On the Structured Design for Efficient Machine Learning Based PRACH Preamble Detection

Du Hui Yang
School of Electronic Engineering
Kyonggi University
Suwon-si, South Korea
yangdh95@kyonggi.ac.kr

Sang Won Choi
School of Electronic Engineering
Kyonggi University
Suwon-si, South Korea
swchoi20@kyonggi.ac.kr

***Abstract*—In this paper, we consider a structured design for efficient PRACH preamble detection in conjunction with devised Machine Learning (ML) methodology. Specifically, the main contribution of this paper is to provide the receiver structure such that all the learned weights and biases in the ML are maintained irrespective of timing offset which varies in the actual PRACH preamble detection situation. Furthermore, by considering an enhanced input signal called Complex power Delay Profile (CDP) rather than Power Delay Profile (PDP), the proposed PRACH preamble detection scheme is shown to have not only efficient structure but also enhanced detector performance in the sense of detection and false alarm probabilities. For that, we show the effectiveness of the proposed detector structure by leveraging mathematical signal interpretation. Consequently, we show that there exists SNR gain where the proposed PRACH preamble detector satisfies the corresponding 3GPP performance requirement in comparison with the existing typical one, which validates the proposed structured design from the perspective of detector performance.**

***Index Terms*—Complex power delay profile (CDP), machine learning (ML), physical random access channel (PRACH), preamble detection, power DP (PDP)**

I. Introduction

In the 5-th Generation (5G) New-Radio (NR) wireless mobile communication system, one of the crucial procedures is a random access (RA) procedure for uplink synchronization, determining the identifier (ID) of the user equipment (UE) and the time advance (TA) between the UE and the base station (BS). The two types of RA exist, i.e., Contention Based RA (CBRA) and Contention Free RA (CFRA) [1]. Unlike the CFRA, in which the transmitted preamble is determined, the UE randomly chooses one of up to 64 PRACH preambles and transmits it to the physical random access channel (PRACH) in CBRA. If each UE selects a different preamble, the BS can identify each UE by detecting the corresponding ID and TA in the physical layer perspective [2].

For that, the PRACH preamble is generated using a Zadoff-Chu (ZC) sequence with ideal correlation properties, which is widely used for synchronization signal detection [3], [4]. Specifically, the conventional threshold-based detection scheme typically makes use of the Power Delay Profile (PDP) obtained by correlating the received PRACH preamble with the locally generated ZC sequence. Based on the preamble related shared information between the BS and the UE by higher layer signaling, the Search Window (SW) in the PDP can be specified, and if the maximum value within the SW, i.e., the peak exceeds the predetermined threshold, the preamble ID and TA as timing information corresponding to the specific SW are identified. The conventional threshold-based scheme works normally for PRACH preamble detection in high Signal to Noise Ratio (SNR) regime. This is mainly due to the desirable correlation properties of ZC sequence. However, in low SNR regime, depending mainly on the feasible correlated power through PDP has inherent limitations for PRACH preamble detection, which results in non-negligible false alarm and miss detection.

To overcome such a problem, several research has been conducted using machine learning (ML) and the preliminaries are [5]– [8]: In [5], [6], classical ML, such as K-Nearest Neighbor (K-NN), naive Bayes (NB), decision tree classifier (DTC), and ensemble learning, based preamble detection algorithm is proposed. The mean and variance of the SW were used as input for each ML model. Although the detection performance is better than that of the conventional algorithm, the inputs, mean and variance of the SW, are difficult to consider as fully using the information of the SW. In [7], a Convolutional Neural Network (CNN)–based algorithm using a time-domain waveform as input data, instead of correlation results, was proposed. By removing the correlation step and keeping the number of CNN parameters smaller than those used for image classification, accurate detection with SNR gain can be achieved using a Deep Learning (DL) model with computational complexity similar to conventional algorithms. However, because the correlation properties of the ZC sequence were not used, it was difficult to ensure that sufficient information was included in the input layer. Furthermore, the shape of the waveform changes depending on the root sequence number of the PRACH preamble; therefore, the number of parameters in the CNN model must be increased to ensure consistent performance for all waveform shapes. Jang *et al*. [8] presented a non-orthogonal DL–based end-to-end RA framework that detects all PRACH preambles Even different

