Comparing model-free motion prediction and on-line model checking for respiratory motion management

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Abstract

Compensating for respiratory motion is a key challenge for stereotactic body radiation therapy. To overcome latencies in the systems, prediction of future motion is necessary. This is related to the assumption of a stable correlation between external and internal motion. We present a new application for on-line model checking to introduce fail-safety to respiratory motion prediction and show its relevance by comparing to the widely used nLMS predictor. We demonstrate that the regularity of the external motion can be modeled and tested using OMC and deviations from regular respiratory motion can be detected.

1 Introduction

Respiratory motion is a key challenge for stereotactic body radiation therapy (SBRT), where typically a high dose of radiation is used to treat cancer. To limit side effects, the high dose region is planned to tightly follow the tumor shape. However, some tumors, e.g., close to the diaphragm, move substantially due to respiration. Recent advances in the treatment systems allow compensation for this motion by moving the treatment beams synchronously to the tumor [DHV+10, SBN+07]. At the moment it is impossible to track the inner organ motion directly, as no clinical systems offer non-ionizing real-time 3D imaging. Hence, a typical approach is to measure surrogate signals [DWE+14] that are correlated to the inner motion to estimate the tumor movements. Moreover, to compensate for the overall system latency it is necessary to predict the expected future position, which is used to control the beam motion such that the movements of tumor and beams are synchronous.

A number of studies have discussed the merits of different prediction methods [EDSS13, DWE+14]. Generally, the prediction error is relatively small, but it can rise substantially for patients with irregular breathing or due to respiratory artifacts, e.g., coughing or yawning. Moreover, the breathing pattern is subject to changes, e.g., when the initially nervous patient calms down during the course of treatment. While the prediction and the overall motion compensation system can adapt to gradual changes in the breathing patterns, more abrupt changes can result in severe misalignments between beams and tumor. We compare different approaches to analyze the time course of respiratory surrogate signals and to identify potential failures. We introduce a respiratory model for on-line model checking (OMC) and discuss how fail-safety could be integrated into SBRT. We show the relevance of OMC for the validation of respiratory motion by looking at situations where the prediction error of common predictors would be inconspicuous but the model of respiratory motion does not hold anymore.

2 Methods

2.1 Model-free prediction

The predictor of a non independent and identically distributed (i.i.d) time series $Y_n = (y_1, \ldots, y_n)$ is called model-free if no assumption about an underlying statistical model is required. In a nutshell, the basic idea involves transforming the non-i.i.d history Y_n to an easy to predict i.i.d dataset and transforming back, deriving the prediction of the time series.

Model-free prediction algorithms include normalized Least Mean Squares filter (nLMS) used in the Synchrony system for the CyberKnife system [SLS$^+$07], Support Vector Regression [ES09] as well as Artifical Neural Networks [MP09].

Performance of a typical model-free prediction is measured by the error between predicted and actual signal. Naturally no model of the underlying signal is available. The additional lack of error estimation and information on likelihoods of errors enable fail-safety only as a reaction to already occurred errors.

2.2 On-line model checking

Regarding respiratory motion SBRT represents a closed-loop treatment of patients. The model of the underlying mapping between internal and external surrogates is checked at equally distributed intervals and after huge errors in the prediction, the predictor of the respiratory motion is only validated retrospectively based on the occurred error.

OMC presents a new iterative verification approach [RSG14a, RSG14b]. Properties of the continuously updated model are verified concurrently at run time of the system.

To represent the respiratory motion we choose the model

$$x(t) = b + d \cdot t + \sum_{i=1}^{4} c_i \cos(i \cdot f \cdot t) + s_i \sin(i \cdot f \cdot t), \tag{1}$$

which is a combination of a discrete Fourier series with four frequency terms and a linear component. The values $x(t)$ represent the predicted state of the system at time $t_0 + t$ where t_0 is the time, the model was derived. The parameters $b, d, s_1, \ldots, s_4, c_1, \ldots, c_4$ and f are computed based on the two last breathing cycles at the time of calculation. A new model is derived at regular time steps of $k \in \mathbb{R}^+$ seconds.

Typically OMC is used to check the validity of the system and the prediction is used alongside with a relaxation parameter to guarantee the system behaves in the sense of the model. This allows to get some estimate of the probability for errors to happen while a model is active.

3 Comparison and discussion

We compare the model-free predictor nLMS with OMC. We focus on the suitability for fail-safety applications. We choose not to compare the quality of prediction explicitly. While OMC by design has some prediction capability (see Figure 1) a typical prediction horizon of well over one second makes it hard to react to sudden changes in respiratory motion. While the long prediction horizon proves to be unsuited for real-time prediction it is essential for the model checking abilities.

