https://doi.org/10.7840/kics.2024.49.9.1236

Sliding Window-Based Spectrum Sensing with Deep Learning for Pulse Radar Signals

Chang Heon Lim◆°, Jin-Yul Kim*

ABSTRACT

A sliding window-based spectrum sensing method determines the presence or absence of a primary user by comparing the maximum of the received signal energies from multiple sliding windows with a threshold. In this letter, aiming to enhance this scheme, we present a deep learning-based approach for exploiting the pattern of the received signal energies from sliding windows and investigate its sensing performance.

Key Words : cognitive radio, spectrum sensing, pulse radar, sliding window, deep learning

Ⅰ. Introduction

With the diversification and widespread adoption of wireless communication services, the demand for spectrum resource to support them has been ever increasing. However, the amount of available spectrum resource is limited, and thus the concept of cognitive radio or spectrum sharing[1] has emerged as a promising means to address the problem of spectrum scarcity. Some familiar examples of this approach are the wireless local area network (LAN) services in the 5GHz radar band and the Citizens Broadband Radio Service (CBRS) in the 3.5GHz band[1].

A popular form of spectrum sharing is to allow a secondary user (SU) to access the frequency band of interest when the band is found to be idle. Therefore the function of spectrum sensing to check if the band of interest is available to an SU is crucial in cognitive radio. In the radar frequency band, the primary user (PU) is the radar system. An initial spectrum sensing approach for a pulse radar signal is to detect the presence of a pulse radar signal by comparing the received signal power with some predetermined threshold[2]. Recently, a waveform-based spectrum sensing method[3] has been published, which detects the radar signal by modeling the PU signal and applying the Generalized Likelihood Ratio Test (GLRT).

Moreover, in order to exploit the sparsity of the pulse radar signal in the time domain, a sliding window-based spectrum sensing scheme[4] has been reported, which employs the maximum of the received signal energies from multiple sliding windows as a test statistic for spectrum sensing. In this letter, we present an improved version of this approach which employs the deep learning (DL) to utilize the distribution of the received signal energies from the multiple sliding windows. Previously, machine learning (ML) or DL has been employed as alternatives to traditional spectrum sensing methods like energy detection or decision fusion in cooperative spectrum sensing[1]. However, to the best of the authors' knowledge, this is the first attempt to adopt DL for the sliding window based spectrum sensing strategy.

Ⅱ. Proposed Sliding Window-Based Spectrum Sensing

We consider a typical situation of sliding window-based spectrum sensing[4] involving a pulse radar signal received by an SU and sliding windows for spectrum sensing, as illustrated in Fig. 1. Here, the sliding windows are assumed to be regularly spaced in time, with their lengths being identical and fixed. Additionally, consecutive sliding windows may partially overlap in the time domain. For the

※ This work was supported by a Research Grant of Pukyong National University(2023)
◆ First and Corresponding Author : Pukyong National University, Division of Electronics and Communications Eng., chlim@pknu.ac.kr, 종신회원
* The University of Suwon, School of Electrical and Electronic Eng., jykim@suwon.ac.kr, 종신회원
논문번호 : 202406-111-B-LU, Received May 31, 2024; Revised June 18, 2024; Accepted June 18, 2024

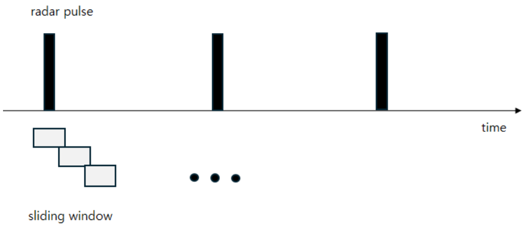

Fig. 1. A typical situation for sliding window-based spectrum sensing

convenience of presentation, we call the sliding window-based spectrum sensing scheme as a reference scheme.

