BEB Conference on Biomedical Engineering and Biotechnology

BEB6297

The effect of fuzzy correlation model parameters on real time tumor tracking at radiotherapy with external surrogates

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Abstract

In this study, a correlation model based on the fuzzy logic concept is proposed for real time tumor tracking during tumor treatment with external surrogates radiotherapy. Several approaches have been proposed for this aim using linear and non-linear prediction models, but a fuzzy environment may be optimal due to its robustness and benefits. The correlation model is configured using training motion dataset provided by motion monitoring systems. This dataset includes internal tumor motion and external rib-cage and abdomen motion, in synchronized fashion. After model configuring, it is ready to trace tumor motion during beam irradiation using only rib cage motion data points as input. In this work, the effect of data clustering and inference system type of correlation model has been investigated, comprehensively. To do this, the motion dataset of five real patients treated with Cyberknife Synchrony system at Georgetown University Hospital were utilized. The final results represent that an optimum data clustering for each patient can significantly improve targeting accuracy during beam irradiation. Therefore, an adaptive data clustering should be taken into account for each patient, uniquely.

Keywords: external surrogates radiotherapy, fuzzy correlation model, data clustering, fuzzy inference system

Introduction

In radiotherapy with external surrogates, exact information of tumor position is one of the key factors that improves treatment delivery [1]. Many dynamic tumors in thorax region of patient move mainly due to respiration and are known as intra-fractional motion error that must be minimized as well [2]. One clinical method to estimate tumor motion is from external rib cage motion using an internal–external correlation model. It should be noted that internal tumor motion and external rib cage motions are detected using proper monitoring systems installed at treatment room. After internal-external data gathering, a proper correlation model is built initially using training dataset and then, the model is ready to trace tumor motion versus time using only external rib cage motion. In this study, we proposed a fuzzy logic based prediction model as inference system [4-5]. The proposed model is robust as real time tumor tracer to address high degree of uncertainty, non-linearity and time-varying properties of breathing. Different data clustering different data clustering and two types of inference systems have been implemented to comprehensively investigate model performance. It should be noted that when our model is configured in training step, the generated model can be updated automatically, using new arrived training data pairs during treatment. The final analyzed results represent that there is a close correlation between the internal/external markers using our fuzzy correlation model even better than utilized model at Cyberknife system. Moreover, the number of data clustering for each patient can remarkably reduce tumor tracking error. Therefore, data clustering method is not same for all patient and an adaptive clustering should be implemented for each patient.