Typical predictors, even when based on a model, will accept and process additional data points as long as the rate of change is not too high. This can result in undesirable behavior: consider a patient holding his breath. The respiratory motion in this case is easy to predict and conventional error measures are of no use. Clearly, for a patient holding his breath the prerequisites of the mapping between internal and external surrogates do not hold, introducing possible extreme but unrecognized errors in SBRT. The long prediction horizon of OMC alongside with the probability measure makes this case easy to detect. The same holds true for similar situation like misplaced or gradually detached tracking markers. Clearly a long prediction horizon is also advantageous when detection of breathing artifacts like coughing, yawning or sneezing is of interest. For an example see Figure 1.

Between approximately 21566 and 21570 seconds regular breathing is disturbed by an irregularity. While the model does not hold, the probability is low and returns to normal values once the irregularity comes to an end.

Taking into account the history of error probabilities introduces additional applications. For sequences of reliable breathing as reported by the OMC the beam width of the linear accelerator in SBRT could be reduced and vice versa. For patients that show continuously irregular respiratory motion it may be advantageous to disable Synchrony motion tracking all together. This idea could also be expanded to test whether a patient is suited for motion correction before hand.

4 Conclusion

In our comparison we lined out, that OMC could become a useful algorithm in validating the quality of respiratory motion correction. Alongside the ability of model-free algorithms to work on any data and thus being easily expandable to multivariate setups [DWE$^+$14] using classic algorithms for prediction is a better choice at the moment and OMC should only be used in addition to common predictors. OMC enables on-line validation of a given model and when compared to traditional model-based predictors [EDSS13] allows for more complete models, also accounting for deformations, e.g., in combination with 4D imaging. This not only introduces the possibility to improve prediction but also provides error probabilities and thus allows for more advanced applications.

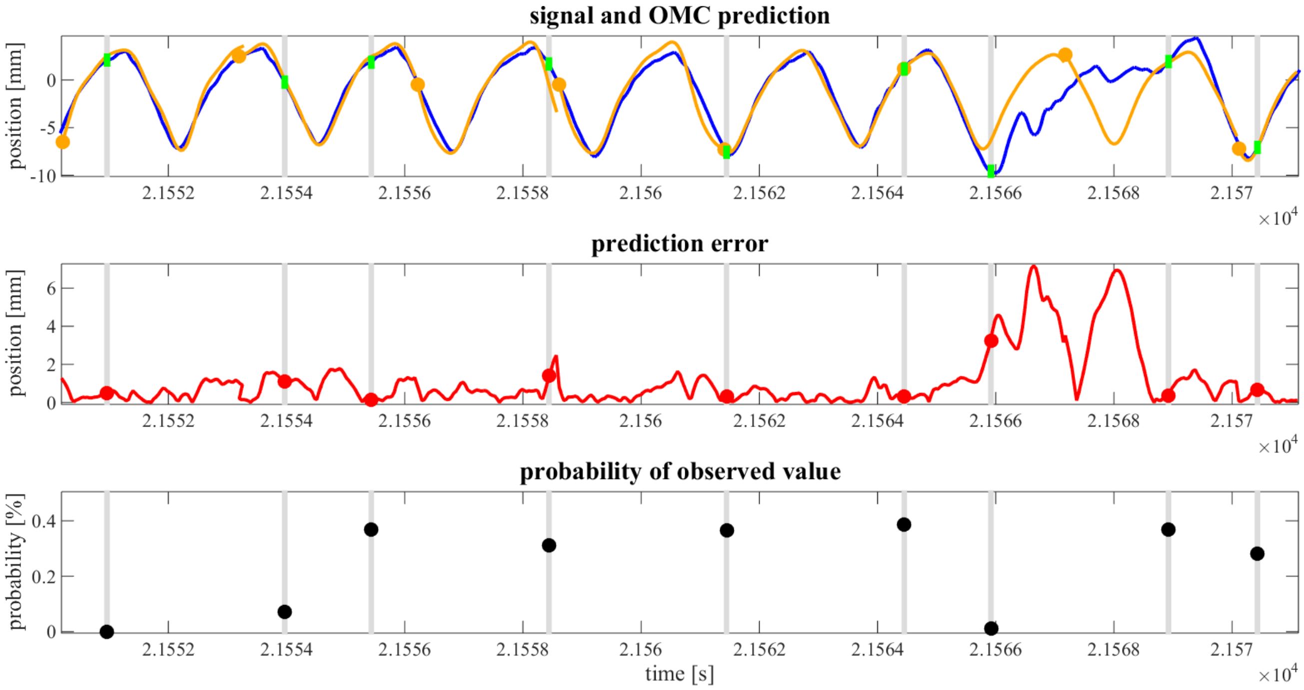

Figure 1: Respiratory signal (top, blue), OMC prediction (top, orange) with $k = 3$s and prediction error (center) of a PCA of a trajectory of respiratory motion recorded during CyberKnife treatments at Georgetown University Hospital and acquired at approximately 26Hz. The orange dots (top) denote the time at which a new model is generated. The gray bars mark the timestamps at which the model is validated. The probability of the model producing values in the interval denoted by the green bar (top) is displayed by the black dots (bottom), the corresponding prediction error is marked by a red dot (center).

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