LPI radar signal recognition with U^2-Net-based denoising

Siho Lee
Hanyang University
Department of Electrical and Electronic Engineering
Ansan, Korea
siho0201@hanyang.ac.kr

Haewoon Nam
Hanyang University
Department of Electrical and Electronic Engineering
Ansan, Korea
hnam@hanyang.ac.kr

***Abstract*—Low Probability of Intercept (LPI) radar signals play a vital role in electronic warfare by maintaining informational superiority. Classifying these LPI radar waveforms is a key capability but remains a challenging task due to strong noise interference. Traditional signal processing techniques often show limitations in effectively removing complex noise signals. While deep learning-based modulation classification has exhibited superior performance, its effectiveness is compromised in the presence of significant noise. In this study, we propose a deep learning-based denoising method using the U²-Net for LPI radar signals, followed by modulation classification using a Convolutional Neural Network (CNN). We further compare the performance of U²-Net with other denoising models such as U-Net and denoising autoencoder. Experimental results demonstrate that the U²-Net outperforms other methods, achieving over 90% classification accuracy for signals with a signal-to-noise ratio above -14dB.**

***Index Terms*—Low Probability of Intercept (LPI) radar, time frequency analysis, U²-Net, U-Net, denoising autoencoder**

I. Introduction

Electronic warfare (EW) is a military strategy that employs electromagnetic waves for offensive and defensive purposes. This involves the identification of enemy waves, the protection of friendly waves, and it is commonly divided into three core components: electronic attack (EA), electronic protection (EP), and electronic support (ES). Particularly, EA serves a pivotal role in achieving dominance over information flow in military engagements. Within the domain of EA, Low Probability of Intercept (LPI) radars are utilized. These radars, due to their low signal power compared to standard pulse radars, are more challenging to detect, providing a strategic advantage in electronic warfare. This elusive feature allows militaries to shield their electromagnetic signals while evading enemy detection. Additionally, LPI radars employ intricate intra-pulse modulation techniques, including Linear Frequency Modulation (LFM), Costas, and Barker [1]. These advanced modulation methods add another layer of complexity to radar signal identification, making them more difficult to discern and decode. As a result, these characteristics have spurred extensive research in the field to develop more effective techniques for recognizing and distinguishing the modulation methods used in radar signals.

With the recent advancements in deep learning technology, new approaches have been developed for distinguishing signal modulation methods. One widely used approach transforms a one-dimensional In-phase and Quadrature (IQ) signal into a two-dimensional time-frequency image. This transformation is achieved using Time-Frequency Analysis (TFA) algorithms such as Short-Time Fourier Transform (STFT), Wigner-Ville Distribution (WVD), and Choi-Williams Distribution (CWD). These time-frequency images are then processed using Convolutional Neural Network (CNN) for the purpose of modulation method classification [2]. In the study cited as [3], the researchers effectively distinguished between a dozen different types of LPI radar waveforms. This was achieved by employing CNN model that used CWD image as input, resulting in substantial classification performance. Despite the promising results of deep learning-based radar waveform identification, there are still challenges when dealing with LPI radars with low Signal-to-Noise Ratio (SNR). The relatively high noise power makes it difficult to discern the features of the radar signal, leading to a decrease in the performance of deep learning models. Traditional signal processing techniques can be employed to denoise LPI radar signals, but these methods are limited in their ability to thoroughly eliminate complex noise signals and isolate only the radar signal. In the field of computer vision, segmentation technology is continually improving, with capabilities to specifically isolate desired elements within an image [4]. When this approach is applied to the Time-Frequency image of LPI radar signal, it becomes possible to extract solely the portions of the image that correspond to radar signals. In this research, we utilize U²-Net, a version of the U-Net deep learning segmentation algorithm, to remove noise from LPI radar signals. After the denoising process is completed, we perform modulation classification using the CNN algorithm. The effectiveness of the denoising model is demonstrated by comparing the classification performance between data processed with and without the noise reduction algorithm.

