AbstractID: 6922 Title: Respiration Motion Prediction using Time-Delay Kernel Regression Modeling

Purpose: The purpose of this study was to develop a novel technique for dynamically predicting respiration motion and uncertainty up to 1.5 seconds in the future in real-time using Time-Delay Kernel Regression (TDKR) modeling. Unlike neural network based prediction techniques, kernel regression models are continuously learning new respiration cycles for each patient without the need for computationally and time intensive re-training.

Method and Materials: Recorded respiration data from a real-time respiratory gating system was used to develop a model to predict the amplitude of the marker block at a future time. An empirical TDKR model was designed to compensate for the latency that occurs between the acquisition of the image and the point at which the beam actually turns on/off in beam tracking systems. This non-parametric model incorporates the temporal information present in the input data. The model was tested using respiration data from 4 patients.

Results: The root mean squared error (*RMSE*) between the model prediction's and the measured data was computed for each patient at different latencies, and then the average was taken over all the patients. For predictions 1.5 seconds into the future the average RMSE was 1.4%. For predictions 1 second into the future, the RMSE dropped to 1.2%, and for 0.5 seconds it was only 0.7%. The average uncertainty for the predictions at 0.5, 1, and 1.5 seconds into the future was 2.4%, 3.2%, and 3.4%, respectively.

Conclusion: This study proves that a TDKR model can learn the complex relationships present in respiration data. The reported results showed that the TDKR model has the same, if not better predictive performance, as previously studied parametric models. However, because TDKR is non-parametric, it has several distinct advantages over these models that make it more suited for respiratory gating applications.