This work was supported by the Institute of Information & communications Technology Planning & Evaluation(IITP) grant funded by the Korea government(MSIT) (No. 2021-0-00165, Development of 5G+ Intelligent Basestation Software Modem)

UEs transmit the same PRACH preamble for massive Internet of Things (mIoT). In this algorithm, SW is classified into multiple classes, the number of preambles in one SW, through the CNN and classification is performed, and the combination of TAs of the corresponding class is estimated through the Fully connected Neural Network (FNN). This algorithm shows that the ML–aided detection algorithm can overcome the limitations of the conventional binary classification algorithm.

In this paper, we propose a structural design for efficient PRACH preamble detection that effectively combines the conventional algorithm with the ML-based algorithm. Specifically, before the preamble detection, the TA estimation step based on the conventional algorithm is performed. Because the TA estimation is simple and noise-robust. After that, the data pre-processing step, which makes all types of SW have a similar shape based on the estimated TA, is performed. Because of this pre-processing step, even if we use an FNN model with a small number of parameters, we can guarantee a more noise-robust detection performance regardless of the TA of the PRACH preambles. In addition, we propose a new data form called the Complex power Delay Profile (CDP), a complex number resulting from correlation. Compared with the PDP, which only has power information, the CDP contains phase information in addition to the information included in the PDP. Using the CDP as the input for the FNN model guarantees a more powerful detection performance than using the PDP as the input.

The rest of the article is organized as follows. Section II introduces the PRACH preamble structure, transmission-reception process, and conventional algorithm with the presentation of its problems. Section III mathematically shows the overall procedure of the proposed algorithm, the TA estimation step, the pre-processing step, and CDP. Section IV proves the validity of the proposed algorithm by numerically comparing the performance of the proposed algorithm with that of the conventional algorithm. Finally, Section V concludes the paper.

II. System Model

Here, we focus on Contention-Based RA (CBRA), assuming that 64 preambles are possible, and only consider the Additive White Gaussian Noise (AWGN) channel environment. Specifically, the UE generates the PRACH preamble as

$$x_{u,v}[n] = x_u((n + C_v) \text{ mod } L_{RA}), \tag{1}$$

where

$$x_u[i] = exp\left(-j\frac{\pi ui(i+1)}{L_{RA}}\right), i = 0, 1, ..., L_{RA} - 1 \tag{2}$$

with $C_v = vN_{CS}$, and $x_{u,v}[n]$ represents the cyclic shift result of $x_u[i]$ and the time domain sequence of the PRACH preamble. L_{RA} denotes the PRACH preamble length, which is 139 or 839 depending on the preamble format, N_{CS} is the amount of cyclic shift and determines the length of SW in PDP; u is the logical sequence number mapped into the root sequence index and v is one of $0, \cdots, \frac{L_{RA}}{N_{CS}} - 1$. The range of the root sequence index is determined from the higher layer parameter shared with UE and BS. The number of possible PRACH preamble corresponding to one u is $\frac{L_{RA}}{N_{CS}}$, same as C_v, and if it is less than 64, then u should be increased till the number of possible PRACH preamble is 64.

A specific UE randomly chooses one of the 64 PRACH preambles. Subsequently, L_{RA}–point FFT proceeds as follows:

$$X_{u,v}[k] = \sum_{n=0}^{L_{RA-1}} x_{u,v}[n]exp\left(\frac{-j2\pi nk}{L_{RA}}\right), \quad k = 0, ..., L_{RA} - 1, \tag{3}$$

where $X_{u,v}[k]$ is L_{RA}–point FFT result of $x_{u,v}[n]$.