II. U²-Net

Owing to the frequency variation of LPI radar signals, the distinctions between modulation types are readily apparent in

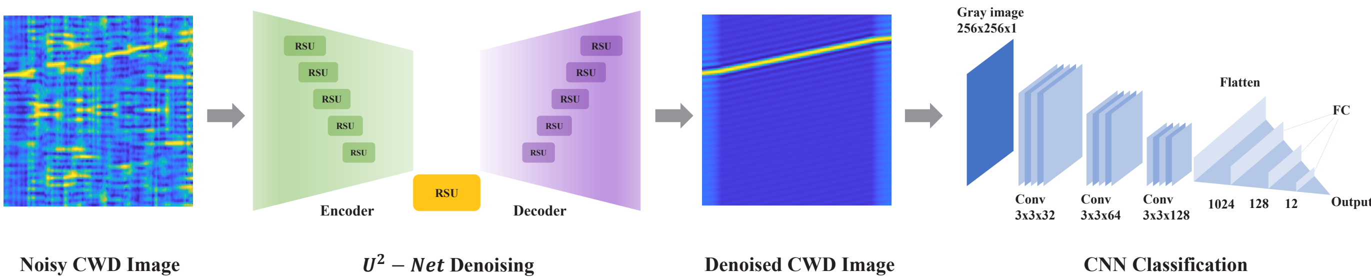


Fig. 1: Classification model using U²-Net and CNN. Noisy CWD images are input into U²-Net, where they are converted to denoised CWD images, and then used as inputs to CNN for classifying the classes.

the time-frequency image. However, for signals with a low SNR, the characteristics specific to the signal can be distorted by potent noise. This distortion complicates the ability of CNN model to discern image-specific features and is a primary factor in subpar classification performance. Thus, a preprocessing algorithm capable of noise removal from the signal is necessary, and such an algorithm can be applied to either one-dimensional IQ data or two-dimensional time-frequency images. The U²-Net is a deep learning model devised for salient object detection, capable of identifying and segmenting the most significant object in an input image [5]. By training this model on time-frequency images of radar signals, we can isolate and restore the radar signal, leading to an image with substantially reduced noise. The model is built on an encoder-decoder structure resembling U-Net, enhanced with a module known as the Residual U-Block. The encoder extracts unique features from the image and the decoder uses these to restore the image's original dimensions. The Residual U-Block, with an input convolution layer and a U-Block, plays a pivotal role in this process by creating an intermediate map of local features, which is used to learn multi-scale contextual information from the data. The outcome is a feature that combines local and multi-scale attributes, used as input for the next block in the process.

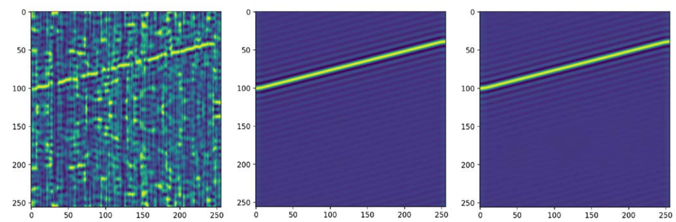
III. PROPOSED METHOD

A. Network Description

Fig. 1 presents a block diagram of the algorithm employed in this study. Initially, the received LPI radar signal is converted into a time-frequency image utilizing the CWD algorithm. CWD is a time-frequency representation used to analyze non-stationary signals. It is defined by the following integral:

$$CWD(t,f) = \int\int x(u+\frac{v}{2})x^*(u-\frac{v}{2})\Phi(v,t-u) \, e^{-2\pi i f v}\,du\,dv \tag{1}$$

where $x(t)$ is the signal, and $\Phi(v,t)$ is the Choi-Williams kernel. The kernel function $\Phi(v,t)$ controls the trade-off between time and frequency resolution, reducing cross-term interference. Each resultant CWD image possesses unique features dictated by the radar waveform. To mitigate the noise



