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High-accuracy target tracking for multistatic passive radar based on a deep feedforward neural network

Key words: Deep feedforward neural network; Filter layer; Passive radar; Target tracking; Tracking accuracy

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High-accuracy tracking

- Target tracking is a fundamental and active research topic in many fields, such as radar, navigation, and smart driving systems. The primary purpose of target tracking is to accurately estimate the target state in motion space.

- High-accuracy tracking is important, especially for the detection of small and low-speed targets (e.g., unmanned aerial vehicles (UAVs)), which may help terminate the sabotage activities of UAVs and ensure better and safer airspace management. How to improve the tracking accuracy remains an important problem.

Challenges and tendency

- The existing tracking algorithms are dependent on an accurate system model. Nevertheless, an accurate system model requires the extraction of more useful information from the measurement data.

- The measurement data are nonlinear and contain errors. Target tracking based on an accurate model is challenging and difficult to adapt to application requirements.

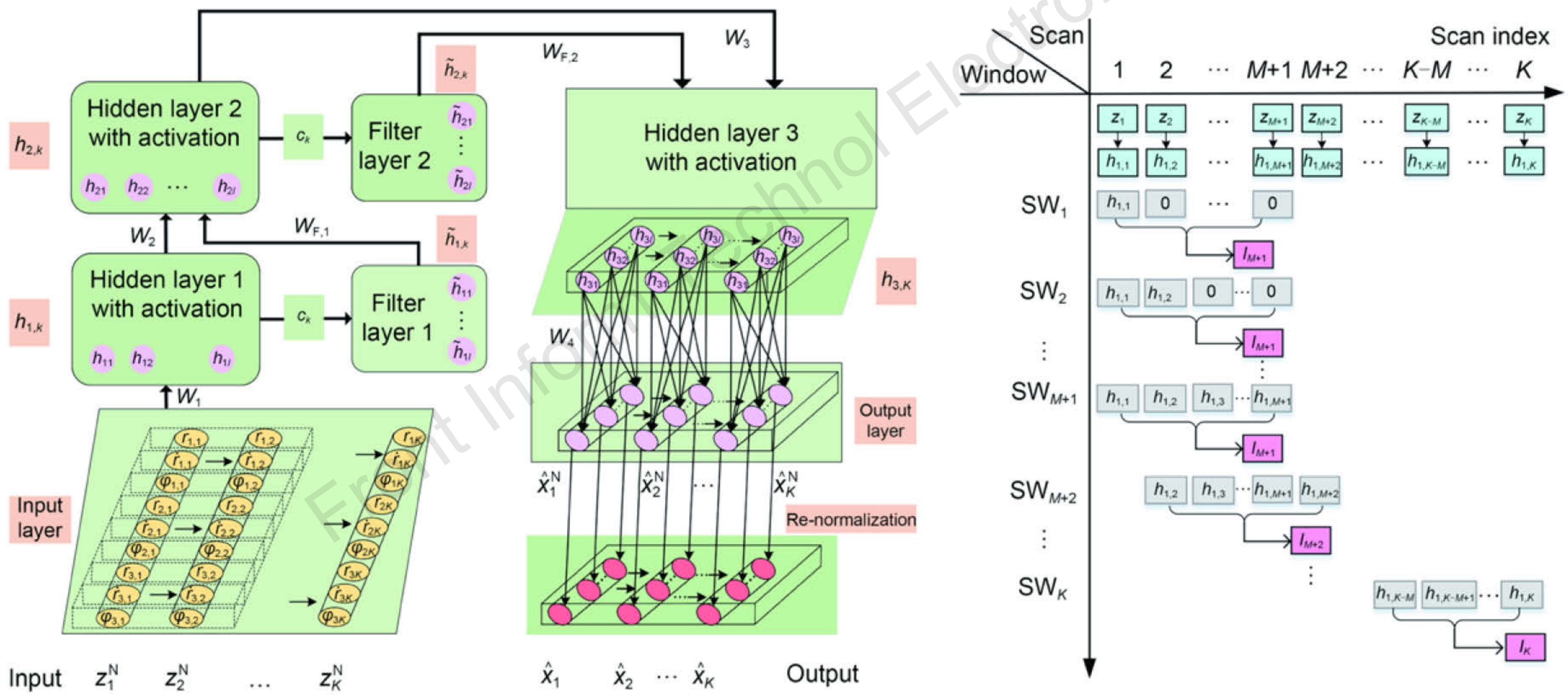
Type	Method
Analytical Gaussian approximate tracking	It is designed by approximating the PDF of the target state to a Gaussian or mixed Gaussian distribution (EKF, UKF, and QKF)
Random sampling approximate tracking	It approximates the conditional probability distribution of the state and realizes the transition of the conditional probability using the Bayesian theory (PF, SPF, UPF, MPF, and GPF)

- Target tracking is evolving from model-driven to data-driven. In recent years, data-driven approaches have achieved great breakthroughs and have been applied to many fields.

Main idea

- We design a new filter layer for modified DFNN (MDFNN)

Target tracking needs to establish the long-term dependency of measurement in time series, but a deep feedforward neural network (DFNN) cannot model the dependency without a recurrence structure. Hence, a finite impulse response (FIR) filter is embedded between the hidden layers to solve the problem.