From N_{FFT}–point IFFT, $z_{u,v}[n]$, the time domain sequence after subcarrier mapping and Orthogonal Frequency Division Multiplexing (OFDM) modulation, is generated as

$$z_{u,v}[n] = \sum_{n=0}^{N_{FFT}-1} Z_{u,v}[k]exp\left(\frac{j2\pi nk}{N_{FFT}}\right), \quad n = 0, ..., N_{FFT} - 1, \tag{4}$$

where,

$$Z_{u,v}[k] = \begin{cases} X_{u,v}[k], & \text{if } n^{sc}_{start} \le k < n^{sc}_{start} + L_{RA}. \\ 0, & \text{else.} \end{cases} \tag{5}$$

Here, n^{sc}_{start} is the start location of the PRACH subcarrier in the frequency domain determined from the high-layer parameter. Finally, $z_{u,v}[n]$ is transmitted to PRACH after N_{rep} repetitions and adding N_{CP} length cyclic prefix (CP) [3].

The BS computes the mean of the repeated part of the time-advanced signal received at the jth antenna.

$$r^j_{u,v}[n] = z_{u,v}[n - \tau] + \omega[n], n = 0, ..., N_{FFT} - 1, \tag{6}$$

where $r^j_{u,v}[n]$ represents the mean of the repeated part of CP removed signal received at jth antenna $(j = 1, 2, ..., N_{RX})$. $\omega[n]$ is the noise owing to the AWGN channel. from OFDM demodulation, $R^j_{u,v}[k]$ is obtained as

$$R^j_{u,v}[k] = \sum_{n=0}^{N_{FFT}-1} r^j_{u,v}[n]exp\left(\frac{-j2\pi nk}{N_{FFT}}\right), \quad k = 0, ..., N_{FFT} - 1 \tag{7}$$

with (4), (6), we can write (7) as

$$R^j_{u,v}[k] = Z_{u,v}[k]exp\left(\frac{-j2\pi\tau k}{N_{FFT}}\right) + \Omega[k], \quad k = 0, ..., N_{FFT} - 1, \tag{8}$$

where $\Omega[k]$ is the noise in the frequency domain. By removing zeros, $Y^j_{u,v}[k]$ can be obtained as

$$Y^j_{u,v}[k] = \left\{R^j_{u,v}[k] | n^{sc}_{start} \le k < n^{sc}_{start} + L_{RA}\right\}. \tag{9}$$

With the locally generated ZC sequence using (2), the BS computes the correlation power of $Y^j_{u,v}[k]$,

$$PDP^j_u[n] = \frac{1}{N_{FFT}} \left|a^j_u[n]\right|^2, \tag{10}$$

where

$$a_u^j[n] = \sum_{k=0}^{N_{FFT}-1} A_u^j[k] exp\left(\frac{j2\pi nk}{N_{FFT}}\right), \quad n = 0, ..., N_{FFT}-1, \tag{11}$$

and

$$A_u^j[k] = \begin{cases} Y_{u,v}^j[k]X_u^*[k], & \text{if } 0 \leq k < L_{RA}-1. \\ 0, & \text{else.} \end{cases} \tag{12}$$

where $X_u[k]$ is L_{RA}-point FFT result of the locally generated ZC sequence with the logical number u. $PDP_u^j[n]$ is the correlation power of the received signal $Y_{u,v}^j[k]$ with $X_u[k]$. After the correlation step, $PDP_u[n]$, the mean of all $PDP_u^j[n] (j \in 1, ..., N_{RX})$, is computed as

$$PDP_u[n] = \frac{1}{N_{RX}} \sum_{j=1}^{N_{RX}} PDP_u^j[n]. \tag{13}$$

The SW with a real peak in the PDP depends on the u, v of the transmitted preamble. Because the BS does not know the exact u,v of the transmitted PRACH preamble, the BS must apply the detection algorithm to all 64 preamble candidates. The SW in $PDP_u[n]$ corresponding to u and v, $D_{u,v}^{PDP}[n]$, is defined as follows:

$$D_{u,v}^{PDP}[n] = \{PDP_u[n] | vN_{SW}+1 \leq n \leq (v+1)N_{SW}\} \tag{14}$$

and

$$N_{SW} = \frac{N_{CS}N_{FFT}}{L_{RA}}, \tag{15}$$

where N_{SW} denotes the length of the SW. The conventional threshold-based algorithm compares the peak of $D_{u,v}^{PDP}[n]$ with a specific threshold γ_{th}. If the peak of $D_{u,v}^{PDP}[n]$ does not exceed the γ_{th}, then that peak is determined as a false peak. If it exceeds, the PRACH preamble for $D_{u,v}^{PDP}[n]$ is treated as detected, and the identifier, ID, and estimated TA, $\hat{\tau}$, for the corresponding SW are $\{u, v\}$ and the peak location, respectively.