The reference spectrum sensing scheme calculates the received signal energies for multiple sliding windows. Let $r(n)$ denote the received signal at the n-th time instance within an observation window, and M sliding windows of length L are supposed to be included in an observation window. Then, the received signal energy E_m corresponding to the m-th sliding window is defined as

$$E_m = \sum_{l=1}^{L} |r((m-1)L+l)|^2 \quad m = 1, 2, \cdots, M \qquad (1)$$

However, the reference spectrum sensing scheme does not exploit the inherent characteristic of a sequence of the received signal energies $\{E_m, m=1, \cdots, M\}$. For instance, when the radar pulse repetition interval is 100 samples long, $M=40$, and $L=5$, Fig. 2 illustrates an instance of such a sequence of $\{E_m, m=1, \cdots, M\}$ in an AWGN channel for two hypotheses: one hypothesis H_0 indicates that the PU is idle and the other one H_1 suggests that the PU is active. As depicted in the figure, the sequence of the received signal energies corresponding to H_1 tends to exhibit periodic peaks whereas the sequence for H_0 does not reveal this characteristic, and the two sequences for H_0 and H_1 differ in their shapes. Thus, we can expect that a detection strategy based on an entire sequence of $\{E_m, m=1, \cdots, M\}$ could provide better sensing performance than the reference spectrum sensing scheme which uses only the maximum value of $\{E_m, m=1, \cdots, M\}$.

In this paper, we propose a DL-based spectrum sensing method aimed at utilizing the distinguished features of the energy sequence associated with two

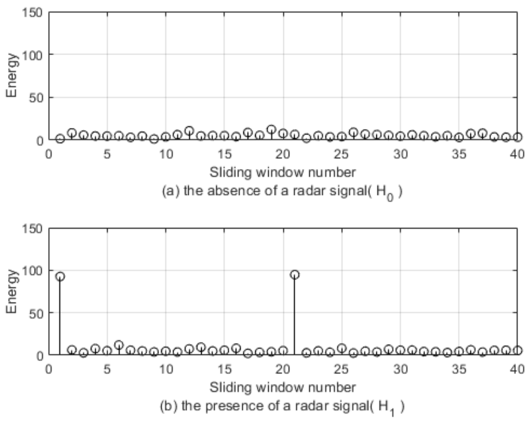

Fig. 2. An example of sliding window energy sequences

hypotheses. We adopt a simple DL model as shown in Table 1. An input sample, which is the received energy sequence $\{E_m, m=1, \cdots, M\}$, is fed into the first fully connected layer consisting of K nodes, followed by batch normalization and rectified linear unit (ReLU) activation function. To mitigate the possibility of overfitting, we use the dropout layer with a 50% dropout ratio. Subsequent to the application of the second layer with the same structure, the output is conveyed to the last fully connected layer with an output size of 2. This layer employs the softmax activation function to convert the two outputs into probabilities, representing the likelihood of hypotheses H_0 and H_1, respectively. By training the DL model, we can determine its model parameters to guarantee a given false alarm probability and to minimize detection error probability which is called the Neyman Pearson criterion.

Table 1. Deep learning model for the proposed scheme

Layers	Note
Input	input size = M
Dense layer 1	output size = K, batch normalization, activation = ReLU, dropout = 50%
Dense layer 2	output size = K, batch normalization, activation = ReLU, dropout = 50%
Dense layer 3	output size = 2, activation = softmax

Ⅲ. Simulation Results

For performance evaluation, a pulse radar signal with a pulse width of 2 μs and a pulse repetition period of 0.1 ms was considered, assumed to be received through the Rayleigh fading channel. The length of the observation window was set to 0.2 ms, and the sampling rate was set to 1 MHz. Detection thresholds were experimentally determined for the three cases of target false alarm probabilities of 0.01, 0.05, and 0.1, which were considered since the high false alarm rate is not of interest in the context of spectrum sensing. The uncertainty of background noise power was set to 0 dB and 2 dB. We assumed that the sliding window is 5 μs long and there is no overlap in time between the consecutive sliding windows. Under these simulation conditions, the input size M for the sensing schemes becomes 40. For the DL model, we chose $K = 30$ nodes for each of the first layer and second layer based on the experimental results that have been conducted. The sizes of training data, validation data, and test data for the DL model were 178,500 samples, 31,500 samples, and 10,000 samples, respectively. Here the training data for H_1 hypothesis were generated with random SNR following a uniform distribution over [-10, 0] dB.