The proposed target tracking algorithm can handle measurement sequences of any length by a filter layer that is formed by FIR, extract more target motion features, and achieve higher tracking accuracy.

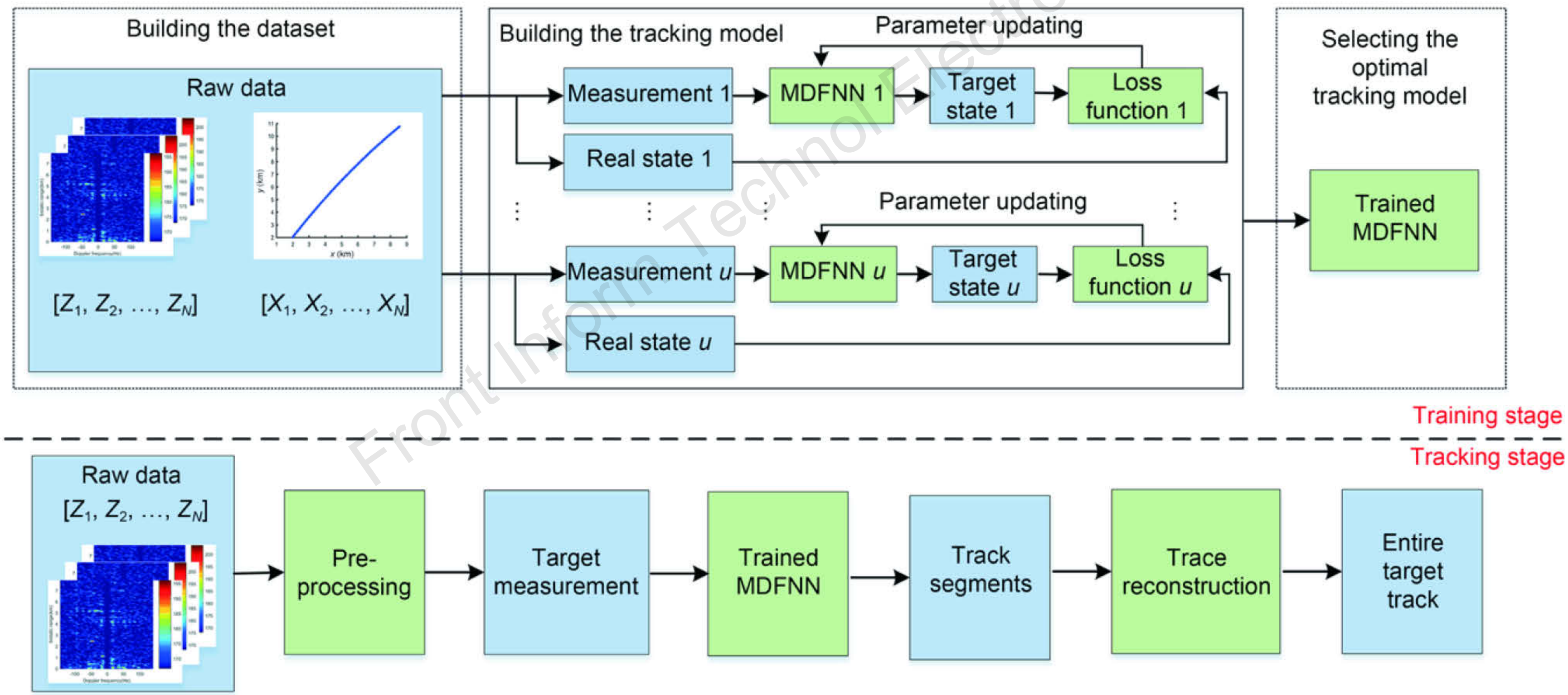
Main idea

- An accurate regression model is established efficiently by exploiting DFNN/MDFNN for target feature extraction and state estimation.

  Compared with other recursive neural networks (NNs), DFNN/MDFNN can achieve better generalization performance with a much higher learning rate. In addition, the influence of the measurement sequence size in the input layer on the tracking network is considered. The difference in measurement sequences affects the acquisition of target information and then influences the tracking performance. A trade-off scheme is developed based on an experiment to select an appropriate sequence length.

Framework

- The upper part shows the training stage where the preprocessed data are used to train the tracking network according to a designed cost function. The lower part shows the tracking stage where the trained tracking network is used to estimate the target state.



