Leveraging Multiple PRF Radar for Target Detection and Sea Clutter Suppression with Deep Learning Network

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***Abstract*—In this paper, we propose a deep learning-based network that combines multiple pulse repetition frequency (PRF) and velocity resolution uniformization (VRU) techniques to improve target detection in the presence of sea clutter, particularly in scenarios with limited datasets. Multiple PRF enhances the ability to distinguish between clutter and target signals by collecting data across various frequency bands, while VRU increases the uniformity of this data, thereby improving the model's generalization performance. Simulation results demonstrate that the proposed method achieves superior detection performance compared to existing techniques.**

***Index Terms*—multiple PRFs, sea clutter, deep learning, velocity resolution uniformization**

I. Introduction

Deep learning is a highly effective tool for identifying patterns and relationships in large datasets, allowing for the resolution of complex and nonlinear problems. In the fields of communications and radar, deep learning has significantly advanced technology by enabling the handling of vast amounts of data and diverse variables that are challenging for traditional methods [1], [2]. Specifically, while traditional radar signal processing relies on manual pattern recognition [3], deep learning enables the effective analysis of complex radar signals, improving accuracy even in noisy environments [4].

The effectiveness of deep learning relies on large datasets, which are often difficult to obtain in real radar applications due to time and cost constraints [5]. An example is maritime target detection in the presence of sea clutter, which is influenced by waves, ocean reflections, and weather conditions [6], as shown in Fig. 1. They create complex and nonlinear noise that can obscure or distort target signals. Although deep learning has the potential to improve detection, the high cost and limited availability of datasets hinder practical model training.

In this paper, we propose a deep learning network that utilizes multiple pulse repetition frequency (PRF) techniques to improve target detection in sea clutter environments, even with limited datasets. The use of multiple PRFs offers two main benefits: 1) From a radar signal perspective, different PRFs yield radar images with varying velocity resolutions, resolving aliasing issues or supporting frequency hoping [7]. 2) From a model training perspective, multiple PRFs provide diverse features, enabling the model to better learn complex data distributions and generalize more accurately to target presence under various conditions. This is especially useful with limited datasets, as it reduces overfitting and allows for more robust feature extraction [8].

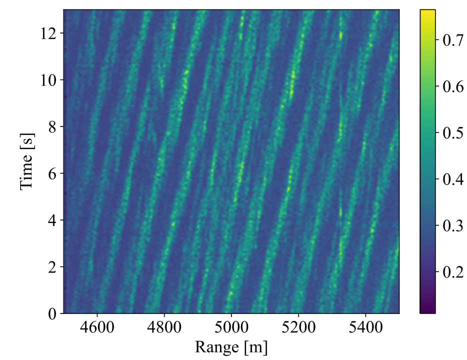

Fig. 1: Range-time intensity map showing sea clutter patterns in radar signals

Deep learning networks generally handle a fixed-size input, but radar images obtained from multiple PRFs have different velocity resolutions, resulting in varied sizes and patterns for the same target and clutter. This variation complicates the generalization process during the network's training. To address this, we propose a velocity resolution uniformization (VRU) technique. This technique enhances the uniformity of data obtained from multiple PRFs, significantly improving the generalization performance of the deep learning network. Simulation results show that the proposed method, which uses multiple PRFs and VRU, outperforms existing techniques.

II. Scenario and Pre-processing

In this section, we present a radar system scenario that utilizes multiple PRFs for more accurate target detection,

