Adaptive Training of Recurrent Neural Networks for Breathing Motion Management in Radiation Therapy

放射線治療における呼吸動作管理のための回帰型ニューラルネットワークの適応的学習

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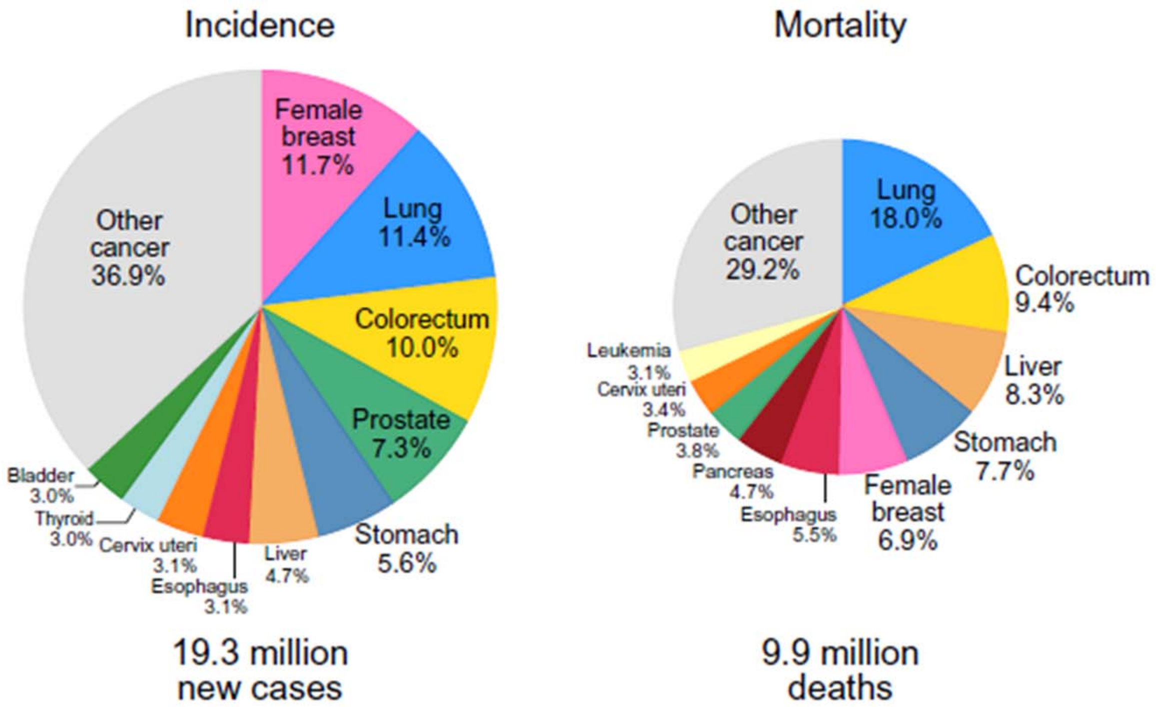
TIEC RESEARCH AND PRESENTATION

1. General Introduction
Cancer statistics

Worldwide incidence and mortality of cancer



Reproduced with permission from Sung, Hyuba, et al. "Global cancer statistics 2010: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries." Copyright 2021 American Cancer Society

Lung cancer 5 year survival rate (2011 – 2017):

21.7%

Source : National Cancer Institute, Surveillance, Epidemiology and End Results Program

1. General Introduction

Artificial Intelligence within the radiotherapy workflow

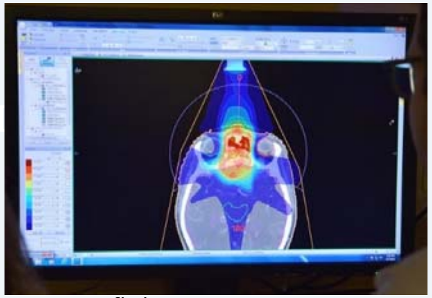
Decision support tools

Treatment decision

Enhance image quality,
Fusion between modalities

Imaging

Tumor contouring,
dose estimation



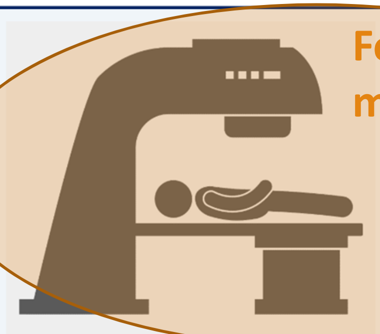
Source : flickr.com

Treatment planning

Replanning

Anomaly detection

Plan approval and Quality Assurance



Focus of my work

Motion management

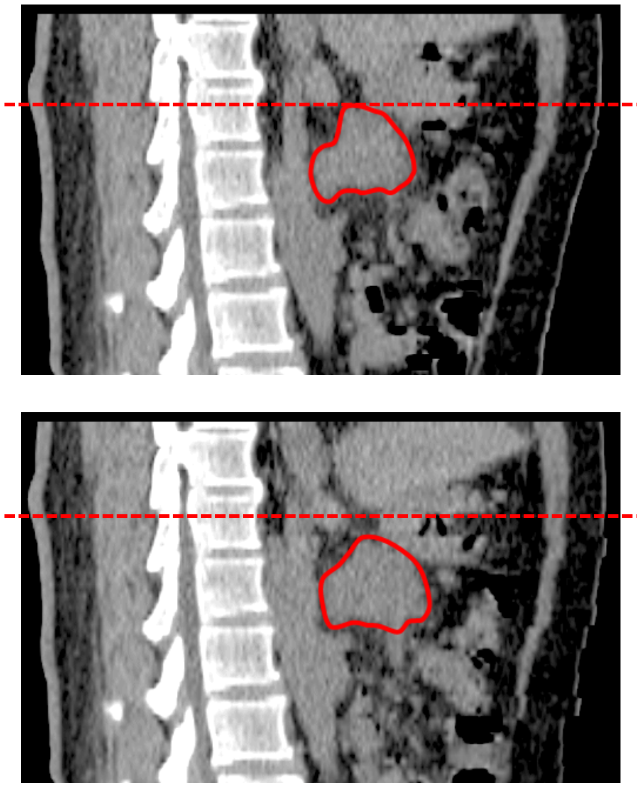
Radiotherapy delivery

Estimation of the response to the treatment

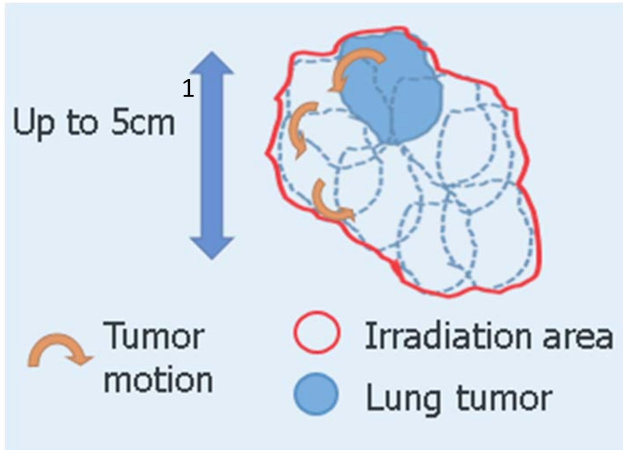
Follow up

1. General Introduction

Conventional therapy for lung cancer



Pancreatic tumor moving with the respiratory motion



- Large area of irradiation (PTV margin : 0.5cm to 1cm [2])
- Tumor deformation during treatment not taken into account

1 – Chen et al, 2001
2 – Yi Li et al, 2016

Possible side effects of lung radiation therapy

- Lung inflammation (pneumonitis)
- Lung scars (pulmonary fibrosis)
- Spinal cord damage
- Cardiovascular damage :
    - Inflammation of the lining surrounding the heart (pericardis)
    - Weakening of the heart muscle (myopathy)
    - Damage to blood vessels supplying the heart

Goal : reduce the dose delivered to healthy tissues through tracking the tumor accurately

1. General Introduction

Motion prediction in lung cancer therapy

Most systems have a latency Δt between 0.1s and 2.0s

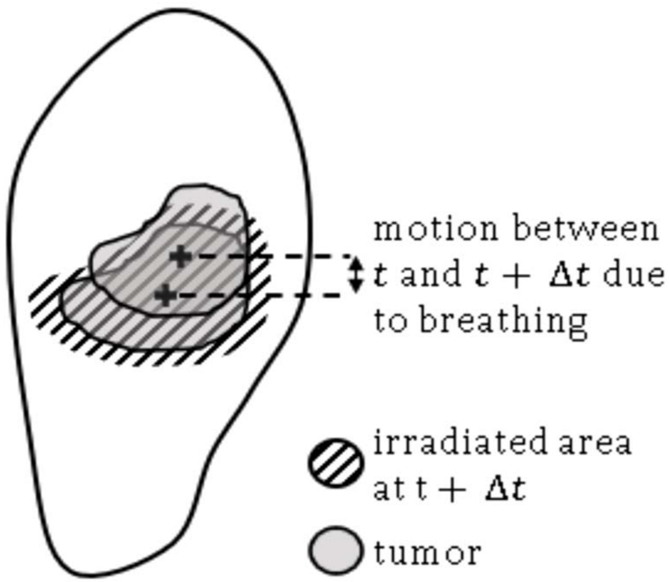
Delay causes :