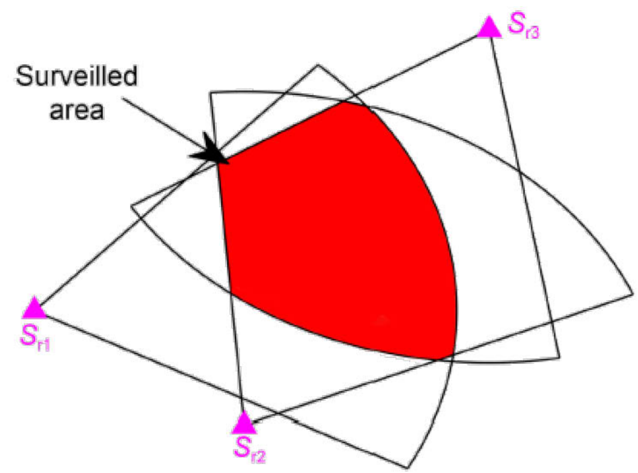
Tracking method

☐ Building the dataset of the target

state equation	$\boldsymbol{x}_k = \boldsymbol{f}(\boldsymbol{x}_{k-1}) + \boldsymbol{\mu}_k$
measurement equation	$\boldsymbol{z}_k = \boldsymbol{h}_n(\boldsymbol{x}_k) + \boldsymbol{\omega}_k = [r_k, \dot{r}_k, \varphi_k]^{\mathrm{T}} + \boldsymbol{\omega}_k$
$\boldsymbol{f}(\cdot)$	Constant acceleration (CA)

Ranges of target states

Parameter	Range
Distance from the passive radar	$0.2 \sim 11\,\mathrm{km}$
Speed of the UAVs	$0 \sim 26\,\mathrm{m/s}$
Azimuth from the passive radar to the UAVs	$-60^{\circ} \sim 60^{\circ}$

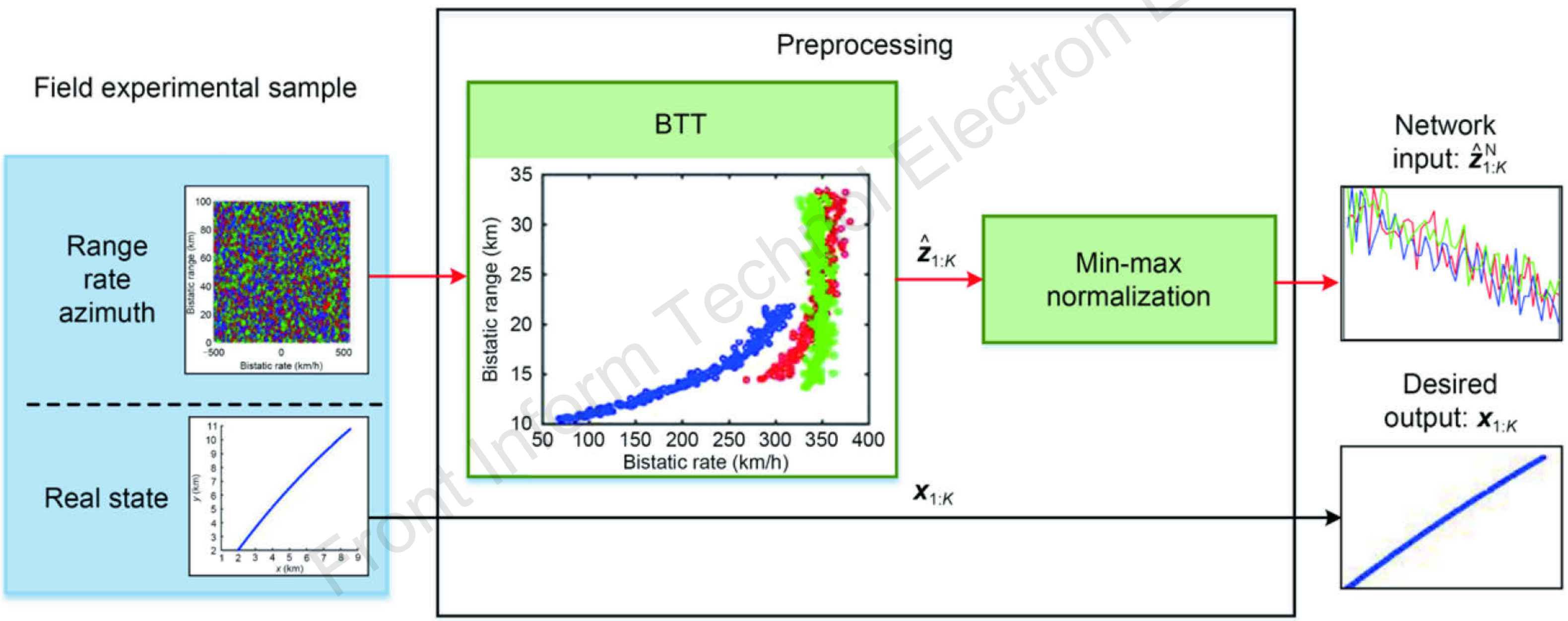


Graphical illustration of the surveilled area for passive radar

Tracking method

- ☐ Building the tracking model

The proposed tracking network is used to learn the information of input sequence $\boldsymbol{z}^{\mathrm{N}}_{1:K}$ to output the estimates of state $\boldsymbol{x}_{1:K}$.



Preprocessing (BTT: bistatic target tracking)

Original measurements and the real states of tracks are processed to generate the normalized input–output pairs, which are suitable for training the tracking network.

