AbstractID: 8662 Title: Inference of Hysteretic Respiratory Tumour Motion from External Surrogates: a State Augmentation Approach

Purpose: To infer internal respiration-induced tumor motion from external surrogate. To systematically resolve mapping ambiguity caused by breathing hysteresis.

Method and Materials: We propose a state-augmentation approach to capture system dynamics. Concatenating real-time surrogate observations with their time-delayed records describes the state information in a higher-dimensional state space. In such space, inhale and exhale "stages" are naturally separated due to the incorporated velocity contents. Any existing inference model migrates effortlessly into this framework. We illustrate the idea with simple polynomial inference models, and derive a closed-form solution for optimal choice of model parameters. Choice of lag length is demonstrated empirically to be robust and may be chosen offline. This approach is tested on synchronized recordings of internal tumor trajectories and external fiducial marker readouts from eight lung patients (multiple fractions and readings) with a Mitsubishi real-time radiotherapy (RTRT) system. Internal recording is obtained by fluoroscopic tracking of implanted 1.5mm-diameter gold ball bearings around the tumor and external surrogates measure relative abdominal skin positions.

Results: Examination of trajectories in the augmented state-space suggests the existence of a consistent and unambiguous inference map. Empirical tests with clinical data show that using state augmentation decreases the 3D RMSE from 2.01mm to 1.74mm with the linear model and 1.93mm to 1.63 with the quadratic model. Paired student-t tests with P-values on the order of 10e-13 indicate statistical significance of the improvement.

Conclusion: We proposed a simple state-augmentation approach to implicitly incorporate the hysteretic internal-external response pattern into the estimation framework with any existing inference model. For the general class of correspondence models that are linear in their parameters, closed-form solutions for the optimal parameter values and the error evaluations are derived. Tests with clinical data demonstrate statistically significant improvement over direct models.

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