ISAR Range Alignment Under Sparse Aperture Condition Based on CRAN

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Abstract

Range alignment (RA) is the first step of inverse synthetic aperture radar (ISAR) translational compensation. However, the precision of traditional range alignment method for non-cooperative targets will dramatically decreases under sparse aperture condition. We propose a CRAN-RA (CNN RNN Attention mechanism Network-Range Alignment) method to address the problem by combining convolutional neural networks (CNN) and recurrent neural networks (RNN) with attention mechanism. The unified network can effectively integrate regional features extracted by CNN and temporal features extracted by RNN. Input unaligned echoes, the network can predict the aligned echoes. Compared with the traditional methods and RNN-based methods, the experiments show that the proposed network can significantly improve the alignment accuracy under sparse aperture and low SNR condition.

Introduction

Traditional RA methods rely on high signal-to-noise ratio (SNR) and the correlation between adjacent pulses. However, the correlation between adjacent pulses will be dramatically reduced under low SNR and sparse aperture conditions, resulting in the accuracy decline of RA and the degradation of the final imaging quality.

Applying deep learning to ISAR sparse imaging, the accuracy and efficiency of signal reconstruction could be significantly improved.

Yuan et al. proposed a range alignment method based on deep recurrent neural network(RNN). But it still depends on the complete echo data, it's not suitable for sparse aperture. Deep neural networks combining CNN and RNN can complement each other in terms of temporal features and regional features, and CNN-RNN methods have been proved superior performance in image classification, text classification and machine translation. Inspired by this, we present a new range alignment method based on CRAN, which adopt an attention mechanism to integrate regional and temporal feature information extracted by CNN and RNN. Simulation experiments show that the proposed method can efficaciously achieve range alignment of non-cooperative targets under sparse aperture condition.

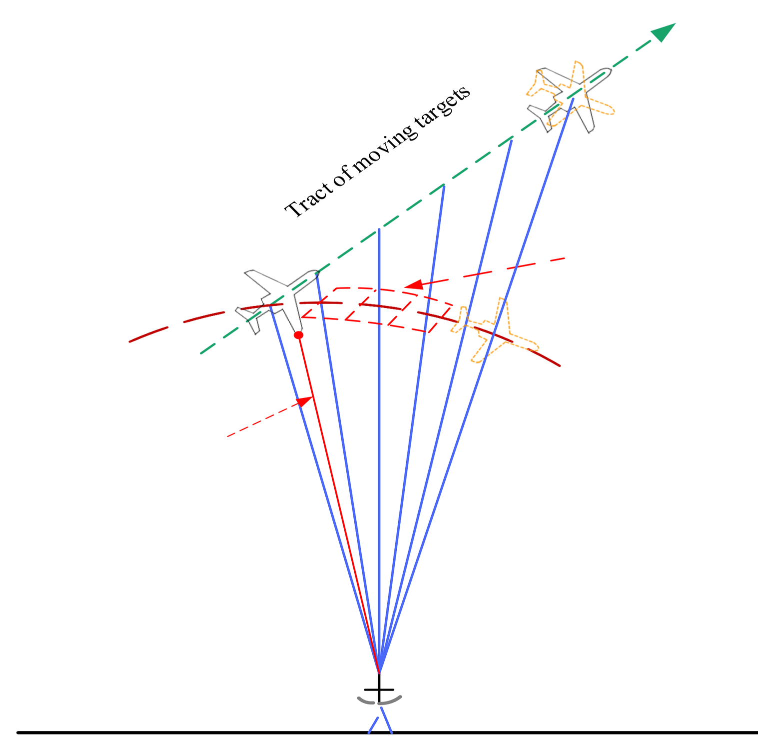

Figure 1. Geometry of translation compensation.

CRAN-Based RA Method

Fig. 1 shows the schematic of translation compensation in ISAR imaging. The radar echo can be written as:

$$s_P(t,t_m)=\sigma_P \mathrm{rect}\left[\frac{t-2R_P(t_m)/c}{T_p}\right]\cdot\exp\left\{\mathrm{j}2\pi f_c\left[t-\frac{2R_P(t_m)}{c}\right]\right\}\cdot\exp\left\{\mathrm{j}\pi\mu\left[t-\frac{2R_P(t_m)}{c}\right]^2\right\} \quad (1)$$

For P, the distance difference of contiguous pulse index is:

$$\Delta R_p(t_m)=R_p(t_m+\mathrm{I})-R_p(t_m) \quad (2)$$

where I means a pulse repetition interval (PRI).

Fig. 2 shows the shift of the range profile of the target caused by the translational component at a slow time moment under the sparse aperture condition. The blue line indicates the aligned echo and the red line indicates the unaligned echo.