- Image acquisition and processing
- Treatment robot control
- Radiation beam preparation & delivery

Latency is compensated via prediction

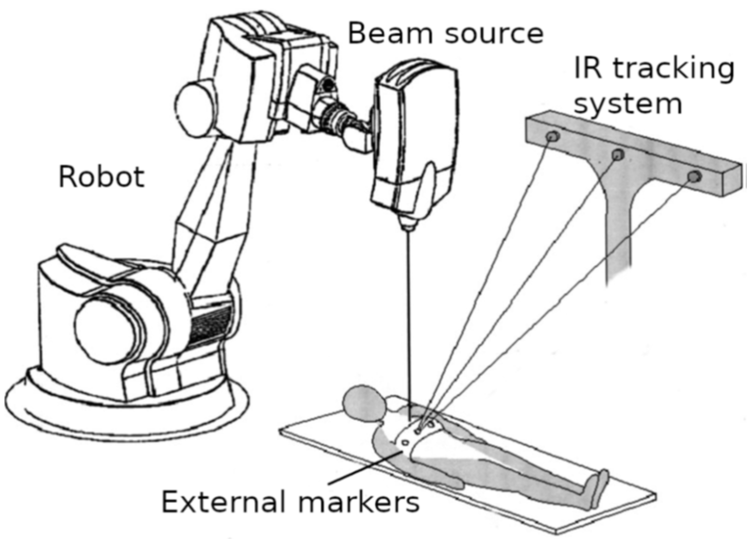
- ❑ Low tracking error
- ❑ Low oscillation of the predicted signals
- ❑ Real-time processing
- ❑ Robustness to irregular breathing patterns

Uncompensated latency
→ much damage to healthy tissues
& unaccurate tumor targeting



2. Prediction of the position of external markers on the chest and abdomen

Objectives



Objectives :

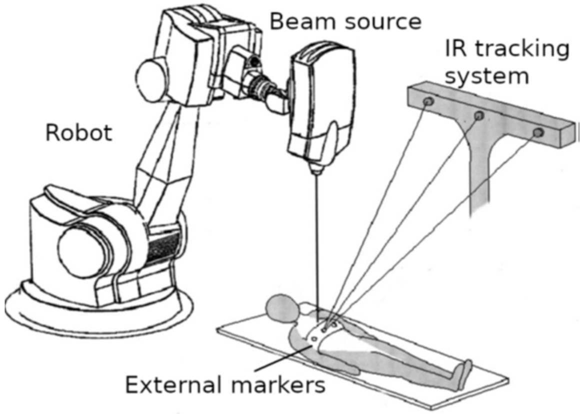
- ❑ Predict the position of external markers using Recurrent Neural Networks
- ❑ Evaluate the robustness to irregular breathing

Position of the markers at t ⇨ **Prediction** ⇨ Position of the markers at $t + \Delta t$ ⇨ **Geometric correspondance model** ⇨ Position and shape of the tumor at $t + \Delta t$

Focus of my study

2. Prediction of the position of external markers on the chest and abdomen

Method : Dataset used and training/evaluation partition



Input data :

- ❑ 9 time series sequence of the 3D position of infra-red emitting markers on the chest (3 recordings from 3 people)
- ❑ 10 Hz
- ❑ Duration : 73s to 222s
- ❑ Amplitude: 6mm to 40mm in the spine axis

0s to 30s : algorithm training

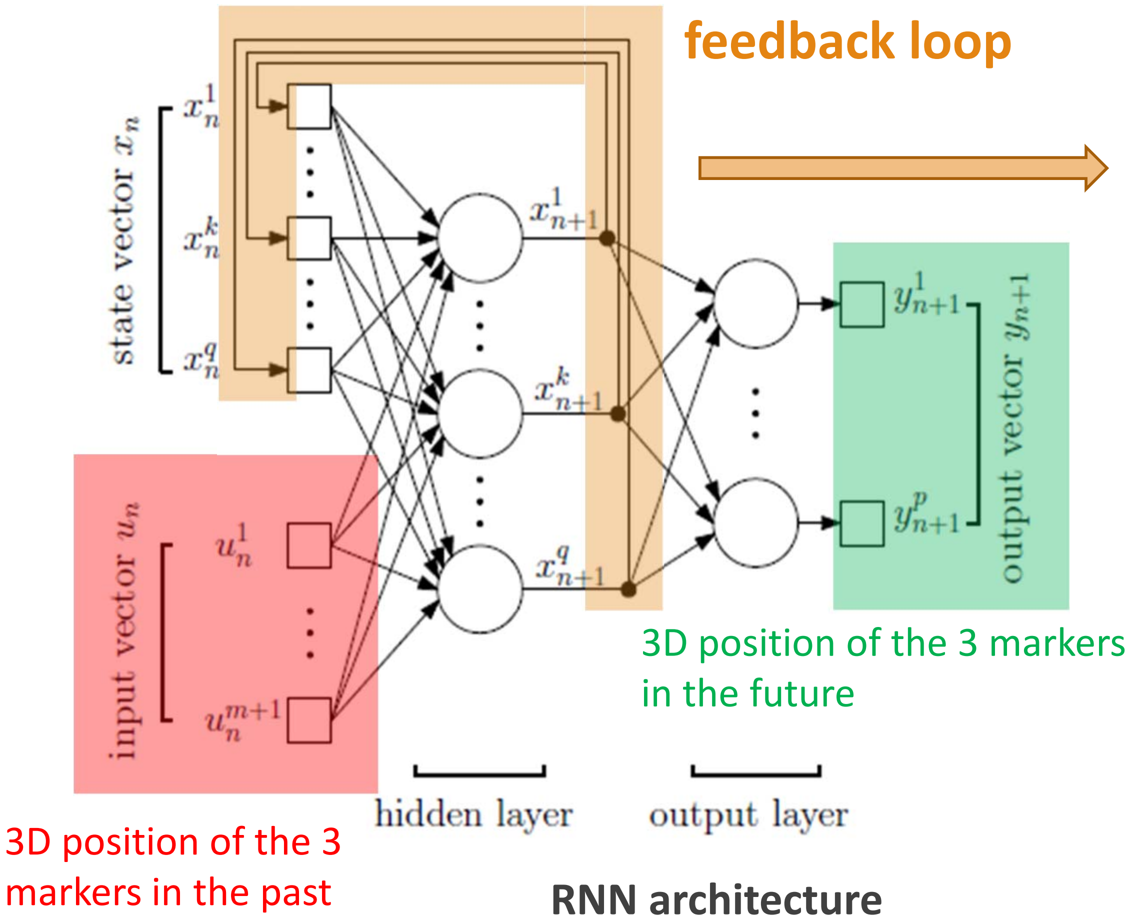
30s to 60s : automatic parameter tuning with grid search

Parallel computing for search speedup

60s to tmax : algorithm prediction performance evaluation

2. Prediction of the position of external markers on the chest and abdomen

Method : Prediction with a recurrent neural network (RNN)



RNN architecture

Recurrent Neural Network (RNN) : neural network with a **feedback loop**, suited for time series processing

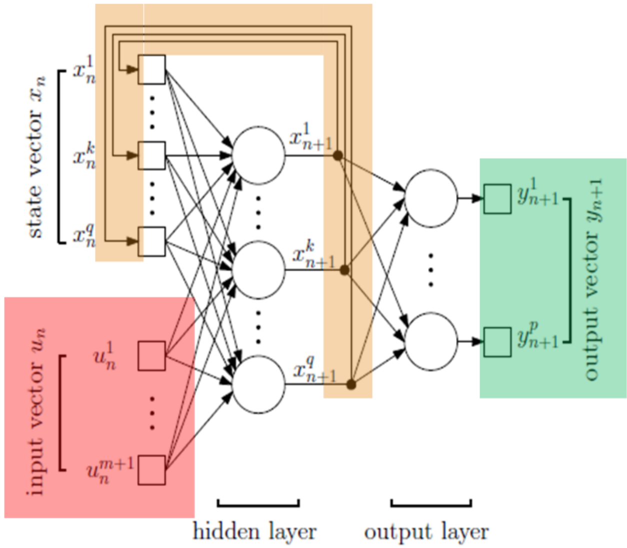
We perform **adaptive training** : the neurons are updated continuously :

- ❑ adaptation to changing respiratory patterns
- ❑ lack of very large training database

