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JOINT AAPM | COMP MEETING

"A simulation study of the safety and efficiency of respiratory-gated radiotherapy using a hybrid deep-learning network adaptable to breathing irregularity to predict internal motion."

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ABSTRACT

Object: To evaluate the safety and efficiency of respiratory-gated radiotherapy by using a long-short-term memory (LSTM) model and its hybridized version with time-domain cross-correlation (TCC) to adapt to breathing motion irregularities in near real0time without remodeling.

Methods: Subject-specific deep-learning LSTM networks were trained using concurrent external-internal motion waveforms (20Hz, 88s-300s) from 10 subjects, and the LSTM motion prediction (with a latency of 200ms) was safeguarded with a conventional TCC technique (LSTM-TCC) to check and correct (latency <100ms) any residual time/phase shifts in the LSTM predictions. The LSTM-TCC model yields an equal or better external-internal correlation by eliminating the residual time (phase) shifts. The LSTM model was trained with 1,760-60,000 time points (88-300s, 20Hz) of external-internal motion waveforms to predict internal motion over 20-30-minute timeframes. The 30% breathing amplitude from the simulation 4DCT was used as the gating threshold for the breamOn window. Using the native motions, TCC, LSTM, and LSTM-TCC predictions, the gating uncertainty (percentage of false beamOn time over all beamOn time, %harm) and gating efficiency (percentage of correct beamOn time over the available gating window, %efficiency) were used to quantify the gating quality.

Results: The LSTM and LSTM-TCC models produce low %harm=8.3±8.4% and 5.2±5.7% in 20-30 minutes, improved from %harm=17.1±18.2% by TCC and 45.1±23.8% for native data. High %efficiency of 64.5±15.9% and 66.5±15.1% are achieved by using LSTM and LSTM-TCC models, respectively, better than the conventional TCC method (%efficiency=48.2±18.8%). The adaptive LSTM-TCC demonstrates its advantage for subjects 4 and 7, who experience substantial breathing irregularities. A higher gating performance is observed within shorter timeframes (5-10 minutes) from the training dataset.

Conclusion: The simulation results demonstrate that the LSTM-TCC model is superior to LSTM alone, especially for patients with large breathing irregularities, as TCC safeguards against any residual time/phase shifts within the LSTM prediction caused by breathing motion irregularities.

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INTRODUCTION

A long short-term memory (LSTM) deep learning network has been applied to predict external-to-internal organ motion, and the model prediction in the presence of breathing irregularities beyond the training dataset has been improved by correcting the residual phase shift in the predicted motion using a time-domain cross-correlation (TCC) method as an effective adaptation. Therefore, both accuracy and stability of LSTM model prediction are significantly improved over the conventional approach and LSTM model alone[1,2]. The clinical value of this adaptive LSTM-TCC model is worth further exploring by assessing the accuracy, safety, and efficiency of LSTM-TCC-guided respiratory gating.

In this study, we simulate and evaluate respiratory-gating quality by comparing patient-specific LSTM and adaptive LSTM-TCC predictions as gating signals over a 20-30-minute timeframe, which is comparable to the time to deliver a fraction of radiotherapy.

METHODS AND MATERIALS

Subject-specific LSTM models were trained using 2-5-min concurrent motion waveforms from external bellow and internal navigator at the diaphragm. The models were tested using the waveforms acquired during next 2-5 mins and anther 10 mins after 20-30 mins time interval. The TCC method was applied to check the LSTM predictions and correct any residual phase shifts. Ten healthy subjects participated in the IRB-approved MRI protocol study, in which MRI navigator (1D motion signal within 6x3x3 cm^3 FOV) was set on the right diaphragm dome.

METHODS AND MATERIALS (con't)

Respiratory gating threshold was set 30% at external signal to ensure accurate 50% internal gating. The original, TCC, LSTM, and LSTM-TCC external-to-internal motion models were used to guide the gating (beamOn and beamOff). First, the temporal accuracy of gating window prediction was assessed. ting The fraction of incorrect beamOn time over all predicted beamOn time (%harm) and the fraction of correct beamOn time over the available gating window (%efficiency) were used to quantify the quality of respiratory gating. The gating results were analyzed and compared.

RESULTS

The external-to-internal motion correlation (C) calculated using the 4 different models is presented in Figure 1, showing significant improvements when using LSTM and LSTM-TCC models for mid-term prediction (Fig. 1A) and the advantage of LSTM-TCC models in subjects 4 and 7, who experienced substantial breathing irregularities in long-term (20-30mins). The adaptive LSTM-TCC model resecured the LSTM predictions, boosting the correlation from C=0.6 to C>0.8 (C=0.90±0.04 on average).

The lowest %harm = 5% on average was achieved using the LSTM-TCC predictions, improved from %harm = 8% by LSTM alone, %harm = 30% by TCC model, and %harm = 37% by native correlation, as shown in Table 1. At the same time, the %effic. was improved from %effic=38% (Native), %effic=43% (TCC), to %effic=64% (LSTM) and %effic=66% (LSTM-TCC).

When the LSTM model works, applying TCC to check its prediction produces almost the same results, as shown in Table 2 (mid-term and long-term, except subjects 4 & 7).