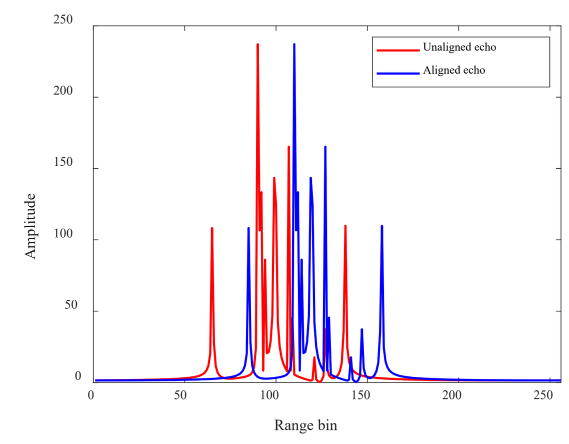

Figure 2. Geometry of translation compensation.

Fig. 3 demonstrates that the CRAN-RA architecture contains four components: input layer, CNN layer, RNN layer, attention layer and output layer.

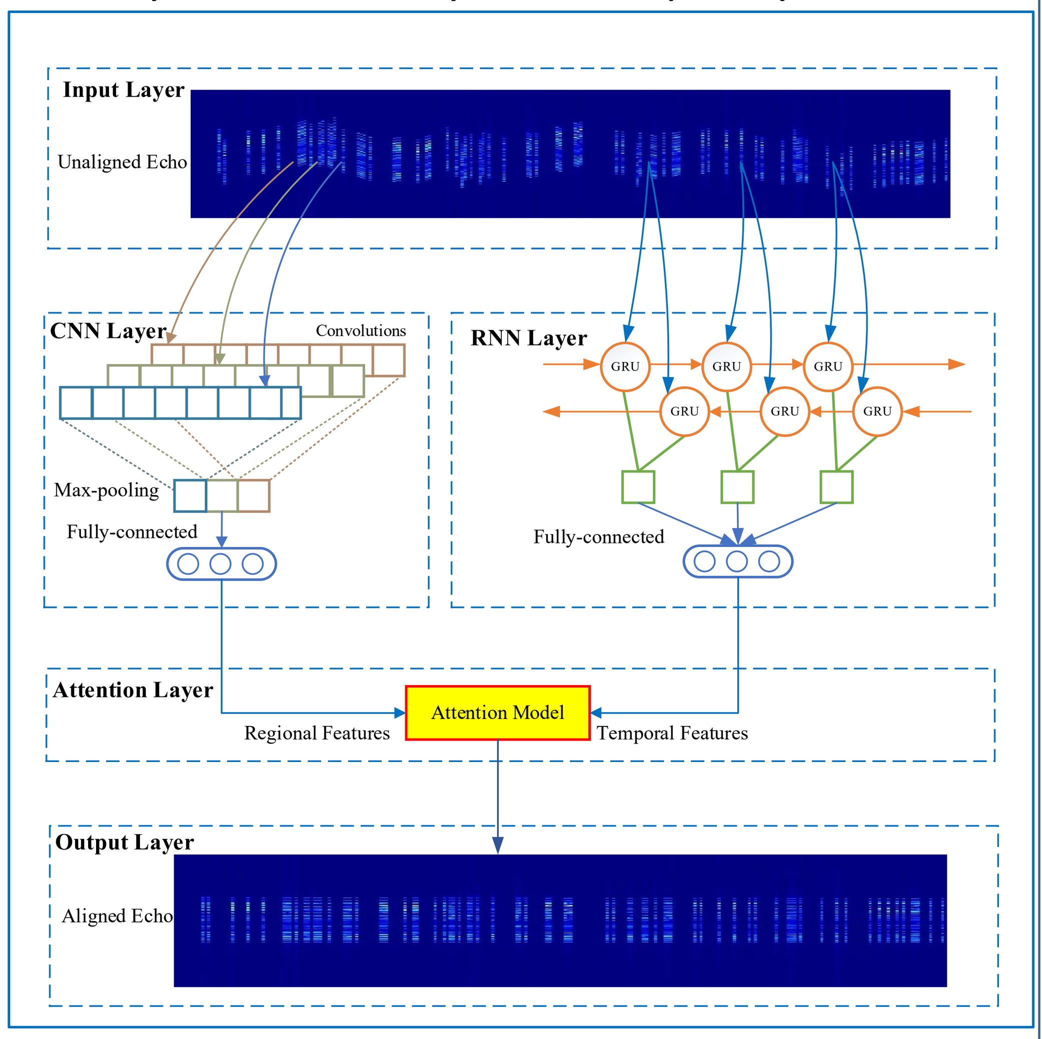

Fig. 3. The architecture of the CRAN-RA method.

Results

We use the echo data from the testing set to verify the performance of the proposed network. In order to prove the advantages of the proposed method, we choose three groups of testing samples with different SNR and down-sampling rates to compare the alignment results with the traditional MCRA method and RNN-RA method. The CSE and image ENT of different methods under different conditions are shown in TABLE 1. Fig. 4 shows the alignment results. The first row gives the echoes with different random down-sampling rate and SNR; the second, third, and fourth give the RA results of MCRA, RNN-RA, and CRAN-RA, respectively.

Table 1. CSE/ENT of different RA methods.

