A DEEP NEURAL NETWORK BASED MANEUVERING-TARGET TRACKING ALGORITHM

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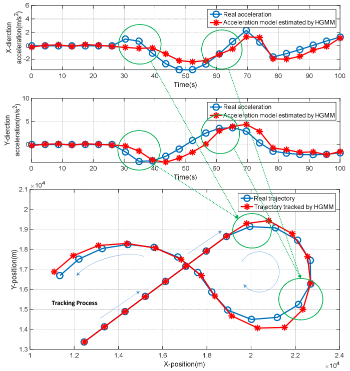
I. Introduction

Motivation

For maneuvering-target tracking (MTT), traditional MTT algorithms need time to accumulate sufficient information of target state to estimate the current maneuvering models. However, the maneuvering models are always unknown and changing in practical MTT scenarios, causing a time-delay issue of model estimation and affecting the performance of tracking.



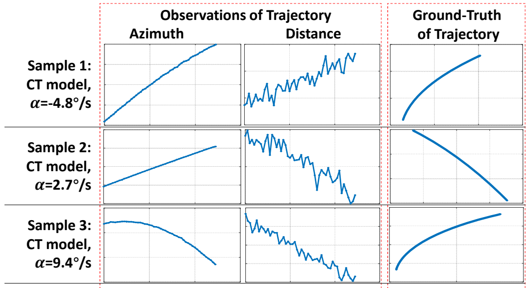
Contribution

1. An LAST database is built to offer sufficient training data for tracking maneuvering targets.
2. A DeepMTT network is proposed to track a maneuvering target by learning from the extensive trajectory data of the LAST database.

II. LAST Database

Samples in LAST database:

1. Trajectory segments (ground-truth). Each segment lasts 5s. All segments cover the target distances from 0.5 to 20 nautical miles, the target velocities from 0 to 340 m/s and the maneuvering turn rates from -10 to 10 °/s.
2. Observations of trajectory segments (input-data).
3. 10 million samples in LAST database.

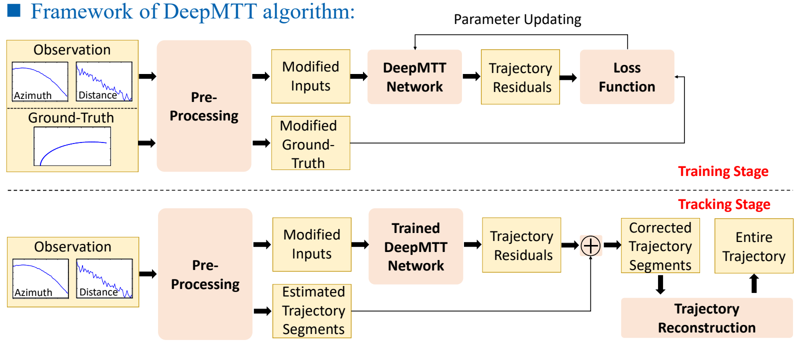


Sample generator:

1. Based on the state space model.
2. Under the constraints of practical maneuvering scenarios.

III. DeepMTT Algorithm

Framework of DeepMTT algorithm:

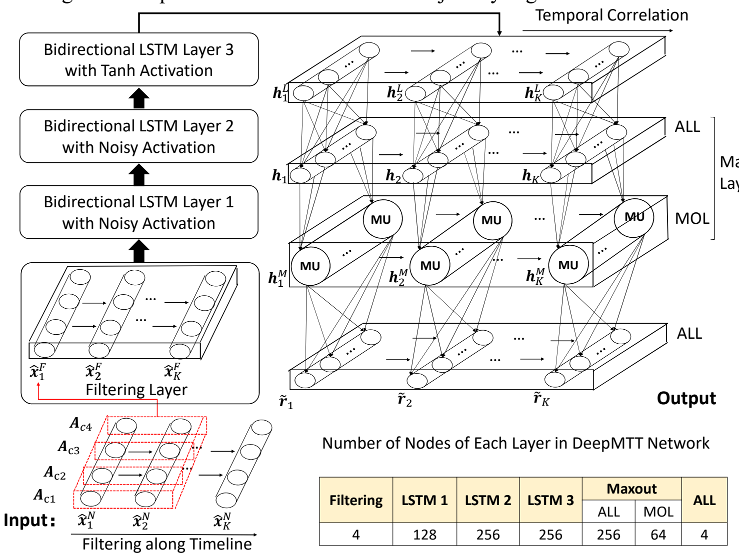


Pre-processing:

- Filter the observation data by standard UKF algorithm with constant-velocity model.
- Output normalized filtering results of target state sequence $\{\hat{\boldsymbol{x}}_1^N, \hat{\boldsymbol{x}}_2^N, \dots, \hat{\boldsymbol{x}}_K^N\}$ as modified inputs of DeepMTT network and trajectory residual sequence $\{\boldsymbol{r}_1, \boldsymbol{r}_2, \dots, \boldsymbol{r}_K\}$ as modified ground-truth of DeepMTT network.

