Prediction of the position of external markers on the chest and abdomen using a recurrent neural network trained with real-time recurrent learning for accurate and safe lung cancer radiotherapy

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During lung cancer radiotherapy, targeting the tumor with the treatment beam is difficult due to patient breathing motion. In this work, we evaluate the capabilities of recurrent neural networks trained with real-time recurrent learning to predict the position of external markers on the chest and abdomen to compensate for the radiotherapy system latency.

Keywords : Lung cancer radiotherapy, latency compensation, recurrent neural network, real-time recurrent learning, external markers

1. Introduction

During the treatment of lung cancer with radiotherapy, positioning the X-ray beam correctly to minimize damage to healthy tissues is difficult because of the tumor motion due to breathing. Furthermore, the treatment system latency leads to inaccuracies in the beam delivery, which results in turn in unwanted damage to the tumor surrounding tissues. Therefore, predicting the position of tracked surrogates such as external markers is necessary.

2. Materials and Method

In the proposed study, we use observation records of the three-dimensional position of external markers on the chest and abdomen of three healthy males, which constitute in total 9 time-series sequences [1]. These were acquired using an infrared stereo camera with a frequency of 10Hz. The motion amplitude of the markers ranged from 17mm to 45mm in the antero-posterior direction, and from 6mm to 40mm in the superior-inferior direction. We split each series into a 60s training and development set, and the remaining test set. Prediction is performed using a recurrent neural network (RNN) trained with real-time recurrent learning (RTRL) and gradient clipping [2], the least mean-squares (LMS) algorithm, and multivariate linear regression, for the horizon value h=2s.

3. Results and Discussion

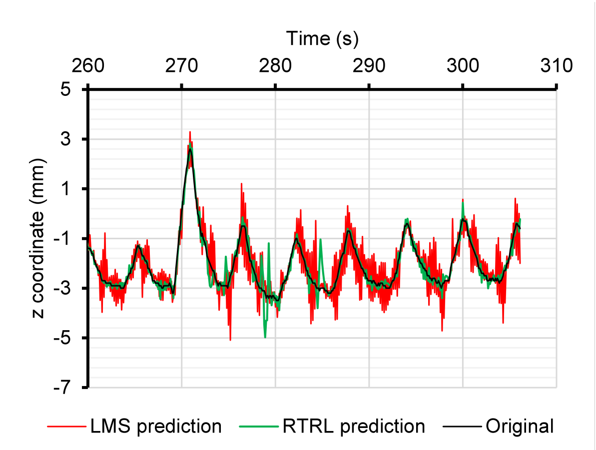

Fig. 1. Prediction of the z coordinate (spine axis) of marker 3 in sequence 9 (normal breathing) between t=260s and t=306.1s with the RNN and the LMS algorithm

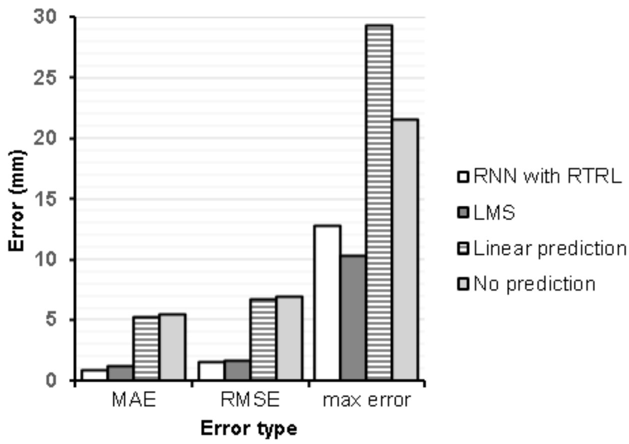

Fig. 2. Comparison of the MAE, RMSE and maximum forecast error for 4 different algorithms, averaged over the 9 breathing sequences.

When performing prediction with the RNN, we found a mean absolute error (MAE) of 0.9mm, a root-mean-square error (RMSE) of 1.6mm, and a maximum error of 12.7mm of the test set. These errors are lower than with the other methods considered, except the LMS method that has a corresponding maximum error equal to 10.2mm.

4. Summary

RNNs trained with RTRL are efficient at predicting breathing signals such as the position of external markers for latency compensation in lung cancer radiotherapy. RNNs indeed benefit from non-linear data processing and the RTRL learning method enables real-time adaptation to the predicted signal.

References

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