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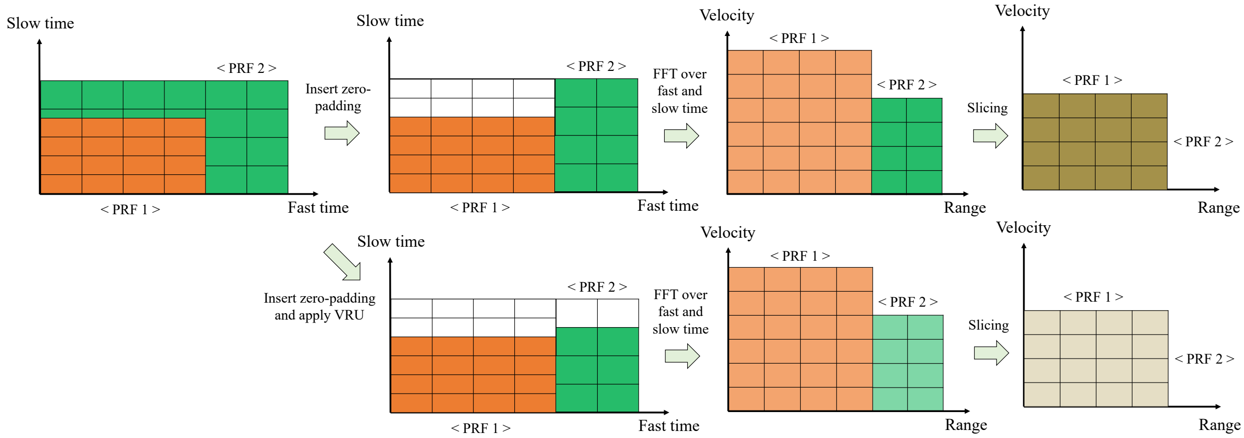
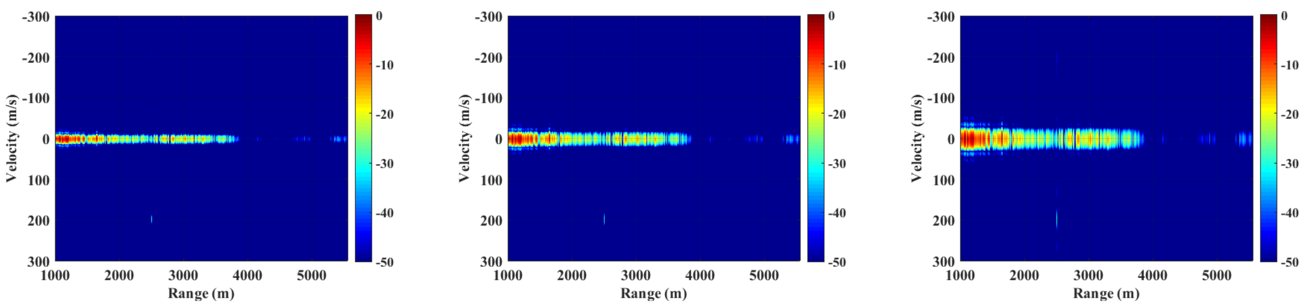


Fig. 2: Process of velocity resolution uniformization and RD map slicing for multiple PRF radar data



(a) (b) (c)

Fig. 3: Comparison of RD maps for target detection in Sea Clutter: (a) $\Delta v_{\text{eff}} = 6.5935$ m/s, (b) $\Delta v_{\text{eff}} = 9.8901$ m/s, and (c) $\Delta v_{\text{eff}} = 14.2857$ m/s

rather than relying on a single PRF. We then introduce a customized pre-processing method for applying these multiple PRF radar images to a deep learning network.

A. Radar System Scenario

We consider a scenario in which a mono-static radar aboard a ship detects maritime radar targets. Unlike ground target detection, maritime radar target detection is hindered by a unique type of clutter caused by waves. Maritime clutter consists of two components: texture and speckle. The texture component is associated with gravity waves and represents the mean intensity, while the speckle component is related to capillary waves and reflects the Doppler characteristics.

To detect the range and velocity of targets, radar data collected through multiple PRF signals is transformed from the range-time domain to the range-Doppler domain, producing a range-Doppler map (RD map). This transformation is achieved by performing a Fourier transform along the time axis. However, the obtained RD map is heavily contaminated by the sidelobes of maritime clutter, making target detection very challenging. To mitigate the effects of clutter sidelobes, we applied a Hanning window.

It is worth noting that although the multiple RD maps obtained through multiple PRFs are used to detect the same targets, they exhibit different characteristics. Specifically, the varying PRFs result in different velocity resolutions. The effective velocity resolution is determined by $\Delta v_{\text{eff}} = f\lambda/2N$, where λ is the wavelength, f is the PRF, and N is the number of pulses. The differing velocity resolutions allow one RD map to resolve velocity ambiguities that may occur in another PRF's RD map. As a result, a system utilizing multiple PRFs can enhance velocity resolution and improve the ability to separate and track multiple targets effectively.

B. Pre-processing for multiple PRF

The RD maps obtained from multiple PRF radar signals each have different velocity resolutions and unambiguous velocities. However, image-based deep learning networks, such as CNNs, require input data to have a fixed size, so all RD maps must be standardized to the same image size. Therefore, we unify the range and velocity axes of the different RD maps to achieve consistent sizes. Fig. 2 illustrates the process of unifying RD map sizes along the range and Doppler axes.

