

Prediction of the position of external markers on the chest and abdomen for latency compensation in radiotherapy

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1. Introduction

During lung cancer radiotherapy, targeting the tumor with the treatment beam is difficult due to patient breathing motion. External markers on the chest may be used to infer the tumor position, for instance with the Cyberknife System. Prediction of breathing signals such as the position of the markers is necessary to compensate for delays inherent to the data acquisition and radiation delivery process, and avoid excessive irradiation of healthy tissues. In this research, we investigate the capabilities of recurrent neural networks (RNNs) trained with real-time recurrent learning (RTRL) in predicting the position of external markers on the chest for accurate and safe lung radiotherapy treatment.

2. Materials and Methods

In this study, we analyze the time-dependent three-dimensional position of three external markers placed on the chest of three healthy males [1]. The data were obtained using an infrared stereo camera with a frequency of 10Hz. In some scenarios, the patients were breathing normally, and in other settings, the individuals were asked to talk or laugh during the data acquisition. We divide the time series data into a training set and cross-validation set, between $t=0s$ and $t=60s$; and the remaining test set. We perform prediction of the position of the three markers using an RNN trained with RTRL [2], and also with the least mean squares (LMS) algorithm, and offline multivariate linear prediction. Besides, we analyze the case when no prediction is performed. We compare the prediction performance for different look-ahead times: the time interval in advance for which the prediction is made, ranging from 0.1s to 2s.

3. Results and Discussion

When performing prediction with the RNN, we found a mean absolute error (MAE) of 0.8mm, a root-mean-square error (RMSE) of 1.4mm, and a maximum error of 11.8mm of the test set.

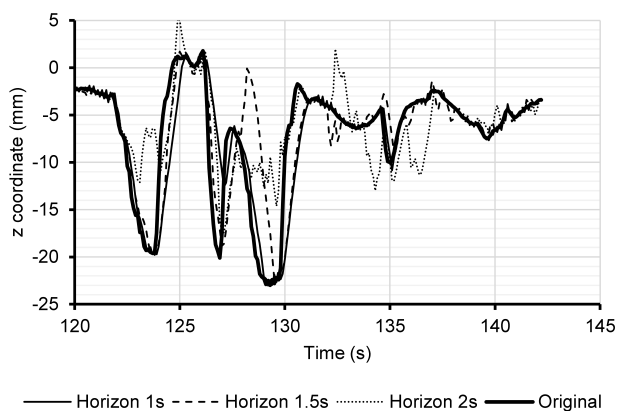


Fig. 1. Predicted z coordinate (spine axis) of marker 3 in sequence 4 (person laughing and talking) between $t=120s$ and $t=142.2s$, for several values of the prediction horizon using the RNN.

These errors are lower than with the three other methods considered, except the LMS method which has a corresponding maximum error, averaged over the 9 sequences and all values of the look-ahead times, equal to 8.4mm. The maximum prediction time per time step for the RNN, equal to 55.2ms is the highest among the compared methods (Intel Core i9 3.60Gz 32Gb RAM).

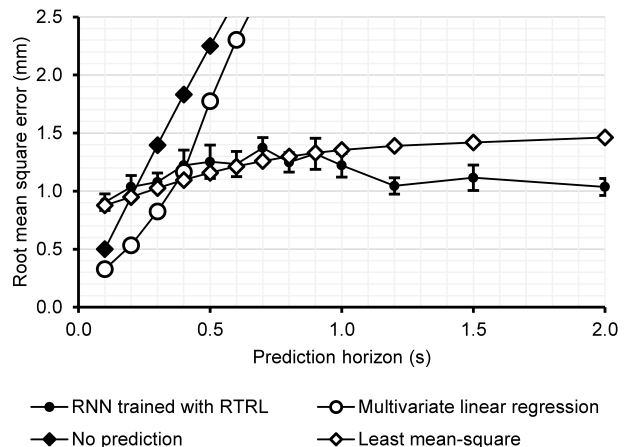


Fig. 2. Comparison of the RMS forecast error for 4 different algorithms as a function of the prediction horizon, averaged over the regular breathing sequences. Since the RNN weights are randomly initialized, the RNN error is displayed with the associated 95% confidence interval.

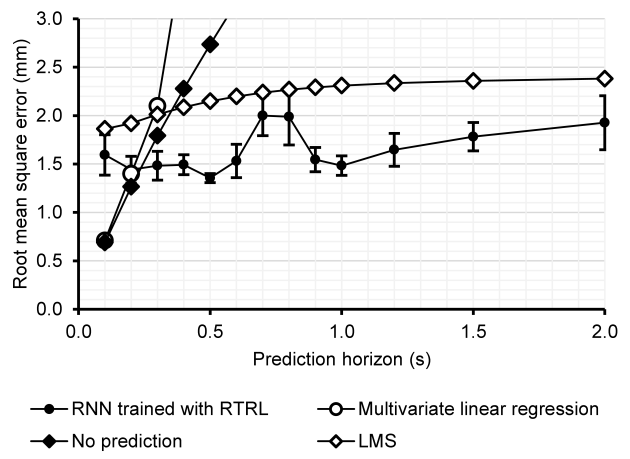


Fig. 3. Comparison of the RMS forecast error for 4 different algorithms as a function of the prediction horizon, averaged over the irregular breathing sequences.

4. Conclusion

This research shows that RNNs trained with RTRL are efficient for predicting respiratory motion for high values of the prediction look-ahead time even under irregular breathing conditions. Accurate prediction was accomplished by using only 1min of training and cross-correlation data, as online learning enables adaptation to individual breathing patterns.

References

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