$$\hat{\tau} = \text{argmax}_n \left(D_{u,v}^{PDP}[n]\right). \tag{16}$$

In a low SNR regime, as the noise power increases, the conventional algorithm has a critical problem, that is, the increase in false alarm probability, P_f, as the false peak exceeds the γ_{th}, and the decrease in the detection probability, P_d, as the true peak does not exceed the γ_{th}. These problems cause serious performance degradation in 5G communication systems.

III. Proposed scheme

In this Section, we propose an efficient ML-based PRACH detection algorithm that can improve the performance in terms of P_d and P_f compared with the conventional threshold-based detection algorithm. We can consider the result of (11) as an input to the machine-learning model to derive an improved machine-learning-based detection algorithm. This is because the PDP, the result of (10), contains only correlation power information. However, the result of (11) contains not only power information but also phase information, making it superior in terms of the amount of information it contains. By using (11), we propose a new form of input data, the complex delay profile(CDP), as follows:

$$CDP_u^j[n] = \sqrt{\frac{1}{N_{FFT}}} a_u^j[n], \tag{17}$$

where $CDP_u^j[n]$ denotes the normalized complex number result of the correlation between the locally generated ZC sequence using u and the signal received from the jth antenna. Depending on the TA, the peak location of SW in PDP changes.

A phase shift, including a change in the peak location, also occurs in SW in CDP. Using (6) and (9), we can write (10) as

$$Y_{u,v}^j[k] = X_{u,v}[k] exp\left(\frac{-j2\pi\tau k}{N_{FFT}}\right) exp(j\theta_\tau), \tag{18}$$

where

$$\theta_\tau = \frac{-2\pi\tau n_{start}^{sc}}{N_{FFT}}. \tag{19}$$

So, the time domain sequence of $Y_{u,v}^j[k]$, $y_{u,v}^j[n]$, is

$$y_{u,v}^j[n] = x_{u,v}[n-\tau] exp(j\theta_\tau). \tag{20}$$

In the proposed ML-based algorithm, data pre-processing aims to guarantee the same detection performance regardless of the TA by making all SWs used as machine learning inputs have a similar shape. To achieve this, the peak location of any SW should be the same, and the phase shift should be corrected. Fig. 1 illustrates the structure of the proposed ML-based PRACH preamble receiver, respectively. First, $CDP_u[n]$, the average of all $CDP_u^j[n]$, is obtained as follows:

$$CDP_u[n] = \frac{1}{N_{RX}} \sum_{j=1}^{N_{RX}} CDP_u^j[n]. \tag{21}$$

Then, SW in $CDP_u[n]$, $D_{u,v}^{CDP}[n]$, is defined as

$$\begin{aligned} &D_{u,v}^{CDP}[n] \\ &= \{CDP_u[n] | vN_{SW}+1 \leq n \leq (v+1)N_{SW}\}. \end{aligned} \tag{22}$$

Using (16), the proposed algorithm estimates the peak location of $D_{u,v}^{CDP}[n]$, $\tilde{\tau}$, in the same manner as in the conventional algorithm. With $\tilde{\tau}$, data pre-processing is performed as follows:

$$\begin{aligned} &D_{u,v}^{CDP,\alpha}[n] \\ &= D_{u,v}^{c}\left[(n+\alpha-\tilde{\tau}) \mod N_{SW}\right] exp(-j\tilde{\theta_\tau}) \end{aligned} \tag{23}$$

for $n = 1, \cdots, N_{SW}$ and

$$\tilde{\theta_\tau} = -\left(\frac{n_{strart}^{sc}\tilde{\tau}}{N_{FFT}}\right), \tag{24}$$

where $\tilde{\theta_\tau}$ denotes the estimated phase-shift value using $\tilde{\tau}$ based on (20). $D_{u,v}^{CDP,\alpha}[n]$ is the data pre-processing result