(a) Received signal (b) Transmitted signal (c) Reconstructed signal

Fig. 2: CWD images of the LFM signal with an SNR of -6dB. (a) is the received signal CWD image, (b) is the transmitted signal CWD image, and (c) is the reconstructed signal CWD image.

present in the image, the CWD image is fed into the U²-Net model. The input to the current algorithm comprises the received signal with added noise, with the objective of the U²-Net model being to restore the noise-free transmitted data. To achieve this, both the transmitted and received data are utilized in the training phase of the U²-Net, while only the received data is used as input in the testing phase. Consequently, the U²-Net model reconstructs the image, filtering out the noise to produce an image that only contains the radar signal. Fig. 2 depicts the received, transmitted, and reconstructed images of LFM signal with a SNR of -6dB. The received image shows a strong noise influence, making the LFM pattern challenging to discern. However, in the U²-Net reconstructed image, most of the noise has been eliminated, making it closely resemble the transmitted image. Finally, this denoised CWD image is used as input to the CNN. The CNN comprises two parts: one section that extracts the features of the input image, and another section that classifies the type of input image based on the extracted features. The type of waveform corresponding to each image serves as the correct label for the CNN, enabling it to classify the waveform type of the input image.

B. Other denoising methods

In this study, we further employed the denoising algorithm through the use of an autoencoder and U-Net, for the purpose of comparing performance with the U²-Net-based denoising technique. The denoising autoencoder is a deep learning

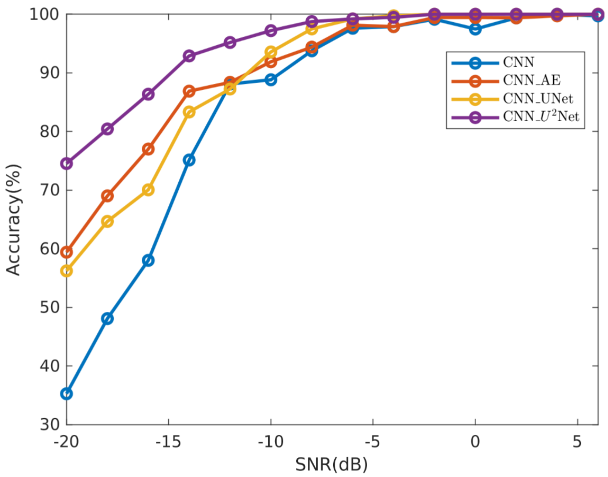


Fig. 3: Classification performance of CNN models with each denoising model applied, across an SNR range of -20dB to 6dB, represented using accuracy(%).

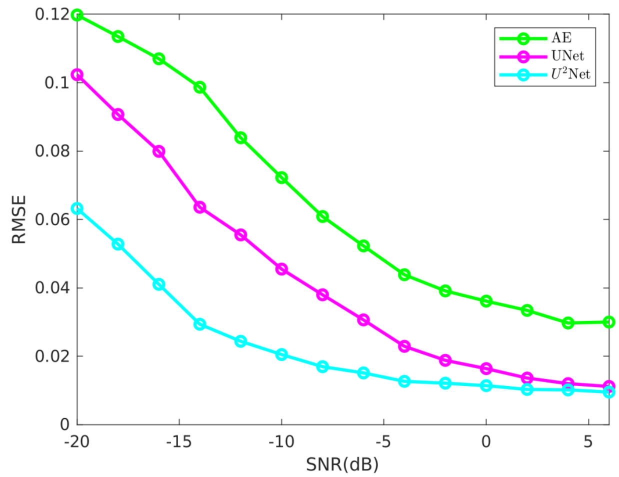


Fig. 4: RMSE by SNR according to the denoising model. The RMSE of each pixel value is calculated between the target image and the model's output image.