Tracking method

- Determination of the optimal tracking model

1 **Training process**

Train inherent parameters

2 **Validation process**

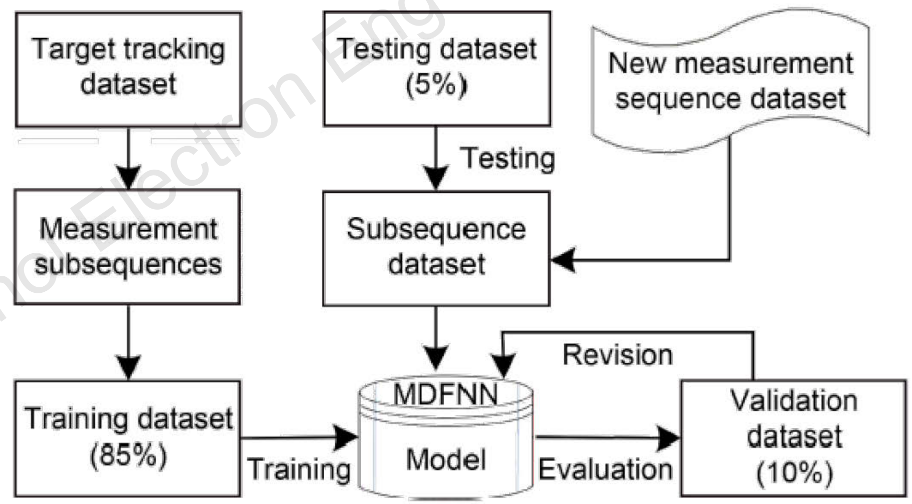
Cross-validate every trained tracking model

