Enhancing respiratory motion prediction accuracy using audiovisual (AV) biofeedback.

Introduction

Optimal delivery of dose to a tumor in external beam radiotherapy requires maximal dose to the tumor while sparing the surrounding tissue of as much dose as possible. A significant source of motion for lung tumors is due to respiration. Should this motion be taken into account, it would result in a smaller treatment volume size, thereby reducing the irradiation of health tissues and decreasing the risk of radiation toxicity.

The accuracy of respiratory-related tumor motion prediction is hampered by any irregularities present in the breathing pattern [1]. The AV biofeedback system is able to guide the human subjects' breathing to produce a more reproducible breathing pattern [2], resulting in a reduction of irregularities often present in free-breathing. A more regular breathing pattern leads to an improvement in the accuracy of respiratory motion prediction and hence more effective radiotherapy treatment.

Method and Materials

The AV biofeedback system (Fig. 1) is comprised of an external marker positioned on the subject's abdomen whose motion is tracked by an infrared camera (RPM system). The subject must then follow the waveguide with their real-time abdominal position. The acquired respiratory data from the RPM is then run through a DMLC simulator developed by Prof. Keall [3] which can implement the prediction algorithm. The prediction algorithm utilized is a kernel density estimation-based real-time prediction algorithm as developed by Dan Ruan [4].

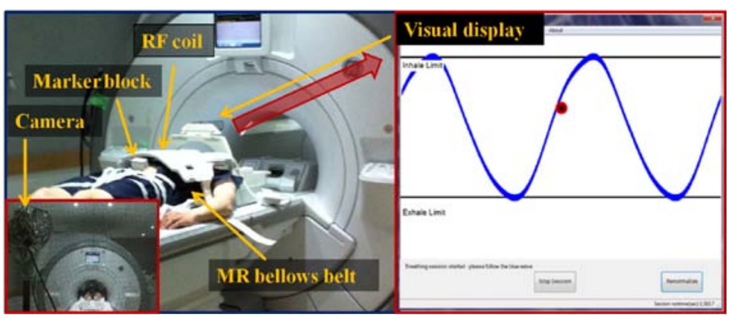

Fig.1. (left) AV biofeedback system in 3T GE MRI. (right) The screen of the audio-visual biofeedback system shows a guiding wave (blue curve) and a marker position (red ball) in real time.

Results and Discussion

The average difference between the measured and predicted data for free-breathing and AV biofeedback, across a range of parameters are shown in Table 1. Of the 20 sets of free-breathing data, 19 were improved with the implementation of the AV biofeedback system. The mean improvement of prediction accuracy with the implementation of AV biofeedback was a 67% reduction in error.

Parameters (DT*ms* / TE)	**Study 1**		**Study 2**		**Study 3**		**Study 4**		**Study 5**		**Average**	
	Free	**AV**	**Free**	**AV**	**Free**	**AV**	**Free**	**AV**	**Free**	**AV**	**Free**	**AV**
2500 / 100	1.97	0.64	3.13	0.93	1.88	0.74	3.28	0.66	2.41	0.51	2.53	0.69
2500 / 1500	1.98	0.63	3.14	0.93	1.88	0.74	3.25	0.64	2.42	0.49	2.53	0.68
1000 / 250	1.44	0.57	1.87	0.74	1.68	0.66	2.19	0.66	1.85	0.44	1.81	0.61
500 / 250	0.92	1.06	0.96	0.56	1.05	0.51	1.21	0.56	1.03	0.34	1.03	0.60

Table 1. Average difference (in *mm*) between the real and predicted data for the 5 human subjects across a

range of prediction algorithm parameters.