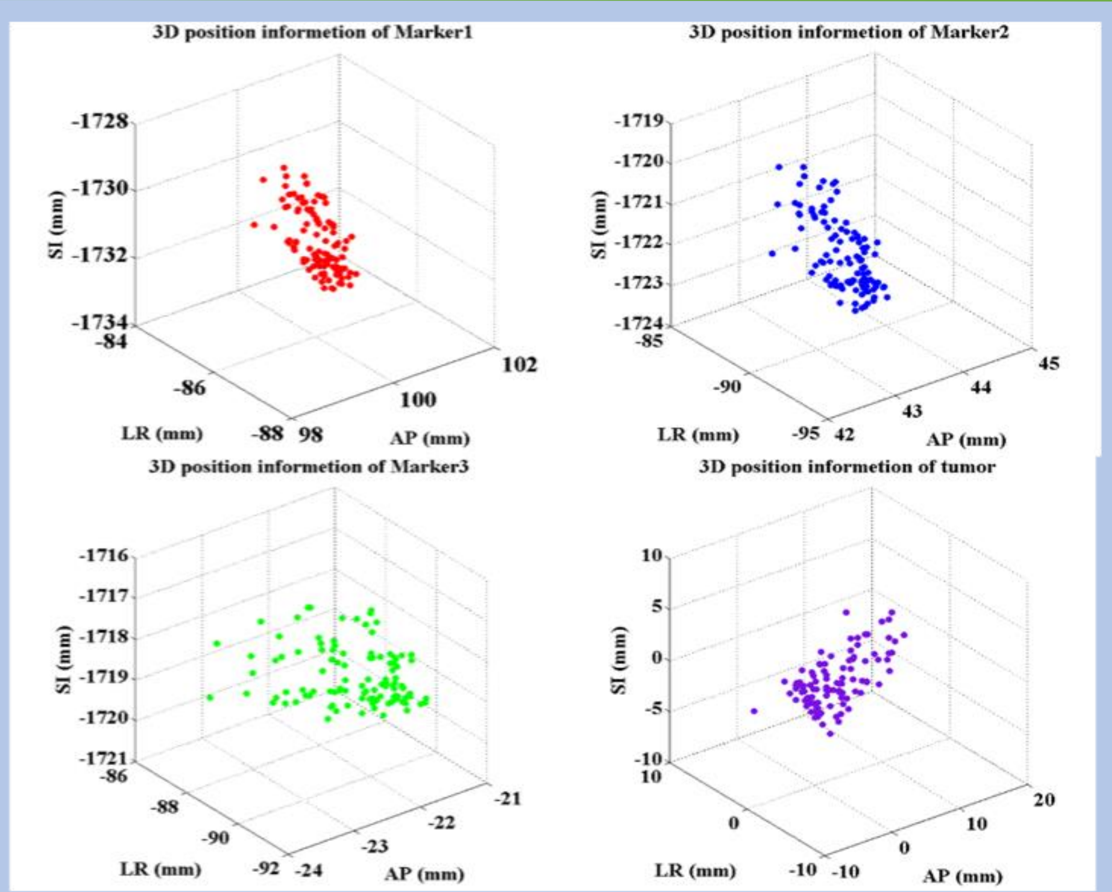
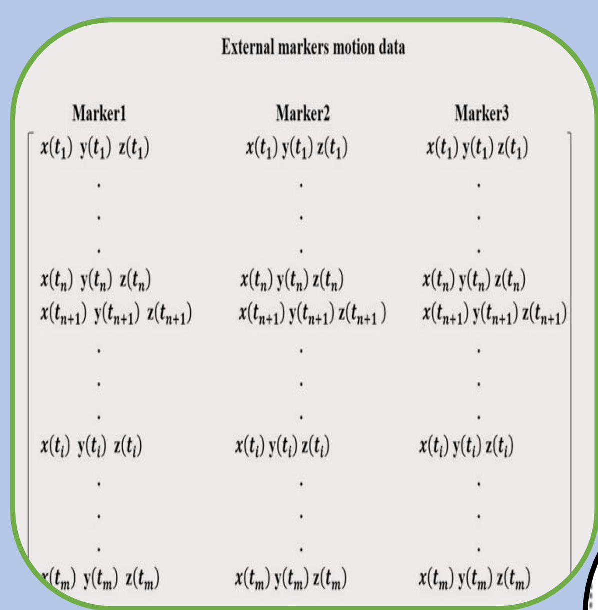
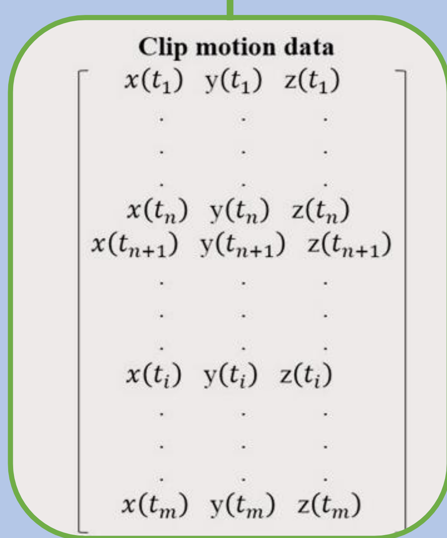