3 **Testing process**

Five percent of the dataset is used to test each MDFNN

4 **Model selection**

Some new datasets are chosen to test each acquired MDFNN

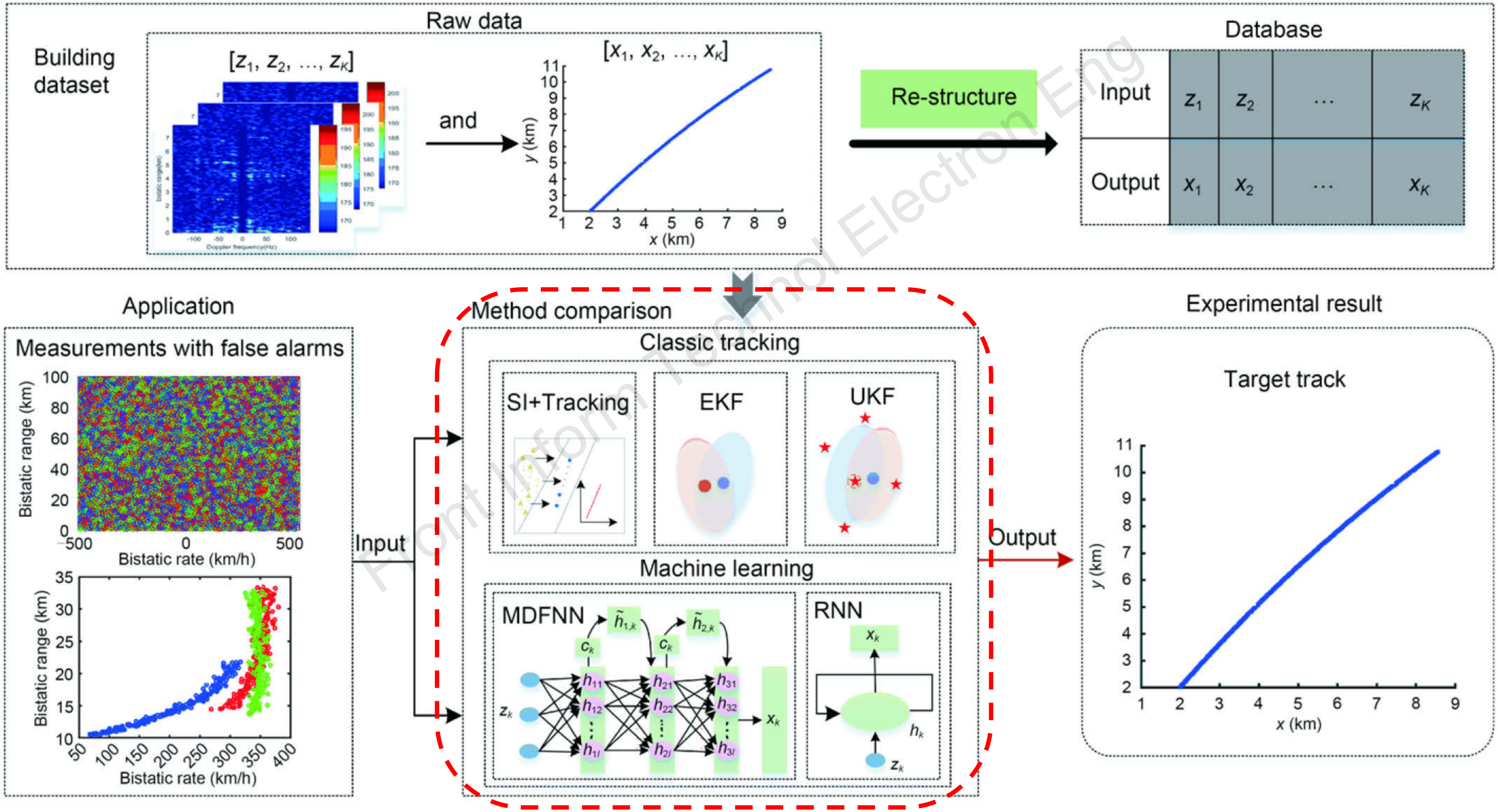


Flowchart of training an MDFNN model

Optimal tracking model

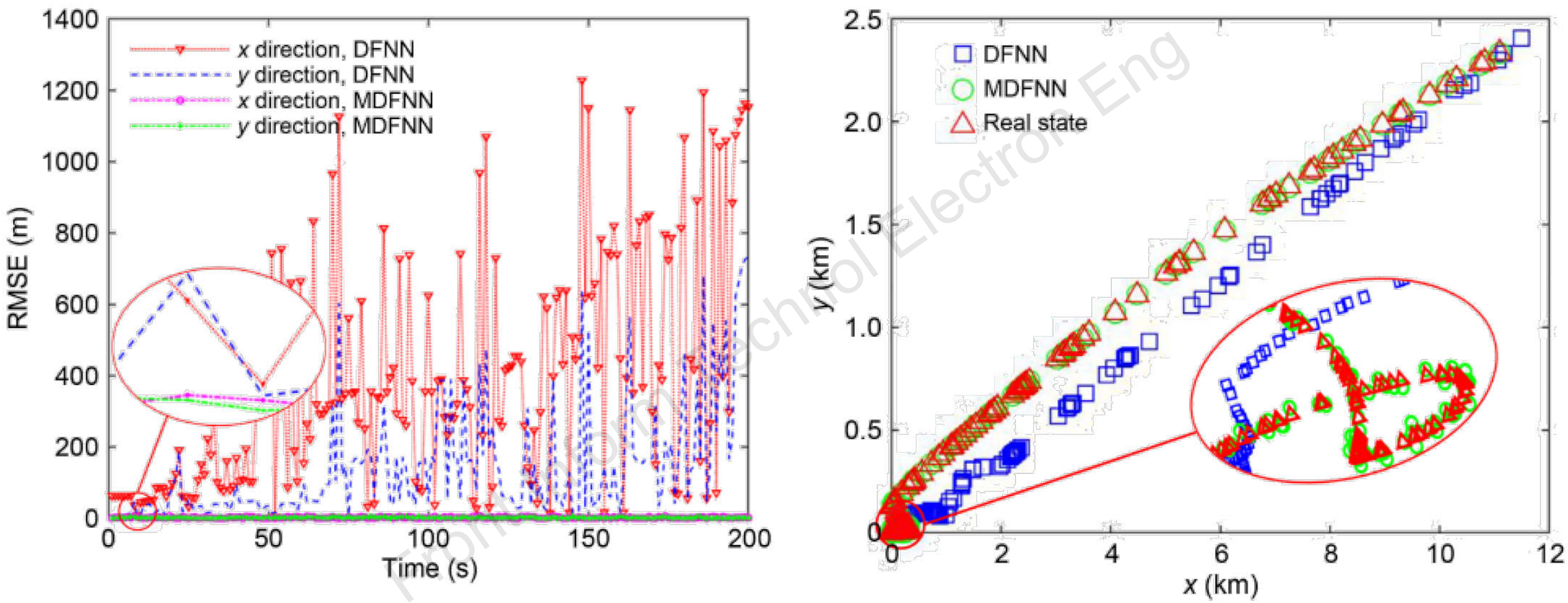
Tracking method

- Target tracking method comparison framework