Range axis: Since all radar signals use the same bandwidth, the range resolution remains consistent, but the unambiguous range differs due to varying PRFs. To create uniformly sized data along the range axis, we adjust the data size to match

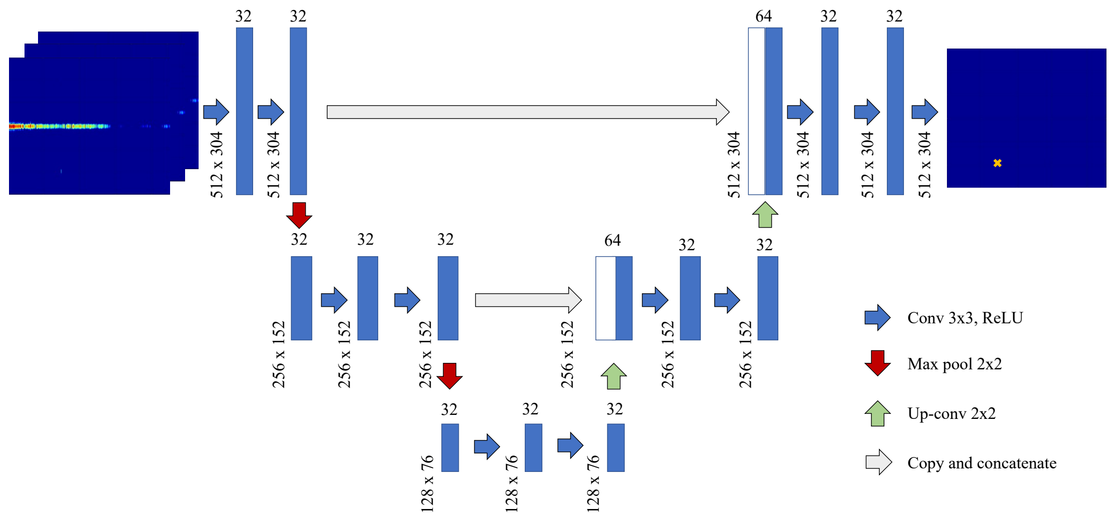


Fig. 4: U-Net architecture for sea clutter suppression and target detection in RD maps

the RD map with the smallest unambiguous range, which corresponds to the radar signal with the highest PRF.

Doppler axis: Unlike the uniform range resolution, both the velocity resolution and unambiguous velocity resolution depend on the PRF. Specifically, the velocity resolution increases proportionally with the PRF when the number of pulses is the same. To match the sizes of the RD maps along the Doppler axis for different PRFs, we artificially add zero pulses and then perform a Fourier transform along the Doppler axis to achieve similar range resolutions. To fine-tune minor discrepancies, interpolation can be applied to precisely adjust the Doppler axis size of each RD map. Finally, we standardize the image sizes by slicing them according to the lowest unambiguous velocity.

Although zero-padding increases the RD map size and aligns the velocity resolution for resizing, the effective velocity resolution remains unchanged. As shown in Fig. 3, the physical velocity resolution differs according to PRF, even though the image sizes are the same. It's important to note that data representing the same target and clutter will have different representations on the RD map depending on the PRF. In deep learning training, such varied representations of the same label can slow convergence or even destabilize the learning process.

C. *Velocity Resolution Uniformization*

To achieve uniformization of data with different representations due to varying PRFs, despite having the same label, we employed a technique called VRU. VRU is a method that artificially unifies the effective velocity resolution by intentionally reducing the number of pulses in RD maps with higher effective velocity resolutions and adding zero-padding. For example, as shown in Fig. 2, during the process of uniformizing the RD map sizes, we reduce the number of pulses in the PRF 2 RD map and add zero-padding to artificially lower its effective velocity resolution, making it similar to the RD map from PRF 1.

While VRU increases data uniformization, it also leads to information loss since it involves the deliberate removal of informative pulses. Therefore, there is a trade-off between the improved learning efficiency gained through data uniformization and the potential degradation in detection performance due to information loss. In this paper, we explore this trade-off through simulations in Section 4.

III. Deep Learning Network for Target Detection

A. *Network Structure*

To remove clutter and extract targets from RD maps where both clutter and targets are present, we utilized a U-Net architecture [9], commonly used in fields such as image restoration, image generation, style transfer, and noise/interference suppression. The encoder-decoder structure of U-Net effectively learns both low-level and high-level features of an image. The encoder extracts important features from the input image, while the decoder generates the desired output based on these features. Through this process, U-Net can suppress unnecessary information, such as sea clutter, and emphasize the information needed for target detection.