Figure 1) 3D position information of tumor (lower right) and external markers as data points of total dataset, including marker 1 (upper left), marker 2 (upper right) and marker 3 (lower left)



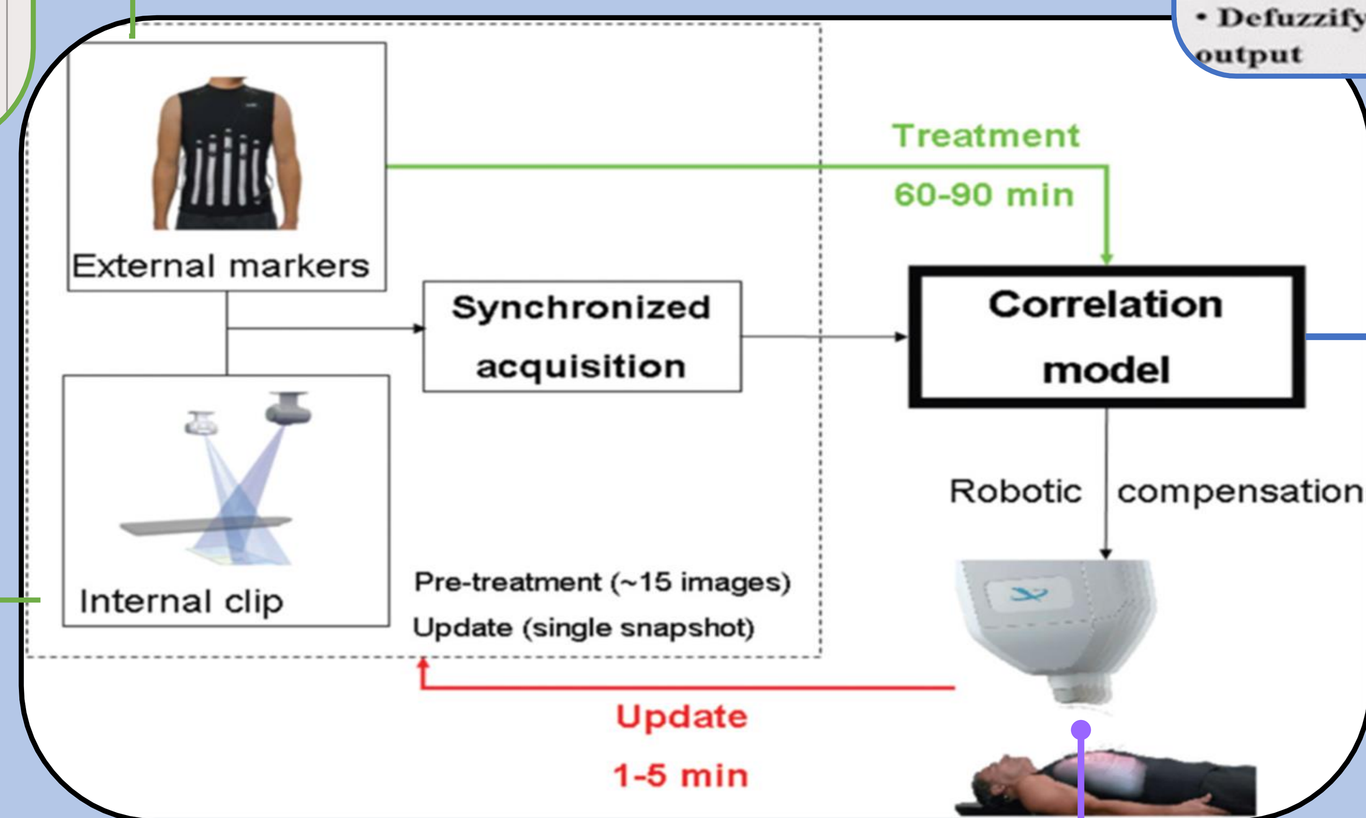


Patient no	Number of cluster	RMSE (mm) (by mamdani method)
P1	2	4.25
	3	3.59
	4	3.43
	5	3.30
P2	2	1.44
	3	1.39
	4	1.31
	5	1.25