DISCUSSION

The LSTM model's predictions work very well when no substantial breathing irregularities occur after the model is built (Tables 1 and 2). In this case, the LSTM model prediction is very accurate (C>0.9 on average and similar gating quality), as it produces little phase shift in the prediction results. Therefore, adding TCC does not change the results. Additionally, the TCC calculation is fast and completed within 100ms, resulting in minimal time delay. Moreover, the LSTM prediction can be applied to predict up to 500ms in advance[3]; therefore, latency is no longer a concern.

When substantial breathing variations occurred, as for subjects 4 and 7, noticeably improved gating performance by LSTM-TCC over LSTM alone was observed (Tables 1 and 2). Otherwise, the LSTM-TCC model's performance was similar to that of LSTM alone, which was superior to the conventional TCC or using native datasets directly. The long-term stability of the LSTM-TCC model in respiratory gating has demonstrated the necessity of safeguarding the LSTM motion prediction to maintain high gating quality and performance over a 20-30-minute timeframe.

It is also worthwhile to point out that we have set 2 different gating thresholds for external signal and internal action. A tighter external threshold (30%) allows a higher error tolerance for internal gating (50%) results. Clinically, the 50% threshold is an acceptable value for respiratory gating. The LSTM model prediction with the adaptation from TCC has, for the first time, produced an accurate and robust respiratory gating based on this simulation study. Further clinical evaluation is expected and would provide added value to respiratory gating in the future.

Table 1. Gating quality for 30 minutes after the LSTM model is built.

Subject	%harm				%efficiency			
	Initial	maxTCC	LSTM	LSTM-TCC	Initial	maxTCC	LSTM	LSTM-TCC
1	7.8	0.0	0.0	0.0	55.4	59.9	62.5	62.5
2	37.9	0.0	0.0	0.0	37.0	60.8	77.4	77.7
3	9.1	0.0	0.0	0.0	54.6	60.7	68.8	68.8
4	*44.5*	*71.0*	***23.7***	***10.0***	*33.3*	*17.7*	***61.8***	***72.0***
5	24.8	19.8	11.6	11.6	44.9	48.0	55.3	55.3
6	36.1	13.5	5.8	5.8	38.3	51.9	69.5	69.5
7	*30.1*	*89.6*	***17.6***	***0.2***	*41.9*	*6.4*	***48.4***	***58.5***
8	79.7	24.0	8.0	8.0	12.2	45.7	99.1	99.1
9	31.9	23.3	1.4	0.9	40.9	46.3	42.8	42.8
10	69.4	50.6	15.1	15.1	18.4	30.4	59.1	59.1
Avg	37.1	29.2	8.3	5.2	37.7	42.8	64.5	66.5
Std	23.1	31.3	8.4	5.7	13.8	18.8	15.9	15.1

Table 2. %harm in mid-term and long-term after the LSTM model is built.

Subject	%harm (%), mid-term (5-10 minutes)				%harm (%), long-term (20-30 minutes)			
	Native	Max TCC	LSTM	LSTM-TCC	Native	Max TCC	LSTM	LSTM-TCC
1	25.8	6.1	1.3	1.3	7.8	0.0	0.0	0.0
2	53.7	14.6	2.2	2.2	37.9	0.0	0.0	0.0
3	2.7	0.0	0.0	0.0	9.1	0.0	0.0	0.0
4	46.0	5.1	4.6	3.3	44.5	71.0	**23.7**	**10.0**
5	26.5	20.5	14.2	13.6	24.8	19.8	11.6	11.6
6	32.5	11.7	6.1	6.1	36.1	13.5	5.8	5.8
7	53.7	5.5	6.4	7.7	30.1	89.6	**17.6**	**0.2**
8	77.2	11.6	5.3	5.3	79.7	24.0	8.0	8.0
9	79.1	60.5	9.6	9.6	31.9	23.3	1.4	0.9
10	54.0	35.3	23.0	23.0	69.4	50.6	15.1	15.1
Avg	45.1	17.1*	7.3†	7.2†	37.1	29.2	**8.3‡**	**5.2‡**
Std	23.8	18.2	6.9	6.9	23.1	31.3	8.4	5.7

CONCLUSIONS

This study assesses the simulated respiratory-gating qualities of four methods, demonstrating that the hybrid LSTM-TCC approach outperforms the native waveforms, the TCC method, and the LSTM models, yielding the highest correlation, gating accuracy, and %effic, but the least %harm. The hybrid LSTM-TCC model can safeguard LSTM predictions and gating accuracy against major breathing irregularities, demonstrating a strong potential for future clinical applications.

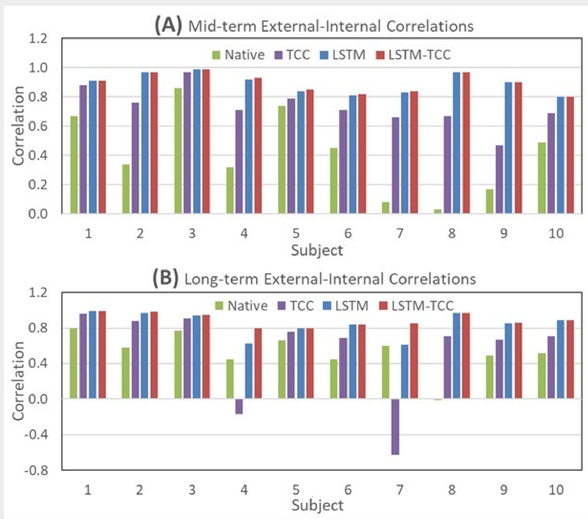

Figure 1. Comparison of the external-to-internal motion predictions among four different prediction models.

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