TABLE I: Detailed information on the Dataset

Parameter	Assignment
Classes	LFM, Barker, Costas, Frank, P1~P4, T1~T4
Number of train datasets	40320
Number of validation datasets	5040
Number of test datasets	5040

model, engineered to restore original data after intentionally introducing noise into the said data [6]. Meanwhile, U-Net is a model that has been designed for the purpose of segmenting distinct objects within the input data [7]. Both of these models incorporate an encoder-decoder structure where the encoder's function is to extract features from the input image, while the decoder uses the extracted features to recreate the target image. Additionally, U-Net incorporates a skip connection feature, which enables the decoder to utilize the features extracted by the encoder at each step during the image reconstruction process. Similar to the U²-Net, these two models can accept noisy input data and are trained to reconstruct clean input data. Despite the similarities these three models share, such as an encoder-decoder structure and the capability to reshape the input image into a specific form, experimental results have demonstrated that U²-Net performs more effectively in terms of denoising compared to the other algorithms. The findings of this comparative study of denoising methods will be discussed further in the SIMULATION AND DISCUSSIONS section.

IV. SIMULATIONS AND DISCUSSIONS

To evaluate the radar waveform classification performance based on the denoising model, we generated 12 types of signals (LFM, Costas, Barker, Frank, T1, T2, T3, T4, P1, P2, P3, P4). These signals were then transformed into images using the CWD algorithm and subsequently used as input for each model. The SNR for each signal spans from -20dB to 6dB with 2dB increments. Each CWD image has dimensions of 256*256, with image pixel values normalized to range between 0 and 1. For each SNR and signal, we generated 300 data samples with a ratio of 8:1:1 for training, validation, and testing respectively. The specifics of the dataset are detailed in Table I. All three denoising models were trained with the same data, and identical CNN models were used for waveform classification. For U-Net and U²-Net, we used models consistent with those employed in [7] and [5] respectively. The autoencoder, on the other hand, is composed of five convolutional layers with a 3x3 kernel. We gauged performance using the classification accuracy, obtained when the CNN model used the data processed by each denoising model as input. Moreover, to assess how effectively each denoising model reconstructed the target image, we computed the Root Mean Squared Error (RMSE) between the target image and the output image produced by the model. The formula for RMSE is defined as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{2}$$

y_i represents the pixel value of the target image, and $\hat{y}_i$ denotes the pixel value of the output image.

The classification accuracy of the CNN model, as depicted in Fig. 3, presents a comparison among scenarios involving no application of a denoising model, and those utilizing an autoencoder, U-Net, and U²-Net. Without any denoising model applied, the accuracy rate drops to the lowest among all methods, particularly plummeting when the SNR dips below -12dB. At an SNR below -16dB, the accuracy falls below 60%. The autoencoder and U-Net models produce nearly identical accuracies across all SNRs. Both methods significantly outperform the scenario without denoising, achieving over 90% accuracy for signals above -10dB and still exceeding 60% accuracy at -18dB. The scenario applying U²-Net achieved the highest accuracy across all SNR values, with an accuracy rate surpassing 90% for signals above -14dB. From these findings, it's evident that the application of a denoising model enhances the CNN model's classification performance, with U²-Net showcasing the most significant improvement among the three models.

Fig. 4 displays the RMSE values according to SNR for each denoising method. For all three cases, as the SNR decreases, there is a tendency for the RMSE values to increase. The RMSE values appeared highest for Autoencoder, followed by U-Net, and then U²-Net. Comparing the autoencoder and U-Net, there's negligible difference in classification accuracy, despite U-Net's relatively lower RMSE value. Conversely, U²-Net achieves the lowest RMSE value and the highest classification performance, indicating that the RMSE value discrepancy does not necessarily dictate the classification model's performance.

V. CONCLUSION

In this study, we examined the influence of applying denoising via deep learning models (U²-Net, U-Net, autoencoder) on the classification of waveforms, using CNN on 12 types of LPI radar CWD images. Experimental results demonstrate that U²-Net-based denoising yields the most effective classification performance, achieving over 90% accuracy for signals above -14 dB. Even at the lowest SNR of -20dB, the difference in classification performance is approximately 40% compared to a scenario without a denoising model.

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