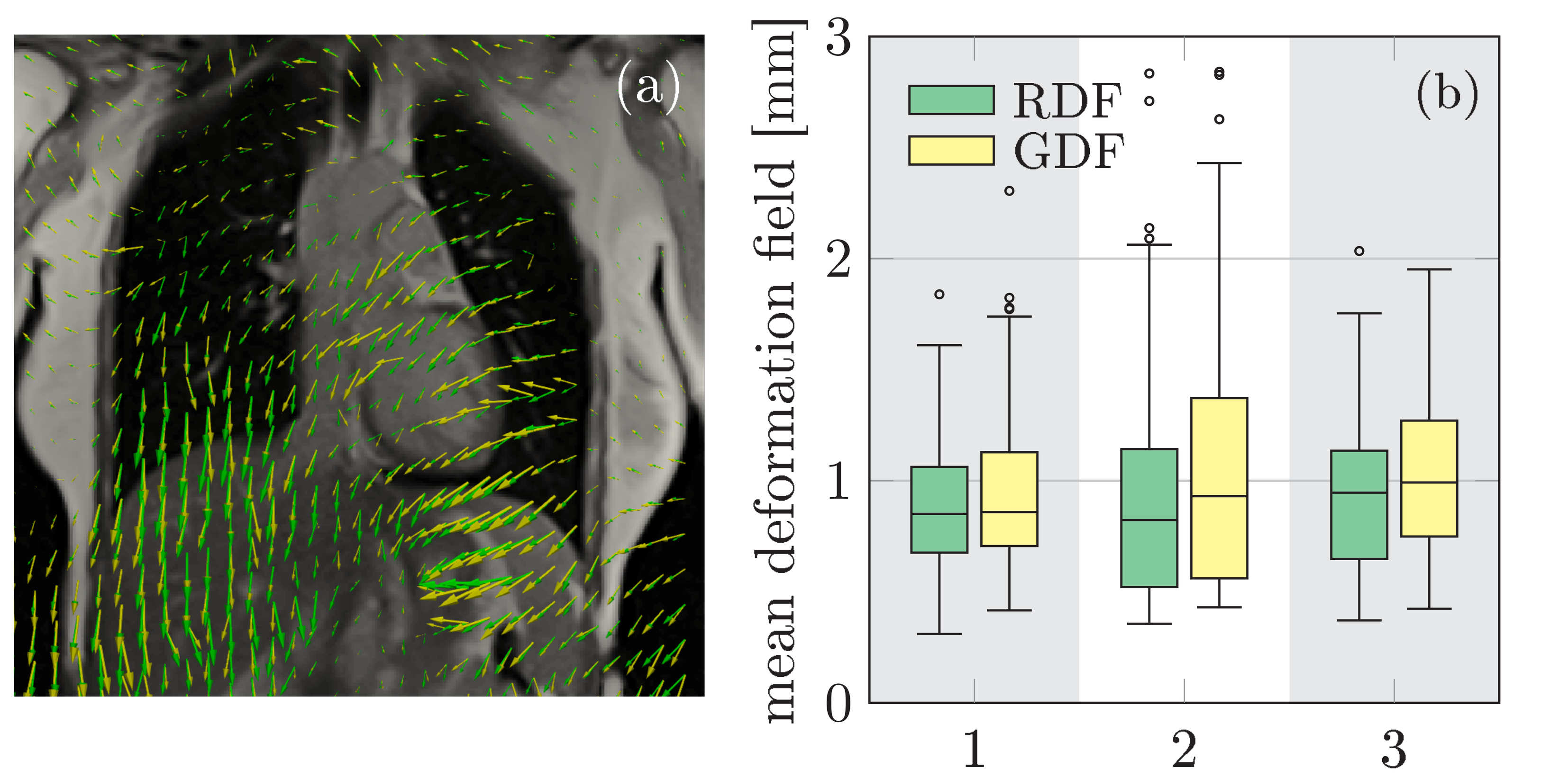

Fig. 3: Qualitative and quantitative results. (a) Sample motion field of dataset 2 with reference (green) and predicted (yellow) deformations, and (b) error distribution of mean deformation field.