Major results

- ☐ Ablation experiment

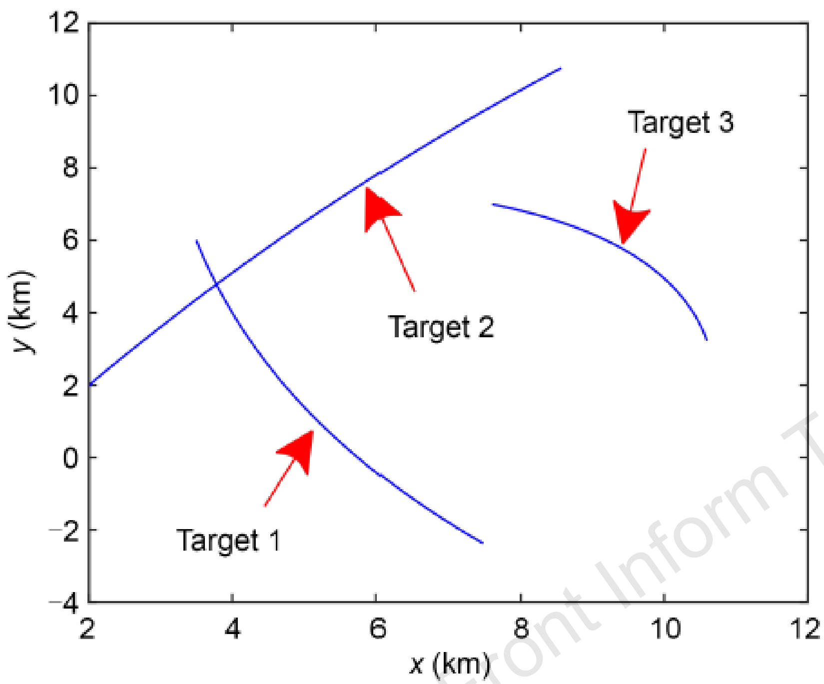


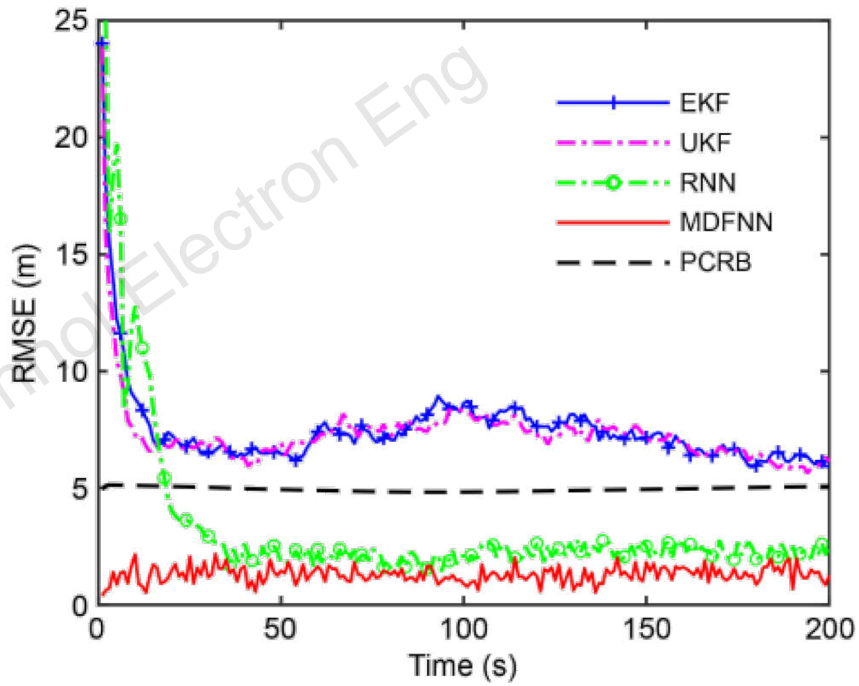
(a) (b)

Training results of the tracking network without the filter layer: (a) position RMSE of the tracking network based on DFNN or MDFNN in testing; (b) results of tracking by the tracking network based on DFNN or MDFNN