Down-sampling rate	50%	35%	20%
SNR	0dB	-5dB	-10dB
MCRA	52/4.73	125/5.21	186/5.98
RNN-RA	348/2.65	372/2.79	439/3.15
CRAN-RA	3/1.24	5/1.47	13/1.62

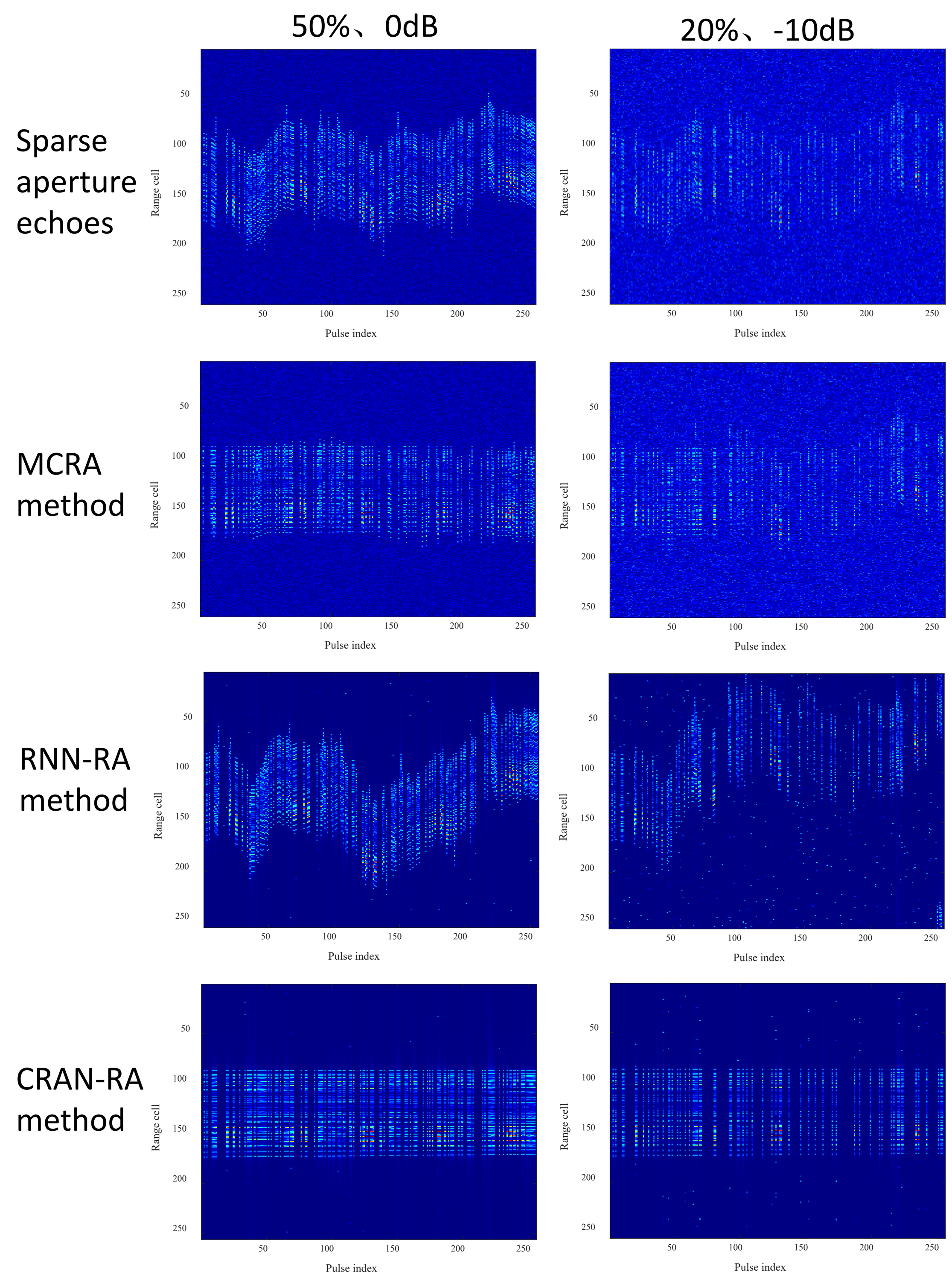

Figure 4. The results of different RA methods.

Discussion

It can be seen from the results in Fig. 4 that the alignment accuracy of the MCRA method is significantly reduced under the condition of low SNR and sparse aperture.

RNN-RA has been shown to be more effective under full-aperture conditions than traditional methods. However, it even makes the echoes more chaotic in processing sparse aperture echoes, this is because the network structure of the RNN-RA method cannot distinguish invalid echo sequences from the sparse aperture echoes, treating all echoes equally.

In contrast, the proposed CRAN-RA method could achieve range alignment under the condition of low SNR and sparse apertures.

Conclusions

We presented a novel CRAN-RA method to achieve high-quality range alignment under sparse aperture condition. The CRAN-RA architecture can effectively integrate regional features extracted by CNN and temporal features extracted by RNN, and precisely learn the mapping from unaligned echoes to aligned echoes. The simulation experiments show that the proposed method perform much better than the traditional method in range alignment of the sparse aperture echoes.

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