≠ back-propagation through time (BPTT) classical offline training algorithm

2. Prediction of the position of external markers on the chest and abdomen

Method : Prediction with a recurrent neural network (RNN)



We compare two algorithms for adaptive training of RNNs:

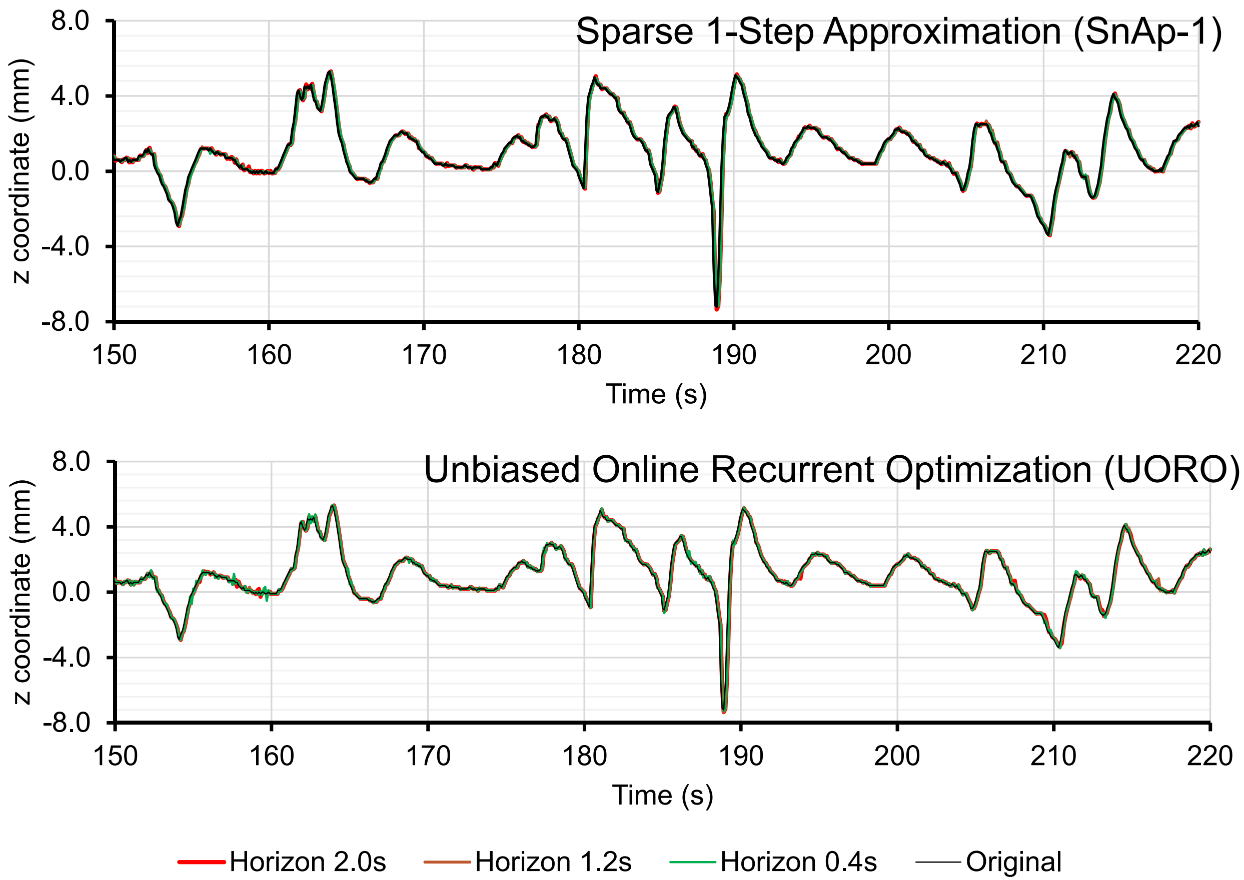
1. **Real-time recurrent learning** (RTRL) – 1989
   - Slow but exact computations
2. **Unbiased online recurrent optimization** (UORO) – 2017
   - Random approximation of the gradient
3. **Sparse n-step Approximation** (SnAp) – 2020
   - Diagonal approximation of the influence matrix

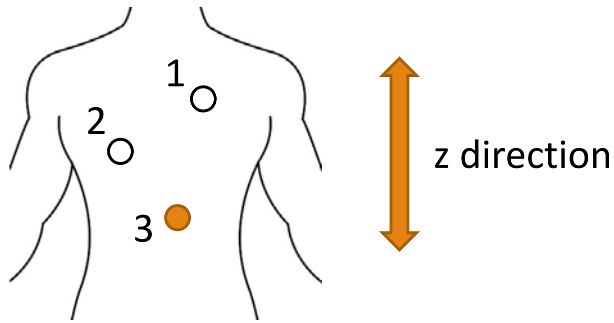
Comparison with classical forecasting algorithms :

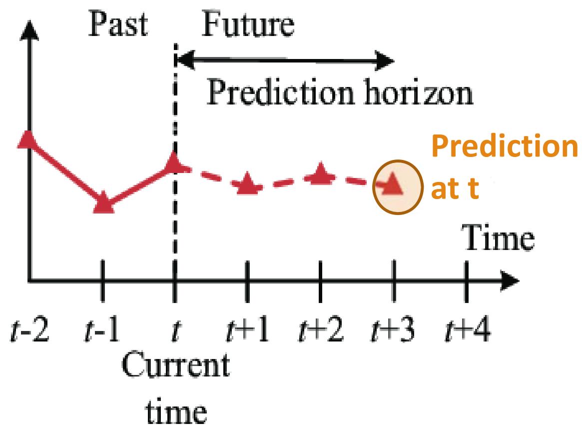
4. **Least mean squares**
5. **Linear regression**

2. Prediction of the position of external markers on the chest and abdomen

Results : Predicted marker position (irregular breathing)