Major results

- Performance comparison



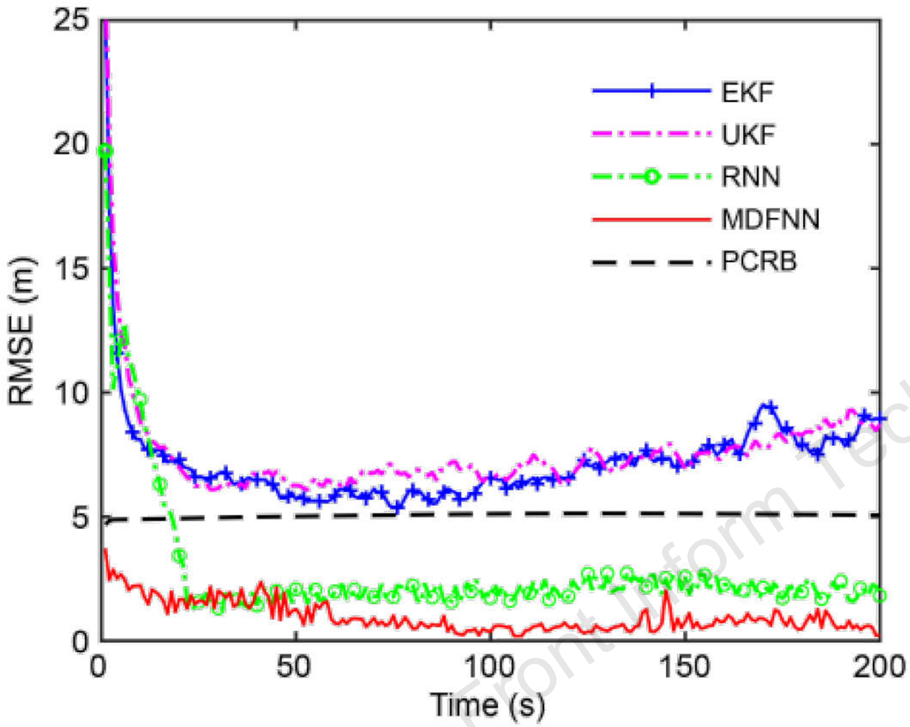


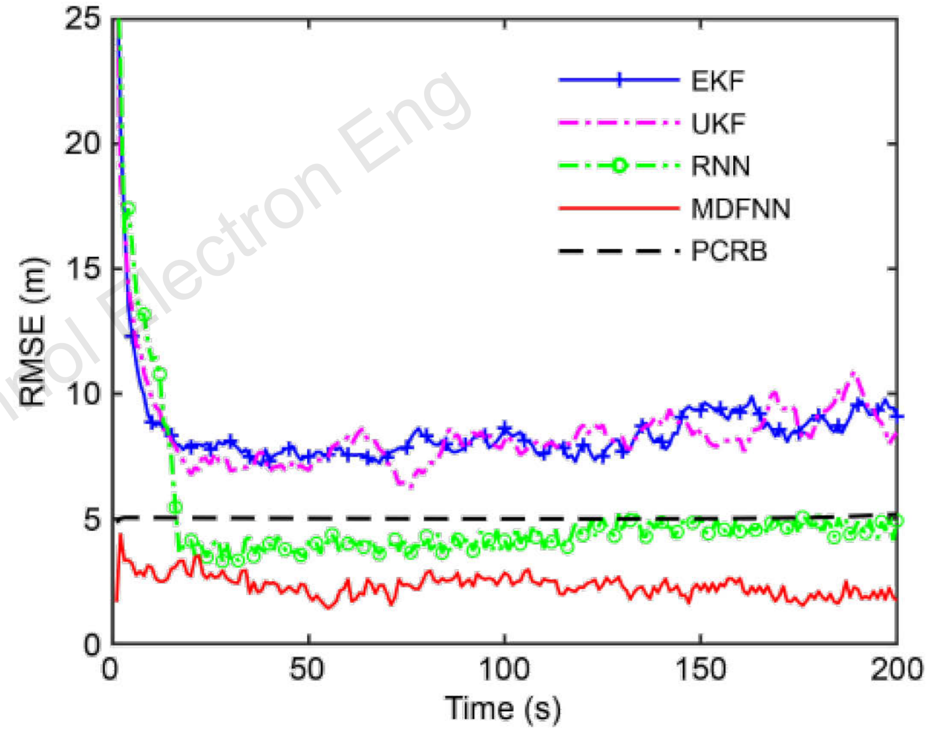
Three aerial targets in Cartesian coordinates (simulation data)

Performance comparison among the proposed tracking algorithm, EKF, UKF, and RNN for trajectory 1

Major results

☐ Performance comparison



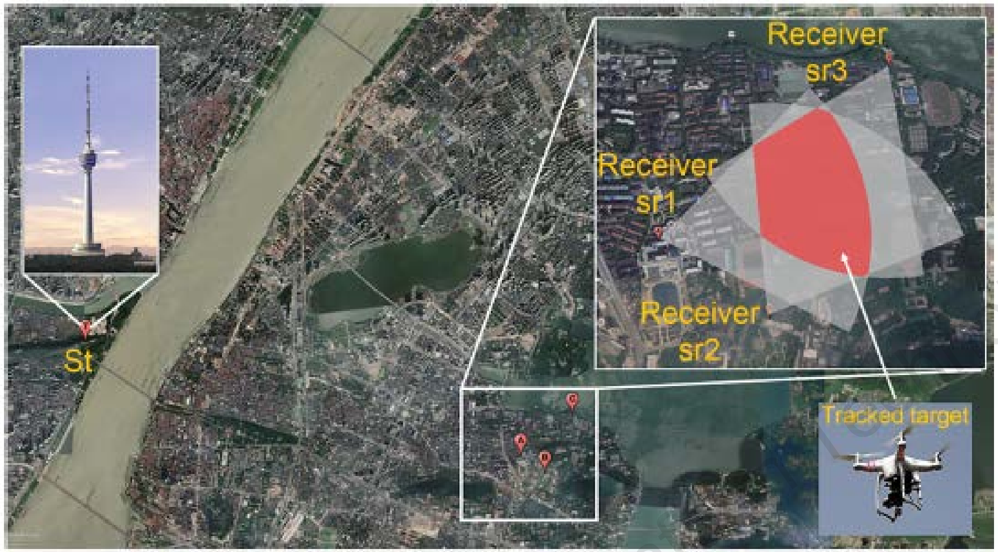


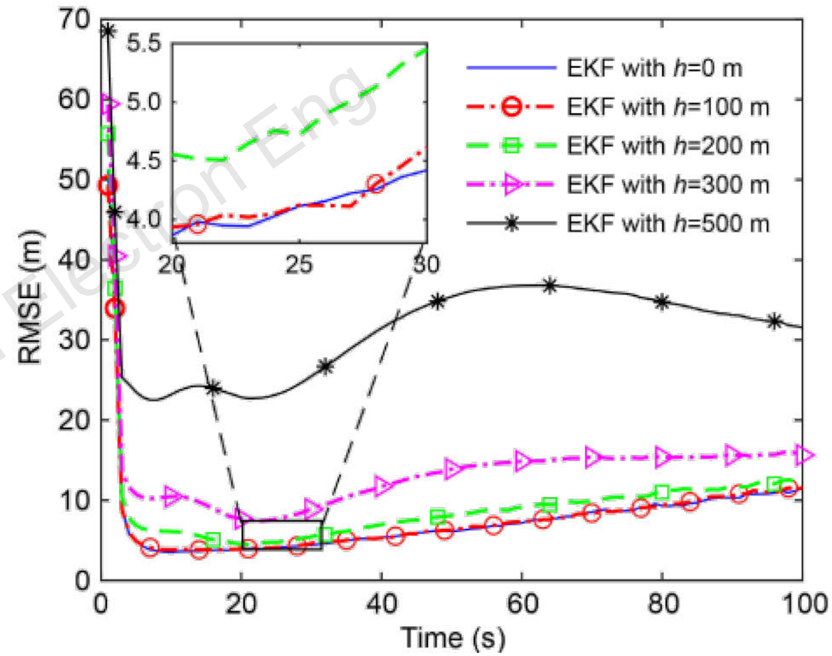
Performance comparison among the proposed tracking algorithm, EKF, UKF, and RNN for trajectory 2