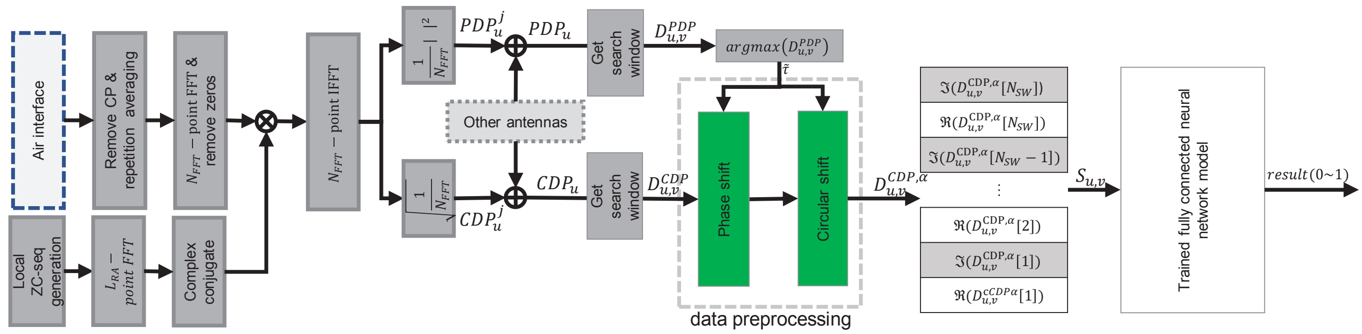

Fig. 1. Structure of proposed PRACH preamble receiver

TABLE I
PROPOSED FNN MODEL STRUCTURE

Layer	Info
Input	nums of nodes : $2N_{SW}$
Dense	nums of nodes : 64
Activation func	ReLu
Dense	nums of nodes : 64
Activation func	ReLu
Dense	nums of nodes : 64
Dense	nums of nodes : 1
Activation func	sigmoid

of $D_{u,v}^{CDP}[n]$, which is an SW with a specific point, α, as a peak location and phased shift corrected.

After the data pre-processing step, the proposed algorithm uses $S_{u,v}[n]$, which comprises the real and imaginary parts of $D_{u,v}^{CDP,\alpha}[n]$, as an input to the ML model.

$$S_{u,v}[m] = \begin{cases} \Re\left(D_{u,v}^{CDP,\alpha}\left[\frac{m}{2}+1\right]\right), & \text{for odd } m. \\ \Im\left(D_{u,v}^{CDP,\alpha}\left[\frac{m}{2}\right]\right), & \text{for even } m. \end{cases} \tag{25}$$

for $m = 1, 2, \cdots, 2N_{SW}$. Here, $\Re(f[n])$ and $\Im(f[n])$ denote real and imaginary parts of $f[n]$ respectively.

The proposed algorithm uses an FNN as the ML model. Table I lists the structure of the proposed FNN model. The training dataset for the ML model comprised Class 1 (detected), an SW generated using a PRACH preamble with noise with a specific SNR. Class 0 (not detected) is an SW generated only using noise with a specific SNR, and the training dataset was used for pre-training the ML model after the pre-processing step. Because the proposed FNN is a binary classification, the sigmoid function is used at the output layer [9]. Hence, if the output is less than 0.5, it is classified as class 0; if it exceeds 0.5, it is classified as class 1. If a specific SW is classified as class 1, the identifier of the UE corresponding to SW, ID, and the estimated TA, $\hat{\tau}$, are set to u, v of that SW and $\tilde{\tau}$ respectively.