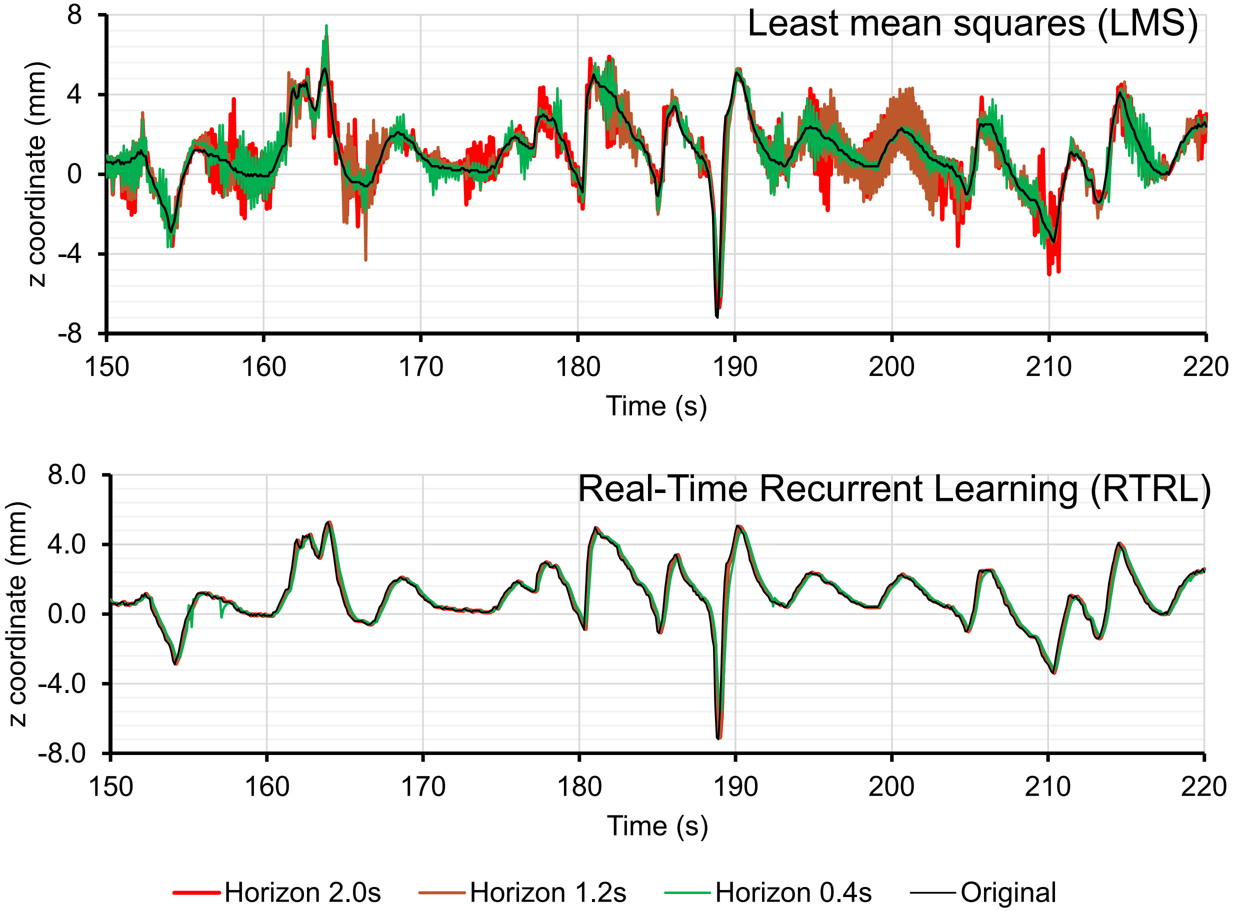


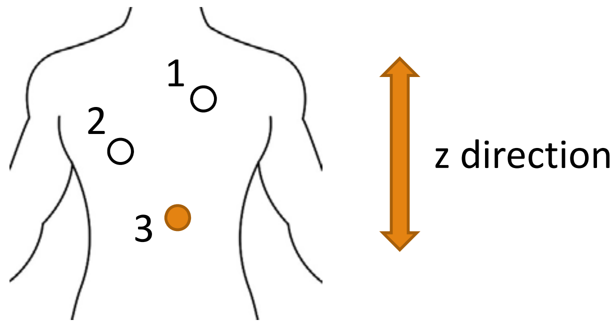


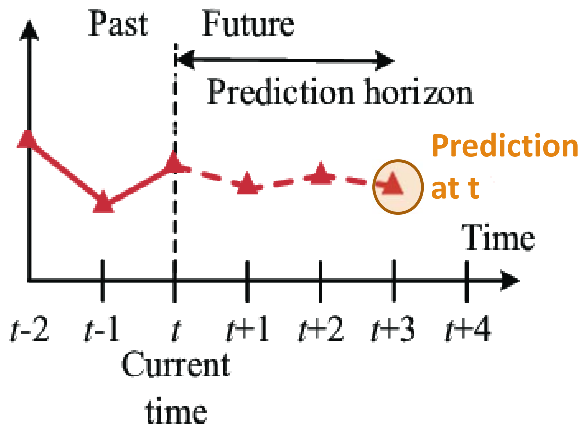
Horizon: time in advance for which the prediction is made

2. Prediction of the position of external markers on the chest and abdomen

Results : Predicted marker position (irregular breathing)



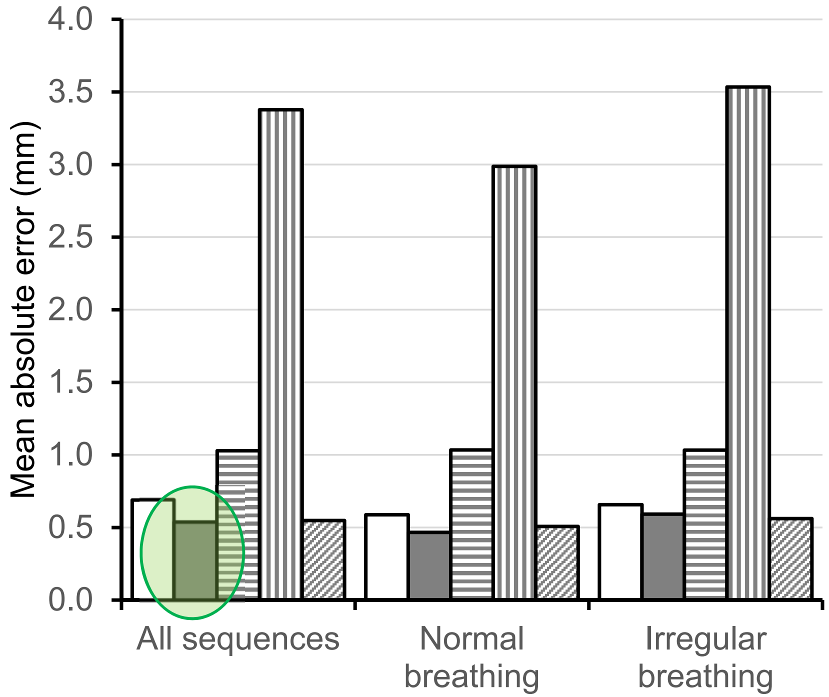


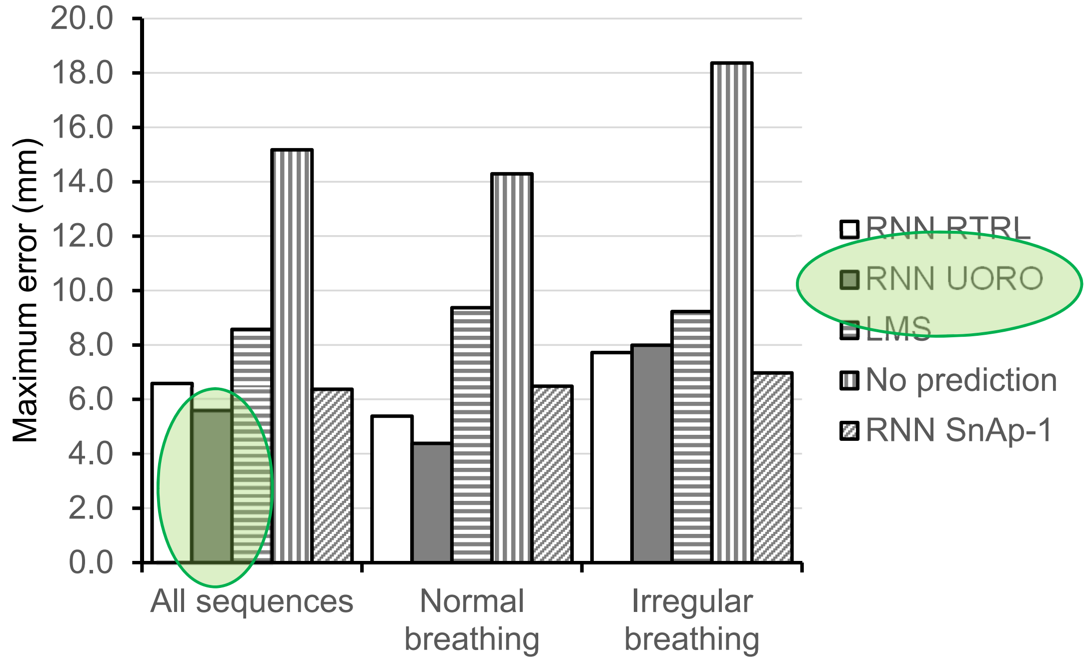


Horizon: time in advance for which the prediction is made

2. Prediction of the position of external markers on the chest and abdomen

Results : Prediction performance (accuracy)





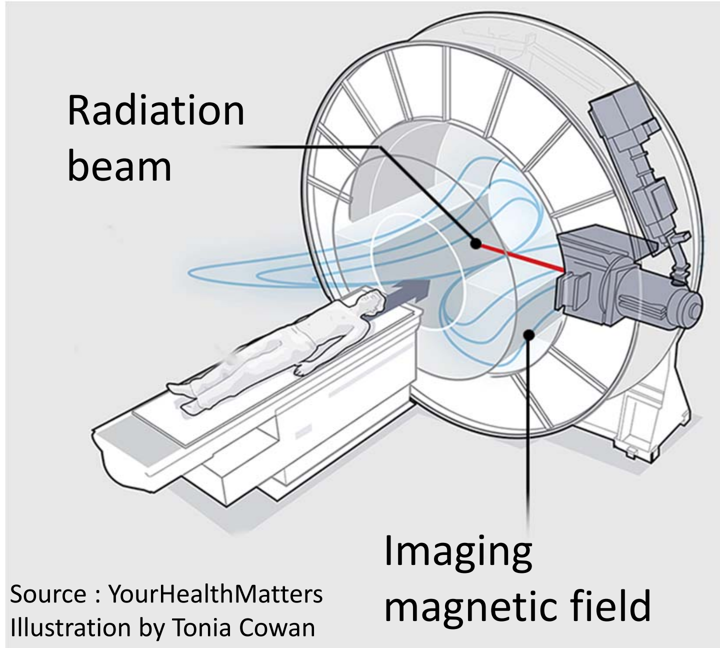
Prediction with UORO achieved the lowest mean absolute prediction error and maximum error

Prediction with linear regression performs well for very low horizon values.
In the diagrams above the performance measures are averaged over all horizon values.