Table 2) RMSE of fuzzy based model output in tumor tracking using Mamdani type with different number of data clustering

Fuzzy Inference system(FIS)

- Fuzzifying data
- Applying implication method
- Aggregating all the outputs
- Defuzzifying the output



Materials and Methods

Our proposed fuzzy prediction model involves data clustering [7-8] for membership function generation, as requirement for fuzzy inference system section. Our fuzzy model was implemented in MatLab (The MathWorks Inc., Natick, MA) using fuzzy logic toolbox. It should be noted that model must be done in pre-treatment step before irradiating using training dataset. Training data configurational includes the combination of 1) the motion of external markers located at thorax region of patient body in x,y and z directions as input of the model and 2) the corresponding internal tumor motion as model output in a synchronized fashion. In fuzzy inference system, internal tumor motion is correlated with external markers motion by data classifying, model learning and rule extraction steps. When the model is configured it is ready to trace tumor motion as real time versus time. Moreover, the model operation is routinely tested during the treatment by taking X ray images from tumor and realizing tumor location. It should be noted that the update data points are accumulated to collected training data for model re-building during treatment. In our fuzzy model, input data are reformed in a matrix with 9 columns, where columns represent the x(t), y(t) and z(t) of each marker position as function of time. In our model fuzzy inference method is working based on Mamdani and Sugeno types, independently and number of clusters are variable from 2 to 5 for Membership functions determination that are in Gaussian shape. Moreover, If-then rules are connected with AND (minimum selection criteria) operator in antecedent and consequent parts of fuzzy inference system. Defuzzification as final step is also achieved by Centroid Calculation method.

In our correlation model, Fuzzy C-Means (FCM) algorithm and Subtractive clustering methods were taken into account in initial data grouping to assess the robust and sensitive points of fuzzy based clustering method versus non-fuzzy case. When data clustering was done by FCM clustering algorithm, a set of fuzzy rules and membership functions according to the number of required clusters are extracted for next prediction processing. The database utilized in this work, belongs to a group of five real patients treated with Synchrony™ Respiratory Tracking System integrated with the CyberKnife® robotic linear accelerator (Accuray Incorporated, Sunnyvale, CA), between 2005 and 2007 [6].

Results

Figure 1 shows graphically position information of external markers (red, blue and green spots) three dimensionally implemented on patient with left lobe lung cancer. It should be noted that the location of tumor position is also shown in this figure (lower right subplot with violet spots). This patient has nine training data points for model configuring at pre-treatment with 98 updating data points captured during treatment and clustered with four groups. In this work we utilized Root Mean Square Error (RMSE) as common available mathematical metric for illustrating the performance uncertainty error of fuzzy prediction model. Table 2 represents RMSE of fuzzy logic based model using Mamdani type in fuzzy inference system in different number of clusters for two patients with left lob lung and chest wall cancers. As seen in this table, the RMSE is reduced by increasing the number of clusters using Mamdani type. We also implemented Sugeno type fuzzy inference system and the value of RMSE was 2.69 constant for each cluster. As resulted, the RMSE by implementing sugeno is remarkably less than the same calculation by means of Mamdani. Moreover, the computational time will be significantly decreased using Sugeno type. For example, the run time improvement is almost 33% for patient number 1 with left lob lung cancer. Figure 2 shows tumor tracking at the Superior Inferior (SI) direction of patient 1 as function of time in a specific treatment time interval versus imaging data points as benchmark dataset. Imaging data pints represents real position of tumor location and are utilized as reference. As shown, the behavior of fuzzy logic based prediction model is very close to the performance of Cyberknife modeler even better than utilized modeler at some times. For example, at three last imaging points fuzzy model perform more accurate than Cyberknife modeler, since fuzzy tracing is on the imaging data points with almost estimation no error.