Fig. 3 illustrates the performances of the reference scheme and the proposed scheme in terms of detection probability versus false alarm probability for an SNR of -10 dB. In the figure, "NPU" represents noise power uncertainty, "REF" refers to the reference scheme and "DL" indicates the proposed

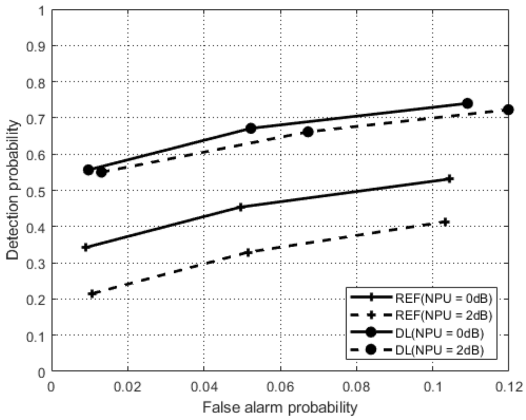

Fig. 3. Detection probability versus false alarm probability for an SNR of -10dB

spectrum sensing scheme adopting deep learning. Also, the actual false alarm rates differ slightly from the target values of 0.01, 0.05, and 0.1 since these values are obtained from computer simulations. As expected, the DL scheme is shown to outperform the reference scheme. Similarly, Fig. 4 presents the spectrum sensing performances of the two schemes for an SNR of 0 dB and illustrates that their performances are improved relative to the case when the SNR is -10 dB. Additionally, the DL scheme is found to be more robust to the NPU than the reference scheme, as it exploits the pattern of the sliding window energy sequence. In conclusion, the proposed sliding window based sensing scheme demonstrates superior performance relative to the reference system. Furthermore, it can be easily generalized to include other types of sensing methods such as feature detection rather than energy detection.

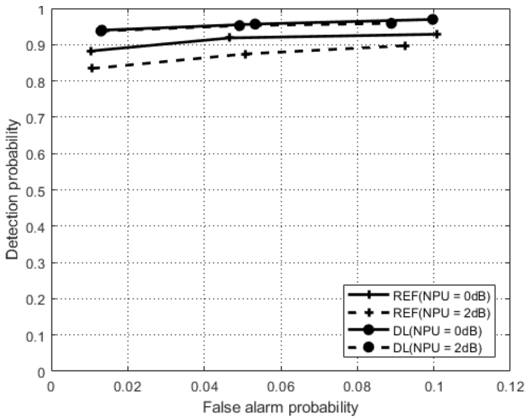

Fig. 4. Detection probability versus false alarm probability for an SNR of 0dB

References

[1] M. Parvini, et al., "Spectrum sharing schemes from 4G to 5G and beyond: Protocol flow, regulation, ecosystem, economic," *IEEE Open J. Commun. Soc.*, vol. 4, pp. 464-517, 2023. (https://doi.org/10.1109/OJCOMS.2023.3238569)

[2] C. H. Lim, et al., "Spectrum sensing techniques for detection of radar signals in radar bands," *J. KICS*, vol. 43, no. 12, pp.

2048-2056, Dec. 2018.
(https://doi.org/10.7840/kics.2018.43.12.2048)

[3] C. H. Lim, et al., "GLRT-Based spectrum sensing techniques for pulse radar signals," *IEEE Commun. Lett.*, vol. 24, no. 2, pp. 447-450, Feb. 2020.
(https://doi.org/10.1109/LCOMM.2019.2954307)

[4] Y. Noh, et al., "Adaptive-sliding-window-based detection for noncooperative spectrum sensing in radar band," *IEEE Syst. J.*, vol. 16, no. 3, pp. 3878-3881, Sep. 2022.
(https://doi.org/10.1109/JSYST.2021.3099349)