3. Next frame prediction in dynamic MRI chest scan sequences

Objective of the proposed study

Development and evaluation of a next frame (image) prediction system for latency compensation in MRI-guided linac radiotherapy



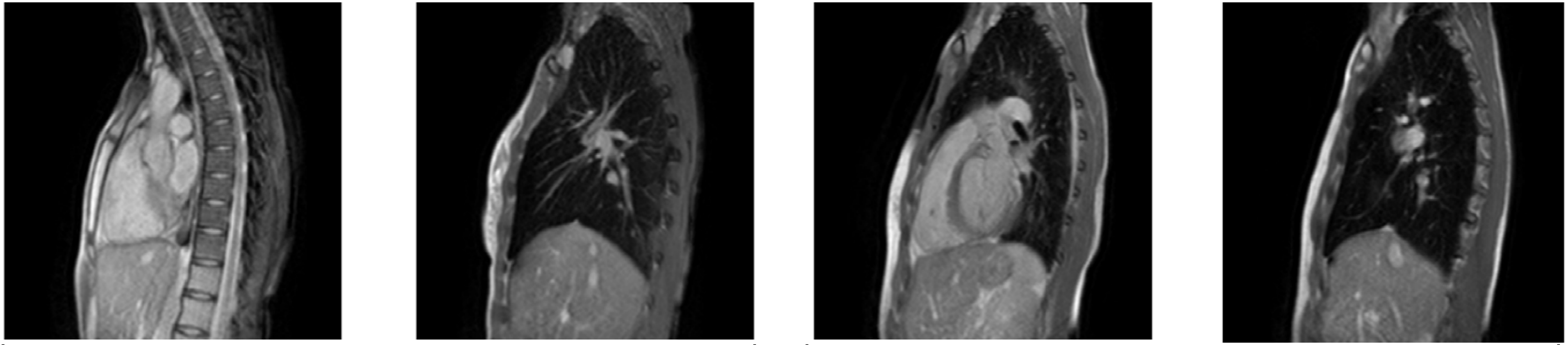
Real-time delay compensation and dose adjustment in radiotherapy

Chest image at t ⇨ **Prediction** ⇨ Chest image at $t + \Delta t$ ⇨ Tumor and organs automatic delination ⇨ Tumor contour at $t + \Delta t$ ⇨ Irradiation plan correction ⇨ Dose distribution at $t + \Delta t$

Focus of my study

3. Next frame prediction in dynamic MRI chest scan sequences

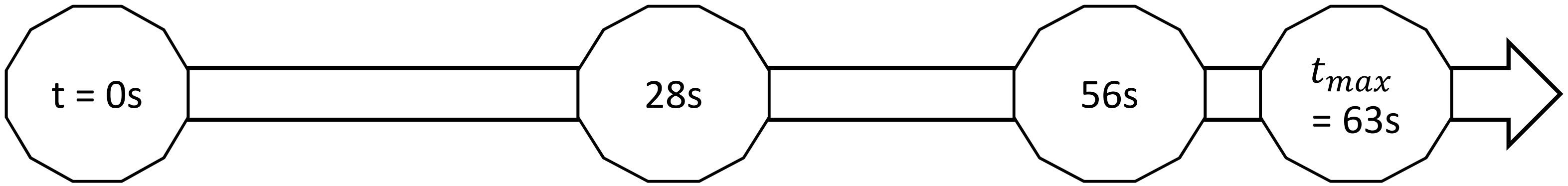
Method: Input images



Individual 1 : 2 sequences

Individual 2 : 2 sequences

dynamic 2D dyanmic MRI sequences from healthy individuals



1. Deformation field computation
2. Training the RNN performing prediction

Parameter selection

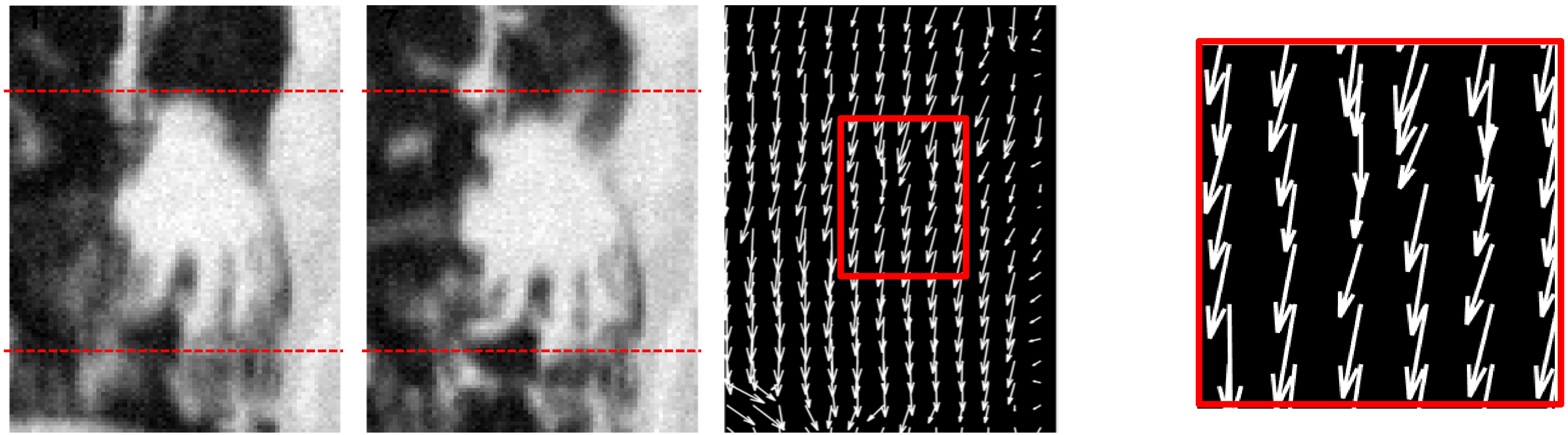
Performance evaluation

3. Next frame prediction in dynamic MRI chest scan sequences

Method: Deformation field calculation

Deformation vector field (DVF) : motion of each pixel/voxel between two images

We compute the DVF in the chest to quantify the local motion of tissues due to breathing.



Ex: tumor image at t

Same tumor at $t + \Delta t$ (breathing motion)

Deformation field between t and $t + \Delta t$

zoom

Method: Deformation field encoding and prediction

I - Dimensionality reduction (encoding)

Time-dependant deformation field data is too high dimensional
Information compression with Principal Components Analysis(PCA)
-> we obtain time series $w_1(t), w_2(t), w_3(t)$

II – RNN prediction

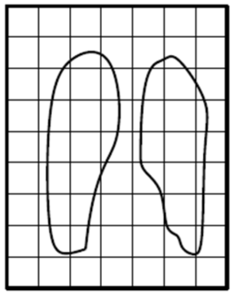
First part of my presentation

$$w_i(t) \longrightarrow w_i(t + \Delta t)$$

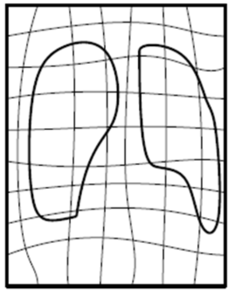
III - Predicted motion info decoding

Information from $w_i(t + \Delta t)$
is used to recover the deformation field in the future

IV – Image warping



Chest image at t1

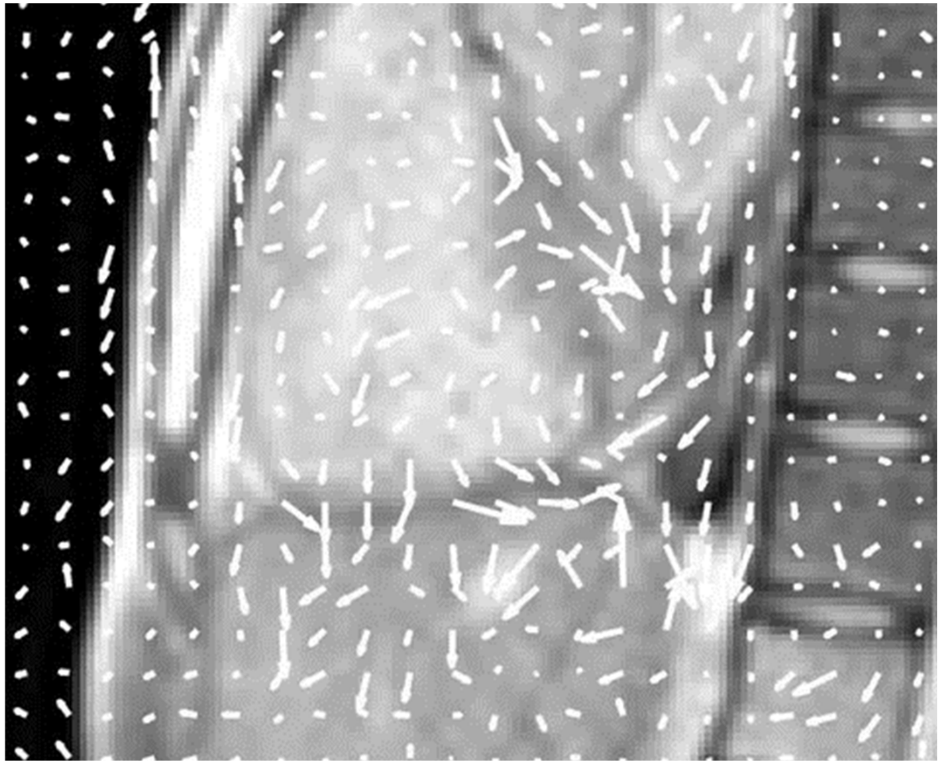


Chest image at $t + \Delta t$

3. Next frame prediction in dynamic MRI chest scan sequences

Results: Deformation vector field (sequence 1)