Leveraging a classical U-Net structure, we constructed a network for sea clutter suppression and target detection, as shown in Fig. 4. The proposed U-Net takes RD maps with three different PRF values as input, treating each RD map as a separate channel, similar to how RGB images are processed. This multi-channel input approach can aid in the convergence of network training by facilitating feature extraction across channels. The input images are then processed through a convolutional neural network (CNN) to extract features of both targets and sea clutter. Since RD maps include not only clutter and targets but also regions with no signals, we apply max-pooling to reduce the spatial dimensions. Pooling preserves key features while discarding unnecessary ones, improving the network's ability to distinguish between target and clutter features. Additionally, since image data involves handling large amounts of high-resolution data, the pooling process

TABLE I: Parameter and effective velocity resolution of training and test datasets

	Training datasets			Test datasets		
	Dataset 1	Dataset 2	Dataset 3	Dataset 1	Dataset 2	Dataset 3
PRF [kHz]	12	18	26	12	12	12
Number of pulses	91	91	91	91	61	41
Effective velocity resolution [m/s]	6.5934	9.8901	14.2857	6.5934	9.8361	14.6341
	Training datasets with VRU			Test datasets with VRU		
	Dataset 1	Dataset 2	Dataset 3	Dataset 1	Dataset 2	Dataset 3
PRF [kHz]	12	18	26	12	12	12
Number of pulses	40	60	87	41	41	41
Effective velocity resolution [m/s]	15.0	15.0	14.9425	14.6341	14.6341	14.6341

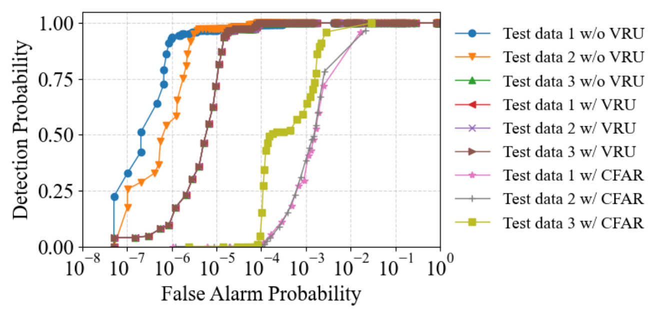
is crucial for enhancing computational efficiency by reducing dimensions. This reduction in dimensions allows the network to use memory more efficiently and increases computational speed, enabling the use of deeper network structures, which are helpful in learning more complex patterns. At the lowest layer of the U-Net, after sufficient feature extraction, the network distinguishes between target and clutter features, removing clutter features and retaining only target features. The output is then upscaled to restore the original RD map size. The final output RD map highlights the areas where targets are predicted to be present. Since the input and output RD maps are of the same size, the range and velocity of the targets can be easily calculated.

B. Training Process

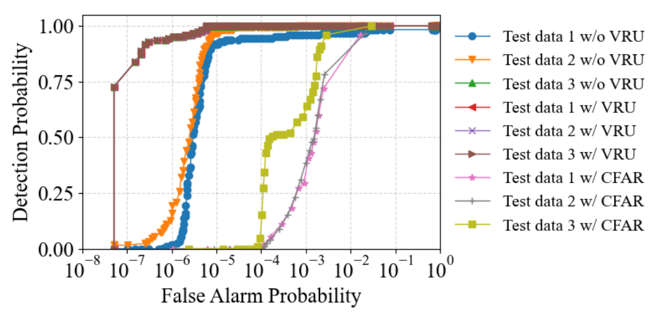
To train the proposed U-Net for sea clutter suppression and target detection, we used a supervised learning framework. We generated the ground truth by creating a binary matrix from the input RD map, where pixels containing targets were assigned a value of 1, and all others were assigned a value of 0. It is important to note that target distributions in RD maps are generally very sparse. This means that the number of target points is very small compared to the total data points, leading to data imbalance. To address this imbalance, we employed focal loss during training. Focal loss helps the model focus more on difficult-to-classify examples (the sparse target points) while paying less attention to easy-to-classify examples (the abundant non-target points). Let the output RD map generated by the proposed U-Net be denoted as $\mathbf{R}$, and the ground truth RD map as $\mathbf{G}$. The focal loss is calculated by

$$\mathcal{L}_{\text{focal}}(\mathbf{R}, \mathbf{G}) = -\sum_{\mu=0}^{M-1} \sum_{n=0}^{N-1} (1 - r_{n,\mu})^{\gamma} \log(r_{n,\mu}), \quad (1)$$

where γ is the tunable focusing parameter, M is the number of sample points in fast-time axis, N is the number of pulses, $r_{n,\mu} = [\mathbf{R}]_{(n,\mu)}$ if $[\mathbf{G}]_{(n,\mu)} = 1$ and $r_{n,\mu} = 1 - [\mathbf{R}]_{(n,\mu)}$ otherwise, and $[\mathbf{R}]_{(n,\mu)}$ is the (n, μ)-th element of a matrix $\mathbf{R}$. By training with this method, the output of the U-Net-based network is an RD map with values between 0 and 1, where each pixel's value represents the probability of a target being present at that location.



