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Prediction and Classification of Respiratory Motion

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Abstract

Radiation therapy is a cancer treatment method that employs high-energy radiation beams to destroy cancer cells by damaging the ability of these cells to reproduce. Thoracic and abdominal tumors may change their positions during respiration by as much as three centimeters during radiation treatment. The prediction of respiratory motion has become an important research area because respiratory motion severely affects precise radiation dose delivery. This study describes recent radiotherapy technologies including tools for measuring target position during radiotherapy and tracking-based delivery systems.

In the first chapter following the Introduction we review three prediction approaches of respiratory motion, i.e., *model-based* methods, *model-free* heuristic learning algorithms, and *hybrid* methods. In the following chapter of our work we present a phantom study—prediction of human motion with distributed body sensors—using a Polhemus Liberty AC magnetic tracker. Next we propose respiratory motion estimation with hybrid implementation of extended Kalman filter. The proposed method uses the recurrent neural network as the role of the predictor and the extended Kalman filter as the role of the corrector. After that we further extend our research work to present customized prediction of respiratory motion with clustering from multiple patient interactions. For the customized prediction we construct the clustering based on breathing patterns of multiple patients using the feature selection metrics that are composed of a variety of breathing features. In the last chapter we retrospectively categorize breathing data into several classes and propose a new approach to detect irregular breathing patterns using neural networks. We have evaluated the proposed new algorithm by comparing the prediction overshoot and the tracking estimation value. The experimental results of 448 patients' breathing patterns validated the proposed irregular breathing classifier.