Original sequence

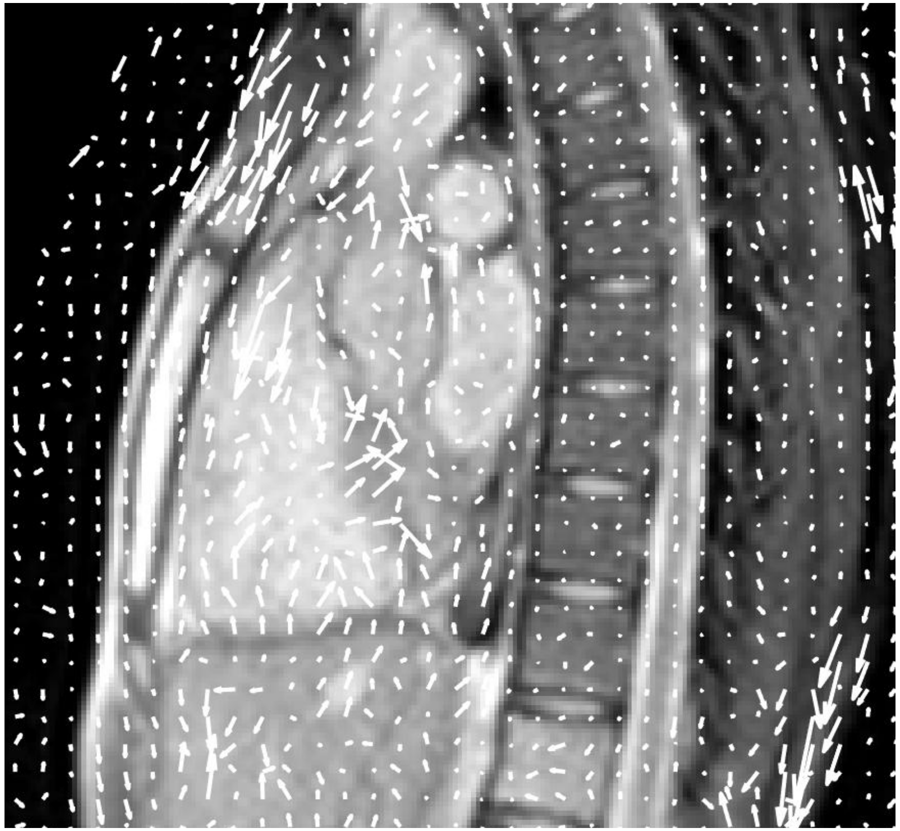


Deformation vector field

3. Next frame prediction in dynamic MRI chest scan sequences

Results: Deformation vector field (sequence 1)

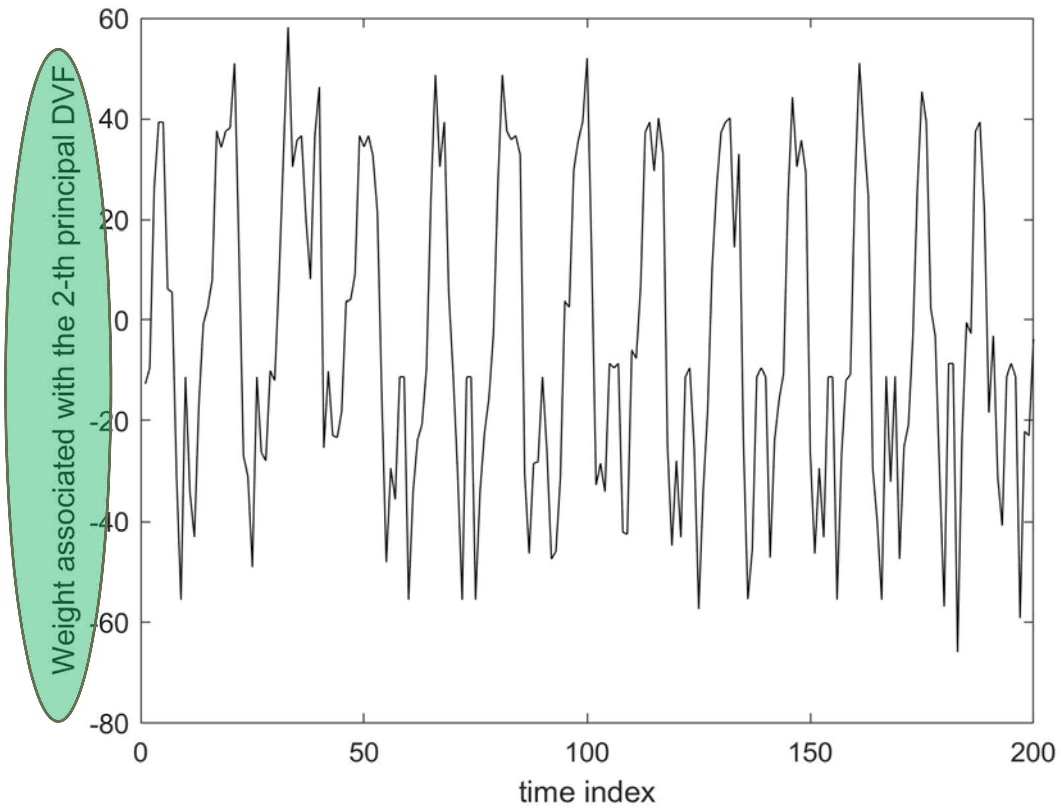
DVF at t_8 = 2.5s (inspiration)



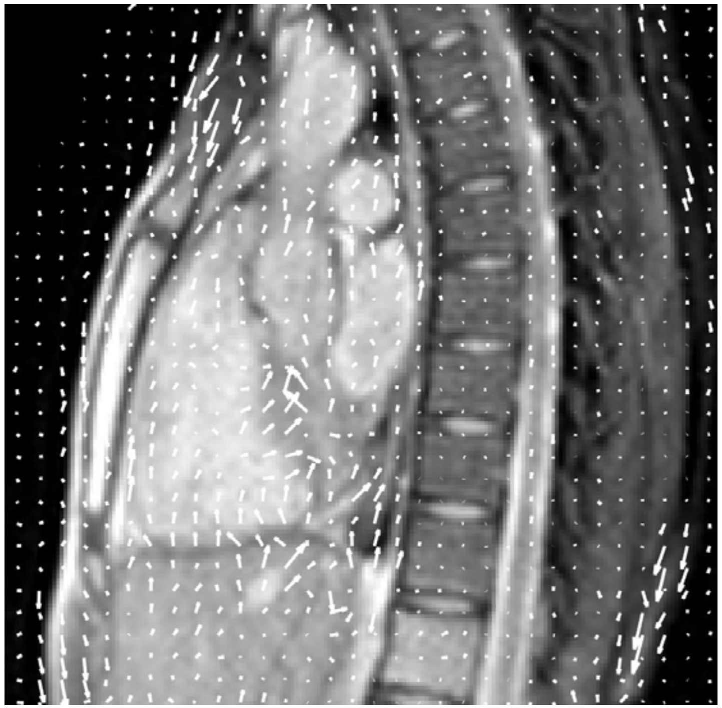
DVF at t_{18} = 5.6s (expiration)

3. Next frame prediction in dynamic MRI chest scan sequences

Results: Principal components and weights



$\vec{v}_2(\vec{x})$: 2nd principal deformation vector field (DVF) at pixel $\vec{x}$

