AbstractID: 13935 Title: Correlated 3D Respiratory Motion Prediction with Low-dimensional Feature-based Learning

Purpose: Current methods of respiratory motion prediction treat each dimension independently. In this study we develop and investigate a low dimensional inference methodology that takes advantage of the correlative relation among various physical dimensions for respiratory motion prediction.

Method and Materials: Covariate-response training pairs are constructed in the original 3D physical space, via state augmentation. Unlike existing methods where independent inference models are built for each of the x,y,z coordinates, we first map these high dimensional paired samples into a lower dimensional feature space, spanned by the principle components. In this feature space, a Gaussian kernel with block-diagonal covariance is employed for learning the joint covariate-response pdf, which upon marginalization yields the distribution for the projected prediction value. Finally, the estimate in the feature space is mapped back into the original physical space to recover the prediction representation in the (x,y,z) coordinate. The proposed method is compared against its counterpart with independent prediction, using 159 lung motion traces from the Synchrony respiratory tracking system. Both methods were tested for predicting 160ms and 570ms, spanning the range of measured DMLC tracing system latencies. Performance is quantified with 3D RMSE and 90% percentile 3D error.

Results: Under fair setup conditions, the proposed method achieves better performance than its independent counterpart. The case-wise 3D RMSE was reduced by 30-40%, with p-values in the order of 10^(-14) for both lookahead lengths. The 90% percentile 3D error was reduced from 1.8mm to 1.1mm for 160ms prediction and from 2.8mm to 2.0mm for 570ms prediction.

Conclusion: We have proposed a general low dimensional feature learning methodology to perform correlated high dimensional inference. Combining it with the already effective kernel density estimation yields a highly efficient approach for real-time respiratory motion prediction.

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