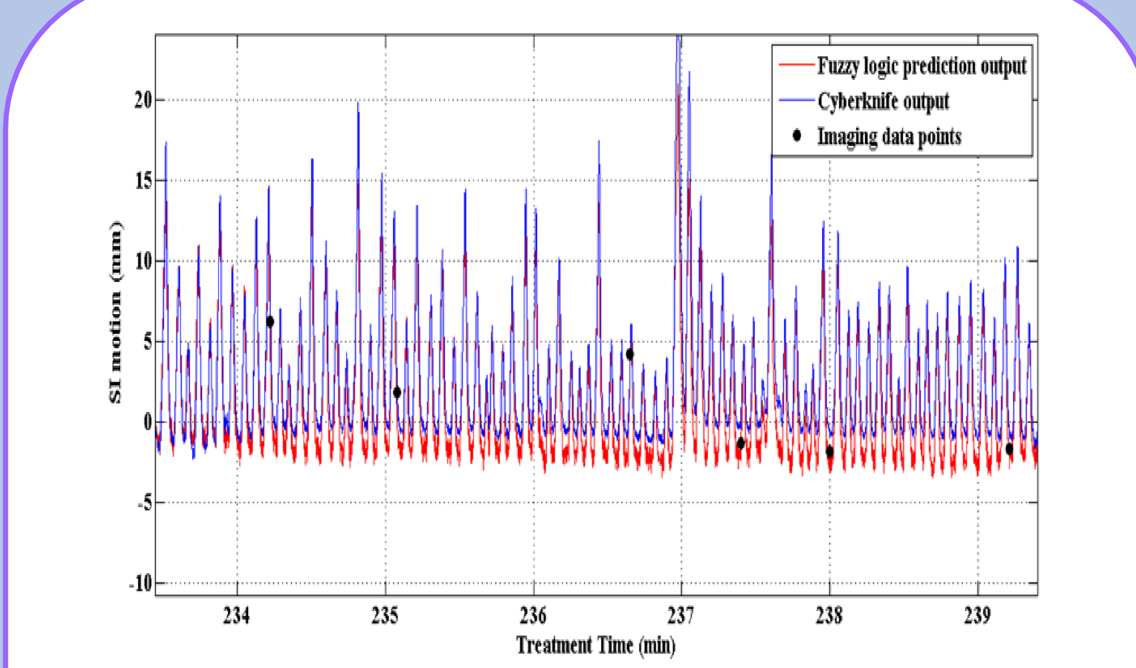


Figure 2) Tumor tracing at the SI direction of tumor motion on a fraction of treatment time using fuzzy model in comparison with Cyberkfine modeler

Discussion

At external surrogates radiotherapy, correlation model is an important component that predict tumor position using motion information of rib cage and abdomen regions. In this strategy, correlation model should be constructed at pre-treatment step using 1) motion information of external rib-cage and abdomen regions and 2) internal tumor motion, synchronously. The properties of motion dataset has been taken into account our previous studies. In this work, we investigated the parameters of proposed fuzzy correlation model. These parameters include the type of fuzzy inference system and the number of data clustering at each given type. Two Mamdani and Sugeno method were considered as fuzzy inference system. A number of data clustering was taken into account ranging from 2 to 5. Final analyzed results showed that the targeting error will be reduced while the number of motion data grouping increases by implementing Mamdani strategy and this error is almost same by implementing Sugeno method. But, the overall targeting error is reduced while implementing Sugeno against Mamdani as fuzzy inference system. But the number of data clustering is not same for all patients and this value is changing for each patient on a case by case basis. In fact, each patient has its unique breathing style and motion variations of respiration is high at each patient and among different patients. Due to this, selecting the optimum number of data clustering for each patient is different. Apart from targeting error, the effect of data clustering on model computational time is also important, since tumor motion tracking should be done as real time to be implemented clinically.

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