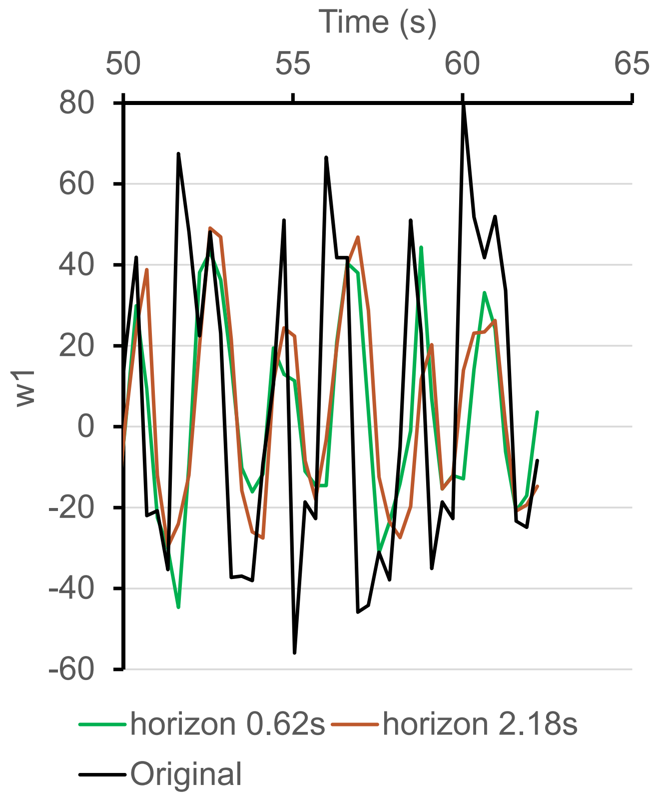


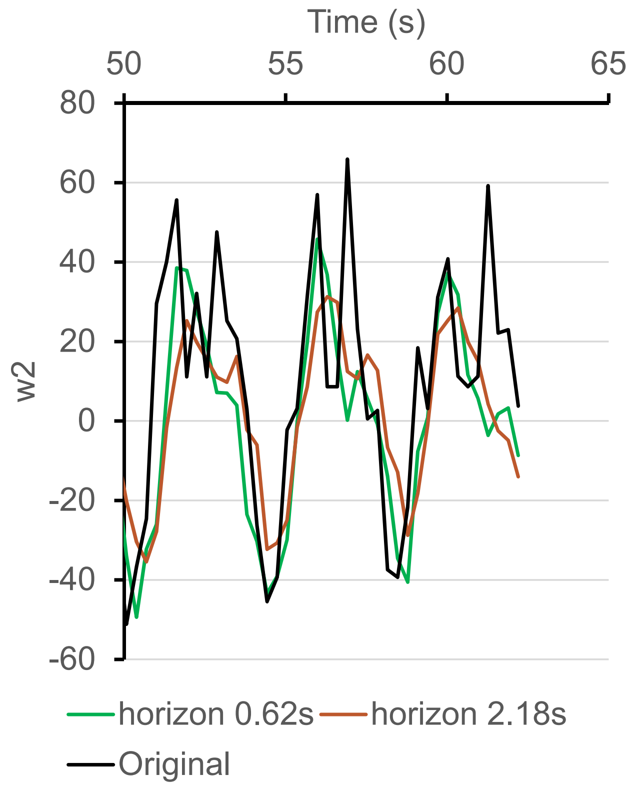
Local motion of tissue at pixel $\vec{x}$ at time t: $\vec{u}(\vec{x},t) = \vec{u}_0(\vec{x}) + w_1(t)\overrightarrow{v_1}(\vec{x}) + w_2(t)\overrightarrow{v_2}(\vec{x}) + w_3(t)\overrightarrow{v_3}(\vec{x})$

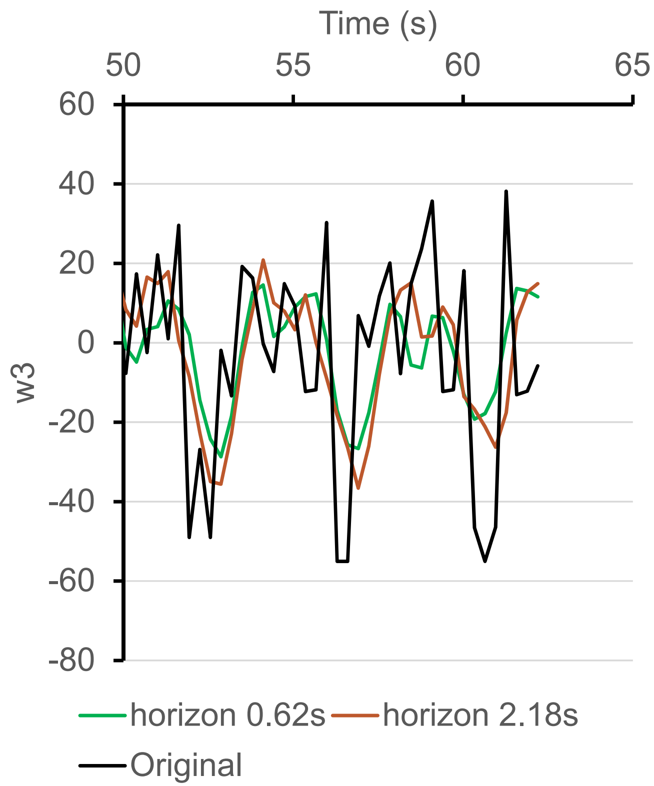
3. Next frame prediction in dynamic MRI chest scan sequences

Results: Prediction of the time dependant PCA weights

The time-dependant PCA weights are a compression of the video information

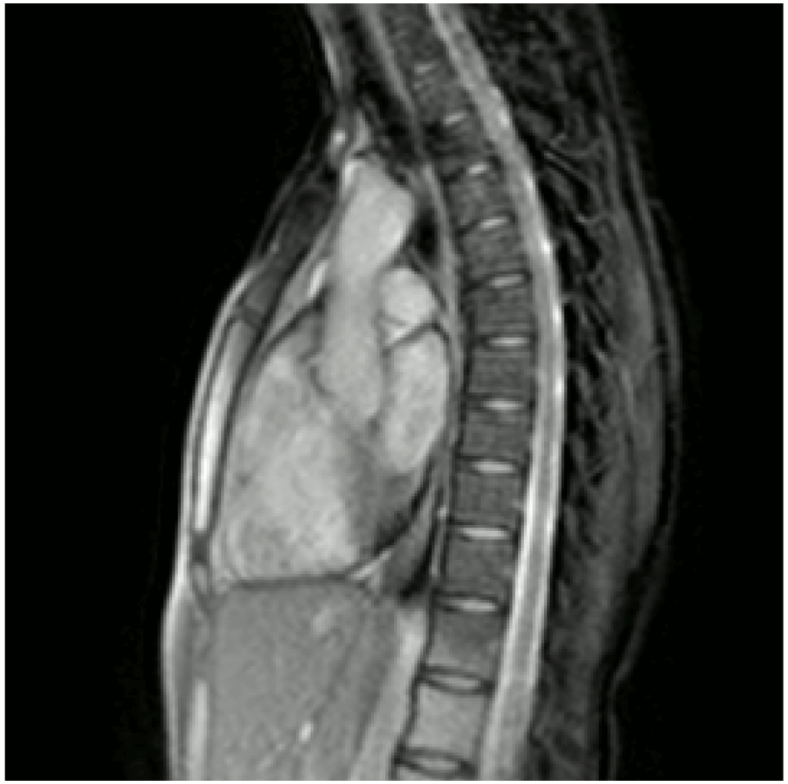




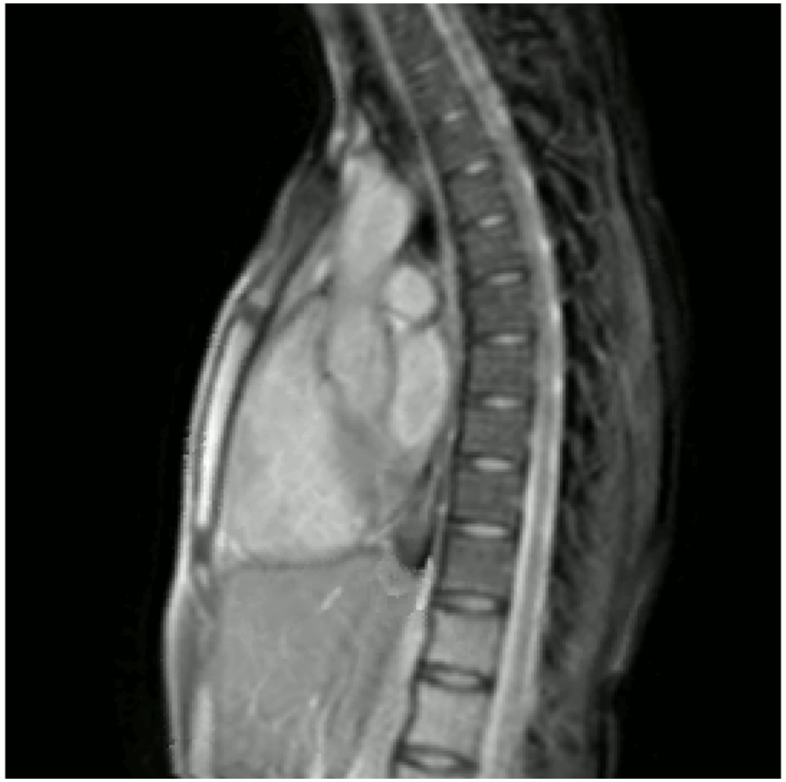


3. Next frame prediction in dynamic MRI chest scan sequences

Results: Predicted images (sequence 1)