(a) Training datasets without VRU

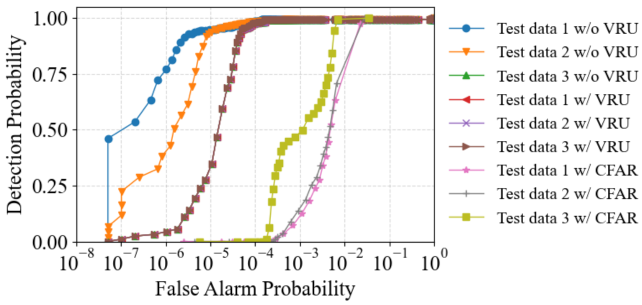


(b) Training datasets with VRU

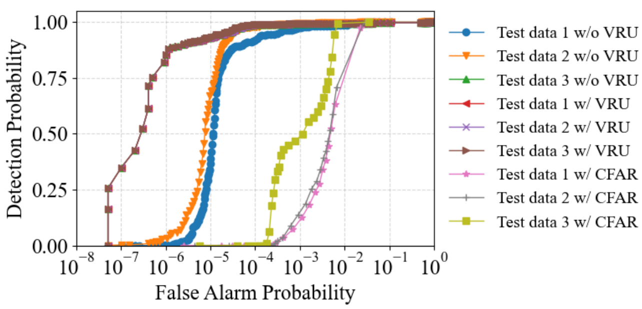
Fig. 5: ROC curves for target detection performance with a single radar target

IV. Simulation Results

In this section, we investigate the ability of VRU to enhance the generalization performance of deep learning models by uniformizing RD maps obtained through multiple PRFs. We modeled sea clutter using radar signals captured off the coast of Namjeong-myeon, Yeongdeok-gun, South Korea, and used



(a) Training datasets without VRU



(b) Training datasets with VRU

Fig. 6: ROC curves for target detection performance with three multiple radar targets

these signals to create both the training and test datasets. The training dataset size is 1500, including all multiple PRFs, while the test dataset consists of 125 samples. We used a carrier frequency of 3 GHz for all datasets, with the PRFs and number of pulses summarized in Table I.

Unlike traditional constant false alarm rate (CFAR) methods, the proposed U-Net-based network cannot theoretically determine the detection threshold based on the false alarm probability. Therefore, considering that the U-Net outputs an RD map with values between 0 and 1 after sea clutter suppression, we incrementally adjusted the threshold value from 0 to 1 to calculate the corresponding false alarm probability and detection probability, thereby evaluating the detection performance.

Fig. 5 shows the detection probability as a function of false alarm probability in the form of a receiver operating characteristic (ROC) curve for a single target. For all false alarm probabilities, the proposed U-Net-based network outperforms the CFAR approach. In the network trained without VRU, the detection probability is high for test data with a relatively low effective velocity resolution, but decreases as the effective velocity resolution increases. In contrast, the network trained with VRU can transform all test data to have a velocity resolution similar to that used in training, thereby improving detection performance. Remarkably, it even outperforms the detection performance measured on low velocity resolution data without VRU. This suggests that despite the information loss, VRU improves the generalization capability of the network, leading to enhanced radar target detection performance. Additionally, the results indicate that a network trained with VRU can maintain high detection performance even with a reduced number of radar pulses. This implies that in real-world operations, the number of pulses required to gather target information can be reduced, allowing for faster scans.

Since the presence of multiple targets is more common in real scenarios, we also generated ROC curves for test datasets containing three radar targets, as shown in Fig. 6. Similar to the previous simulations, the U-Net-based network consistently outperforms the CFAR approach across all levels of false alarm probability. It is also important to note that, as in the previous experiment, the training dataset contains only a single radar target, making multiple targets an unseen case for the deep learning network. The detection performance for multiple targets, whether using VRU or not, shows a similar trend to that of a single target.

V. Conclusion

This paper proposed a deep learning network using multiple PRFs and the VRU technique to improve target detection in sea clutter environments with limited datasets. Our approach enhances data diversity and generalization, leading to better target detection performance than existing methods. The results demonstrate the potential of combining multiple PRFs and VRU for more accurate and robust radar systems.

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