Performance comparison among the proposed tracking algorithm, EKF, UKF, and RNN for trajectory 3

Major results

- Influence of the target height





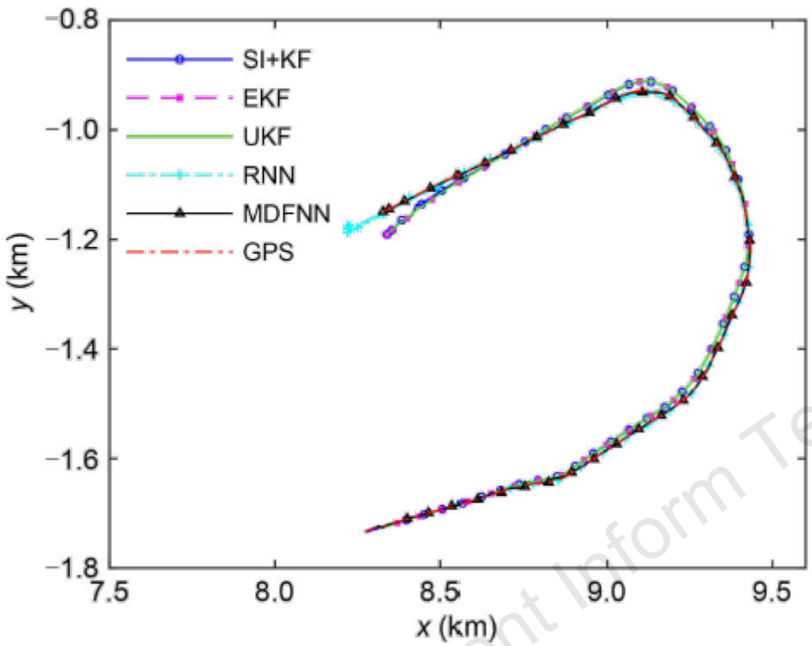
Geometry of one transmitter, three receivers, and the area of interest

Performance comparison with different target altitudes

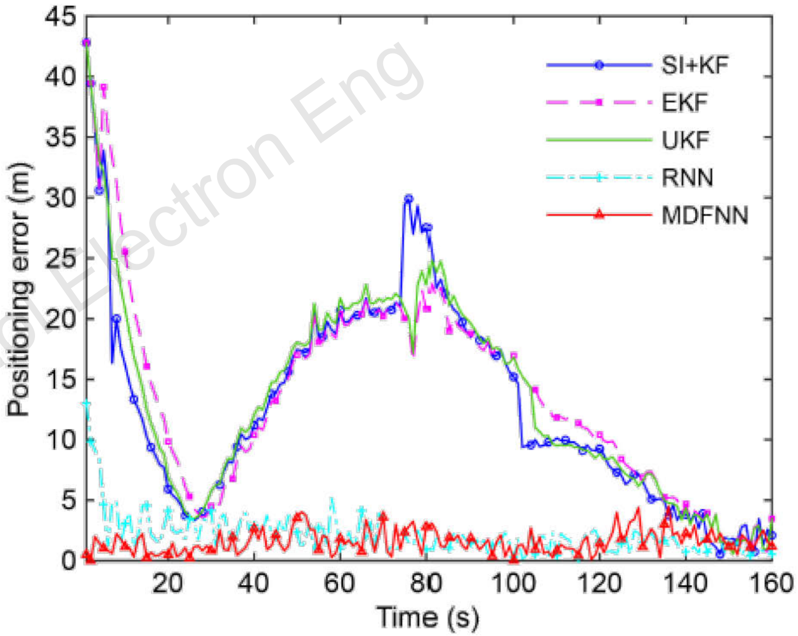
The effect of target altitude on tracking accuracy is relatively small for low-altitude detection.

Major results

- Field experimental results



(a)



(b)

Results of tracking in Cartesian coordinates (real data): (a) tracking results; (b) position deviation of the tracking track

The target is tracked completely by the five tracking schemes. Good agreement is achieved with GPS from a 2D view.

Conclusions

- We develop a high-accuracy target tracking algorithm for multistatic passive radar by exploiting the learning capabilities and easy structure of DFNN.

- A novel MDFNN tracking model based on a new filter layer is advocated for tracking recursion. We have shown by the ablation experiment that the tracking network based on MDFNN models the sequence dependency well, thereby having better reliability and tracking performance.

- A reasonable measurement sequence size is selected to trade-off the acquisition of target information and the computational complexity. Simulations and field data demonstrate that the proposed algorithm presents higher tracking accuracy compared to state-of-the-art methods.