Structure of the DeepMTT network:

- Input normalized filtering results of target state sequence $\{\hat{\boldsymbol{x}}_1^N, \hat{\boldsymbol{x}}_2^N, \dots, \hat{\boldsymbol{x}}_K^N\}$
- Output the estimation of trajectory residual sequence$\{\tilde{\boldsymbol{r}}_1, \tilde{\boldsymbol{r}}_2, \dots, \tilde{\boldsymbol{r}}_K\}$, which is added to target sate sequence to form the corrected trajectory segments.



Number of Nodes of Each Layer in DeepMTT Network

Filtering	LSTM 1	LSTM 2	LSTM 3	Maxout		ALL
				ALL	MOL	
4	128	256	256	256	64	4

Loss function:

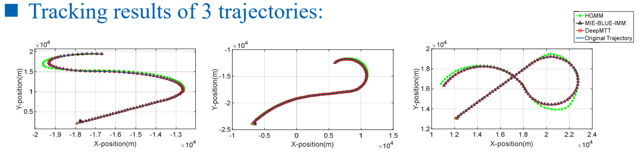
$$\mathcal{L} = \sqrt{\sum_{k=1}^{K} (\tilde{\boldsymbol{r}}_k - \boldsymbol{r}_k)^2}$$

IV. Result

Settings of 3 trajectories of maneuvering targets:

Trajectory	Prior target state x_0	The first part	The second part	The third part
1	[-18000 m, 2000 m, 150 m/s, 200 m/s]	30 s, CV model	40 s, CT model, α=3.18°	30 s, CT model, α=-6.54°
2	[-7000 m, -24000 m, 180 m/s, 220 m/s]	40 s, CT model, α=-1.08°	20 s, CV model	40 s, CT model, α=5.34°
3	[12000 m, 13000 m, 230 m/s, 190 m/s]	30 s, CV model	40 s, CT model, α=-7.16°	30 s, CT model, α=4.24°

Tracking results of 3 trajectories:



Tracking RMSE of DeepMTT algorithm in comparison with HGMM and MIE-BLUE-IMM algorithms:

- Means of the position tracking RMSE for all trajectories.

Trajectories		HGMM (m)	MIE-BLUE-IMM (m)	DeepMTT (m)
1	The first part	22.96	121.66	12.67
	The second part	138.29	55.24	12.98
	The third part	237.29	57.76	24.90
2	The first part	53.47	94.02	13.97
	The second part	23.67	56.45	12.12
	The third part	140.91	55.17	13.24
3	The first part	23.45	56.50	12.42
	The second part	278.06	59.89	17.63
	The third part	160.58	58.12	16.74

- Deviations of the position tracking RMSE for all trajectories.

Trajectories		HGMM (m)	MIE-BLUE-IMM (m)	DeepMTT (m)
1	The first part	2.92	13.99	2.58
	The second part	12.45	3.06(m)	2.77
	The third part	24.45	3.84	15.65
2	The first part	6.87	10.06	2.26
	The second part	3.72	4.61	2.65
	The third part	11.77	2.80	2.57
3	The first part	3.08	3.36	2.37
	The second part	31.43	3.82	12.35
	The third part	20.29	4.21	11.82

- Means of the velocity tracking RMSE for all trajectories.

Trajectories		HGMM (m/s)	MIE-BLUE-IMM (m/s)	DeepMTT (m/s)
1	The first part	12.38	159.55	3.91
	The second part	45.30	161.19	9.08
	The third part	84.74	162.34	13.88
2	The first part	18.57	178.53	4.59
	The second part	12.84	153.39	4.11
	The third part	68.83	183.68	7.85
3	The first part	13.86	190.53	8.45
	The second part	108.93	191.92	7.51
	The third part	59.96	189.75	7.71

- Deviations of the velocity tracking RMSE for all trajectories.

Trajectories		HGMM (m/s)	MIE-BLUE-IMM (m/s)	DeepMTT (m/s)
1	The first part	1.61	2.11	0.91
	The second part	1.30	1.53	1.03
	The third part	2.95	1.59	3.33
2	The first part	0.97	1.95	0.79
	The second part	1.74	2.59	1.04
	The third part	1.76	1.58	1.08
3	The first part	1.70	2.05	1.17
	The second part	2.96	1.54	2.56
	The third part	2.40	1.78	1.48

Conclusion

- A generative trajectory database of maneuvering target was built.
- A new DeepMTT network is proposed based on the bidirectional LSTM structure.
- In comparison with state-of-the-art maneuvering target tracking algorithms, our DeepMTT algorithm improves the performance on maneuvering-civil-aircraft tracking scenarios.

Information

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Code for our DeepMTT algorithm

- https://github.com/ljx43031/DeepMTT-algorithm

Reference

[1] X. R. Li and V. P. Jilkov, "Survey of maneuvering target tracking. part i. dynamic models," IEEE Trans. Aerosp. Electron. Syst., vol. 39, no. 4, pp. 1333 – 1364, 2003.

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