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Realtime long range respiratory prediction

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INTRODUCTION

Adaptive imaging and gated radiotherapy treatment involves making decisions in response to patient respiratory phase. Therefore, the ability to accurately determine phase is paramount and is constrained by adequate past information to inform a model as shown in Figure 1.

Current state of the art struggles to predict beyond a 500 ms horizon which is problematic as current hardware and software latencies are 250 ms.

The aim of this work was to investigate if a 5s phase prediction horizon can be achieved.

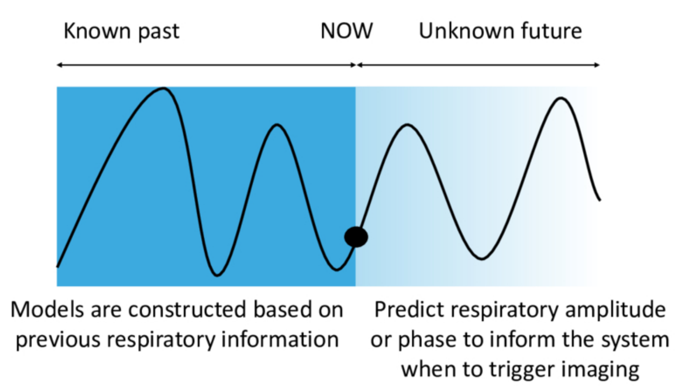


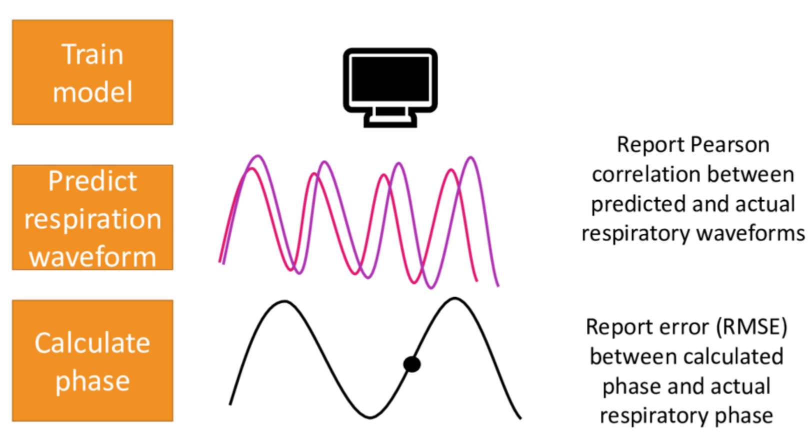
Figure 1: Imaging is triggered based on phase models

METHOD

A 24 lung cancer patient study with ~22 hours of RPM data and CAPNOBASE (42 patients, ~6 hours) datasets [3,4] were fused, resulting in a dataset containing ~2.3 million training/validation examples.

A machine learning (UNET) architecture [2] was trained using reinforcement learning to predict a 5-second respiratory window. The model performance was tested on a 20 respiratory traces from 10 patients acquired through 4DCBCT.

We assessed the performance of the UNET in terms of RMSE and Pearson correlation to the actual respiratory displacement and phase. State-of-art baseline and phase estimation is based on elliptical shape tracking in augmented state space and Poincaré sectioning principle [1]. For comparison we used a state-of-the-art phase prediction method [1].



RESULTS

In Figure 2, the predicted respiratory displacement from the UNET shows a good approximation of the actual displacement (r>0.6 up to 1.5 s). From this prediction, respiratory phase was calculated.

The state-of-the-art phase predictor incorrectly estimated the phase between the 100th and 180th sample due to the previous respiration cycle being smaller (50 vs 150). The UNET calculates the respiratory phase incorrectly in the middle (50th -100th samples) at the end of the respiratory cycle (150th-160th samples) due to incorrectly calculated turning points.

The RMSE linearly increased until 1.5s while the Pearson correlation remained above 0.6 (Figure 3).

Overall, the UNET did not offer any benefit compared to state-of-the-art method to predict phase with RMSE of 0.084 vs 0.019 [1].