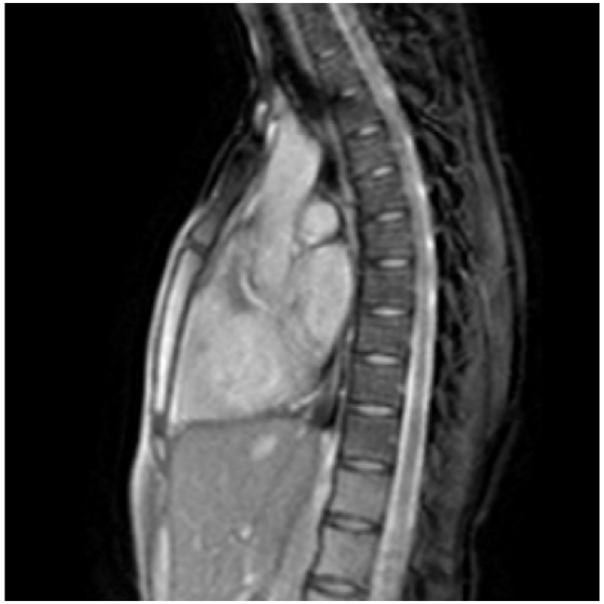
Original images



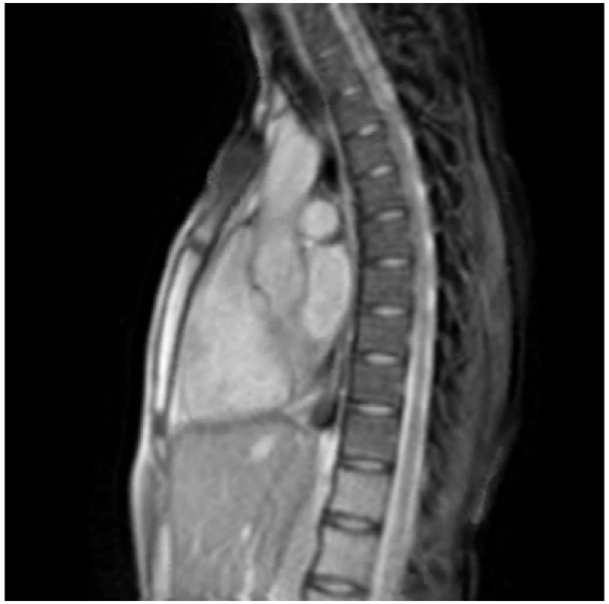
Predicted images - UORO with horizon value h = 2.20s

3. Next frame prediction in dynamic MRI chest scan sequences

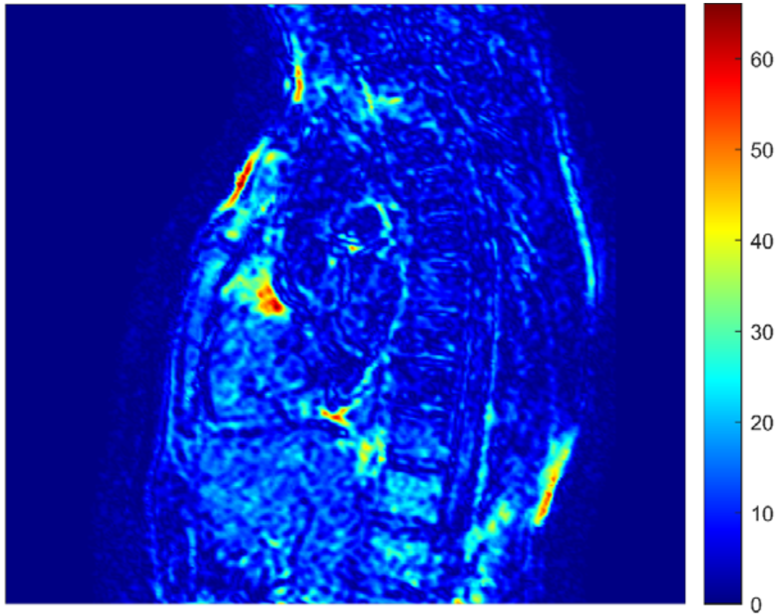
Results: Predicted images (sequence 1)



Original t = 188



Predicted t = 188

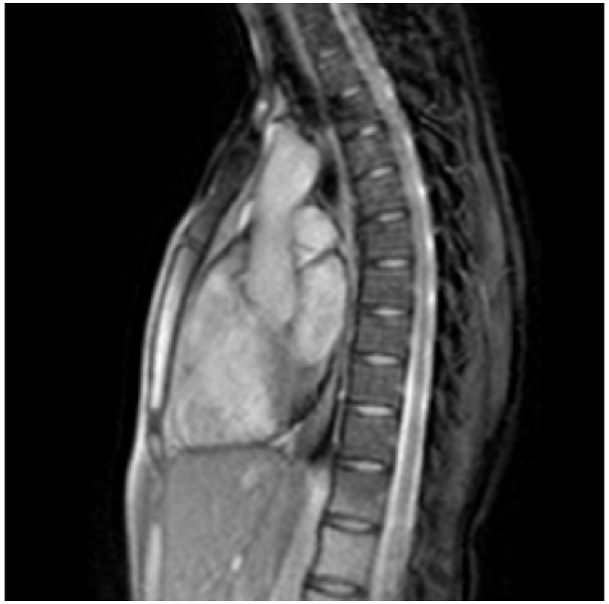


Difference t = 188

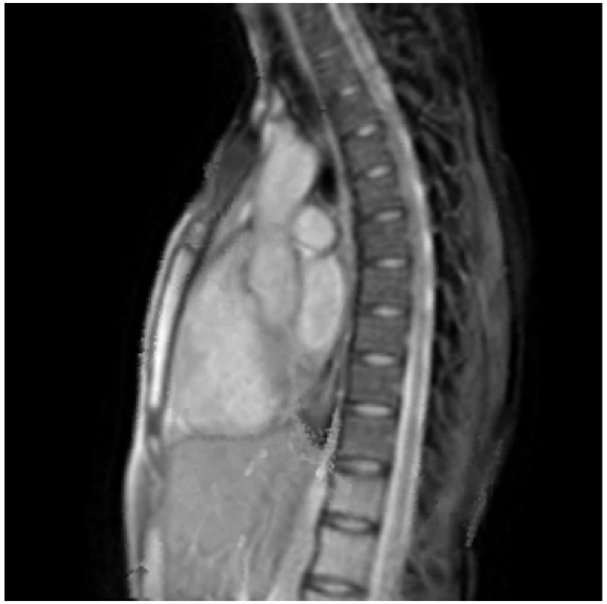
Prediction with an RNN trained with UORO and horizon value h = 2.20s - sequence 1

3. Next frame prediction in dynamic MRI chest scan sequences

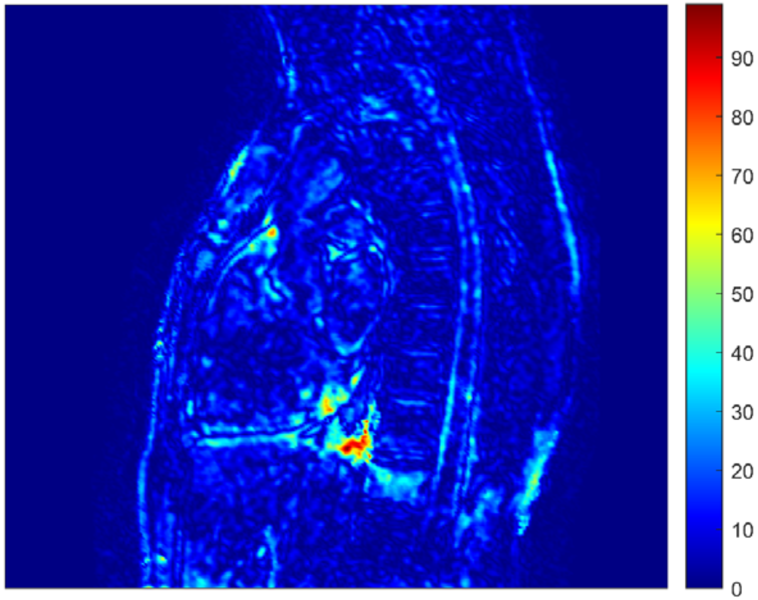
Results: Predicted images (sequence 1)



Original t = 196



Predicted t = 196



Difference t = 196

Prediction with an RNN trained with UORO and horizon value h = 2.20s - sequence 1

Summary

1. Study of online-trained RNNs for external marker position in radiotherapy
2. Design of a next frame prediction algorithm applied to MRI chest dynamic imaging

Online training of RNNs enables adaptation to changing breathing patterns.

Prediction of the breathing motion helps reduce irradiation to healthy tissues and increase irradiation to the moving tumor.

Research article : *Prediction of the motion of chest internal points using a recurrent neural network trained with real-time recurrent learning for latency compensation in lung cancer radiotherapy,* Computerized Medical Imaging and Graphics

Github : https://github.com/pohl-michel