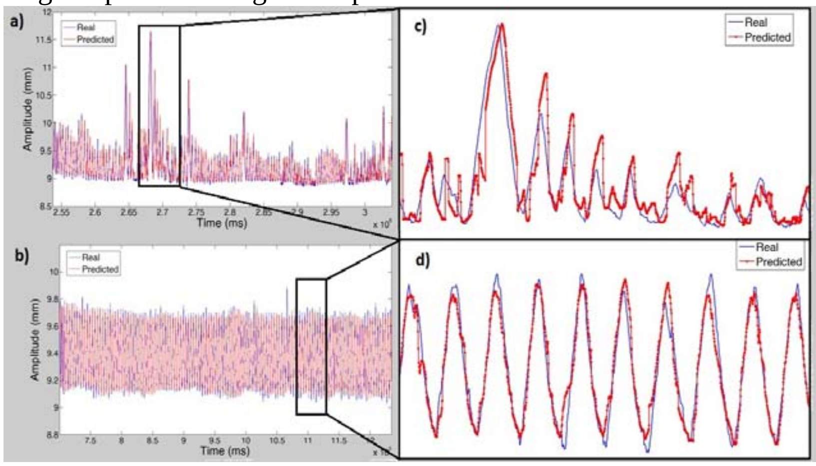

Fig. 2. Breathing data from Study 5: DT/TE = 500/250. a) Free-breathing (blue) and the resultant prediction data (red); similarly for b) except AV biofeedback was implemented. c) and d) show expanded sections of a) and b) respectively with the respiratory data (blue) and the resultant prediction (red dots). Fig. 2c shows that the prediction accuracy is hindered by an irregular breathing pattern, while Fig. 2d demonstrates the improvement of prediction accuracy in the presence of a regular breathing pattern.

Fig. 3 demonstrates the variation of prediction accuracy with breathing pattern irregularity and complexity. Fig. 3a clearly shows that the reduction of amplitude variations (as a result of AV biofeedback implementation) results in increased prediction accuracy across a range of parameters. Similarly, Fig. 3b demonstrates a larger spread prediction inaccuracy for free-breathing in regards to the range of frequencies present in the breathing pattern.

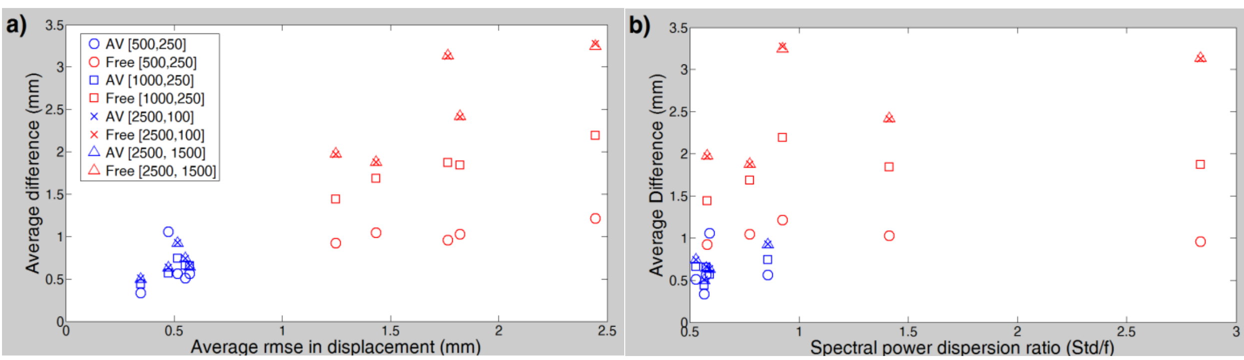

Fig. 3. Variation of motion prediction accuracy with breathing pattern complexity. a) Takes into account the variations in amplitude. b) Takes into account the spread of frequencies present in the breathing pattern.

In addition to the five human subject studies discussed here, there are an additional 25 studies that are currently undergoing motion prediction.

References

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4. Dan Ruan. *Kernel Density Estimation-Based Real-Time Prediction for Respiratory Motion.* Phys. Med. Biol. **55.** (2010). 1311-1326.