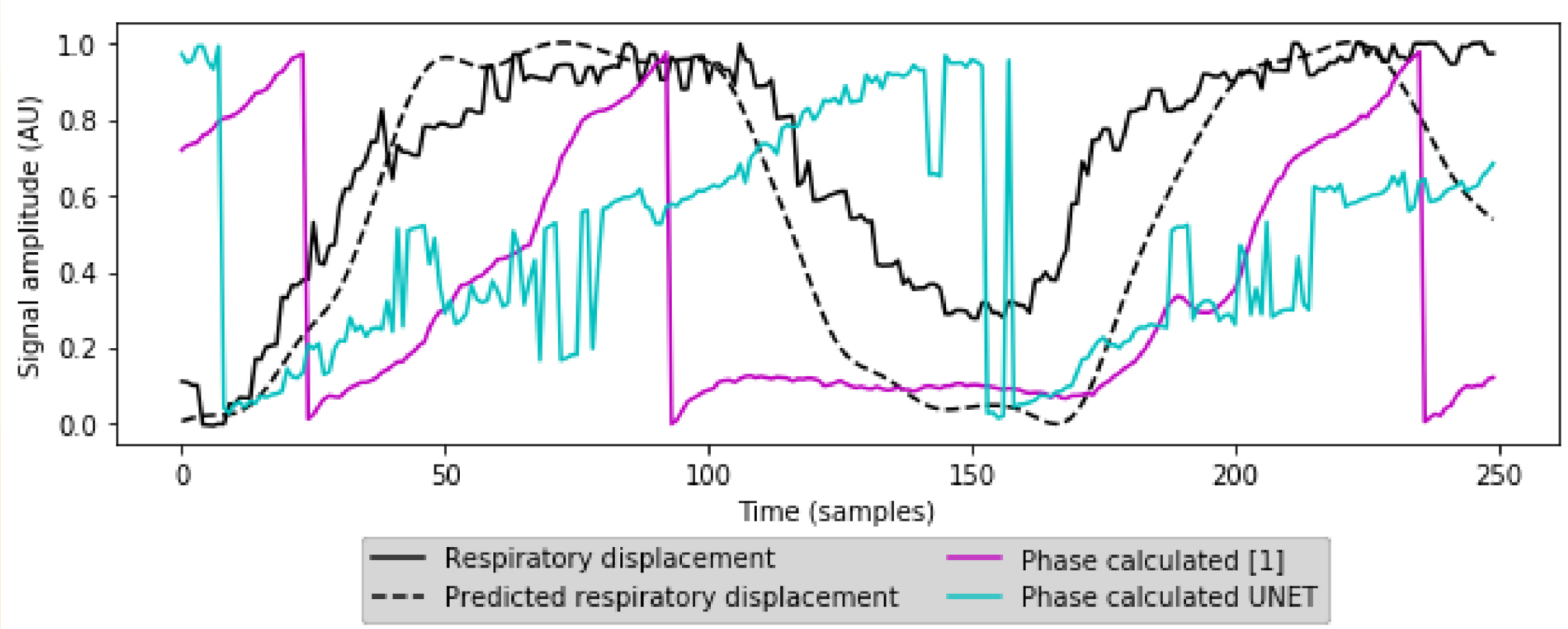


Figure 2: Respiratory displacement and phase calculations

RESULTS

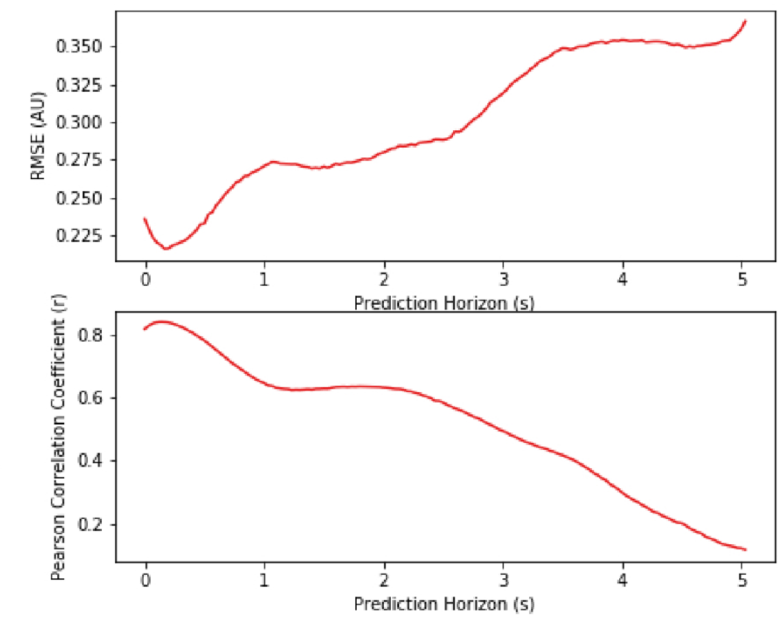


Figure 3: RMSE vs prediction horizon (top).
Pearson correlation vs prediction horizon (bottom)

CONCLUSIONS

This is the first implementation of machine learning to predict respiratory phase. While the overall prediction was not better than the state of art [1], we believe that it would could offer benefits during erratic breathing.

With an increasing demand to perform more complex computations on the fly to improve image quality, it is likely that an associated system lag would increase. Therefore, mitigating against this lag will become more important in the future.

REFERENCES

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