IV. NUMERICAL RESULTS

The 3rd Generation Partnership Project (3GPP) specifies the performance requirement of PRACH preamble detection [10] as follows:

TABLE II
SIMULATION ENVIRONMENT AND PARAMETERS

Items	Value
N_{CS}	23
Preamble format	C0
v	0
L_{RA}	nums of nodes : 64
Sub carrier space (SCS)	15 kHz
N_{FFT}	1024
Number of rx antennas(N_{RX})	2
Number of tx antennas(N_{TX})	1
SNR of training data sets	-16 – -8 dB
Iteration in each SNR	10^5
Channel	AWGN
SNR range	-10.3 – -5.3 dB
Time error tolerance (β)	0.52 μs (7 samples)
Mode	Normal

- If the BS detected only transmitted PRACH preamble, and the estimated TA satisfies the following equation, then this is regarded as detection.

$$|\tau - \hat{\tau}| < \beta, \tag{26}$$

  where τ is the real TA, β is the sampled time error tolerance with sample rate, T_s.
- When only noise is transmitted, if even one SW is determined as detected, then this is regarded as false alarm.
- In PRACH preamble detection, P_d should be higher than 0.99, and P_f should be lower than 0.001.

Table II shows the simulation environment based on 3GPP Specifications [9]. Moreover, T_s was $\frac{1}{N_{FFT}SCS} \cong 0.0651$ μs, so β was $\frac{0.52us}{T_s} = 7$. Simulation results and training datasets were obtained through numerical experiments With a repetition of 10^5 times.

As a training dataset, data in the SNR range of -16 to -8 dB in units of 2 dB were used individually in the AWGN channel. The lowest SNR that satisfies the 3GPP requirement ($P_d \geq 0.99, P_f \leq 0.001$) for the conventional algorithm was –8.5 dB and the lowest SNRs for the proposed algorithm using training data with SNRs of –16dB, -14dB, -12dB, -10dB, and –8dB were –7.5dB, -9.8dB, -9dB, -8.5dB,

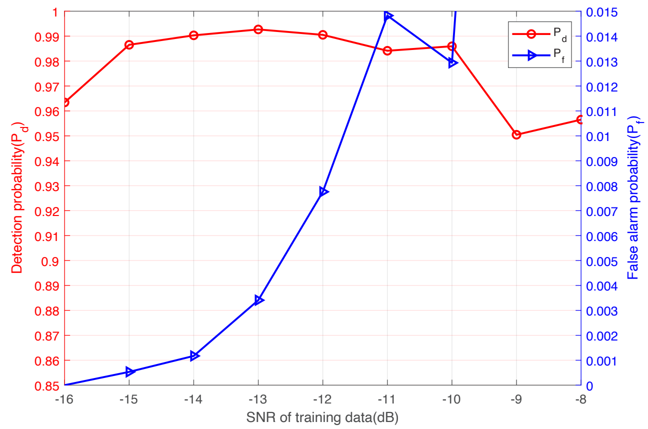

Fig. 2. P_d and P_f for each SNR with the training data with AWGN channel of -10dB

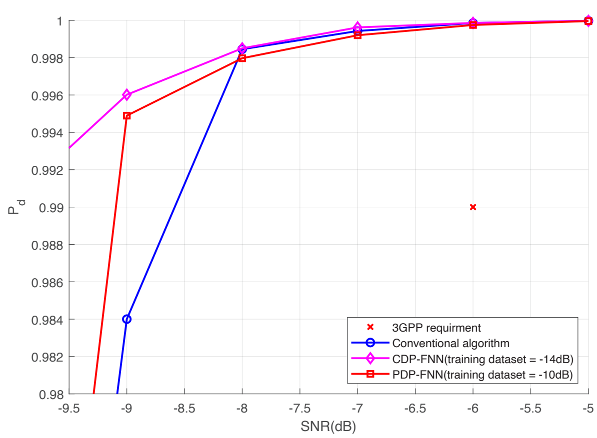

Fig. 3. P_d for detection schemes optimized for each SNR

and -8.1dB, respectively. In addition, to find the optimal SNR of the training dataset in the proposed algorithm, the P_d and P_f of each SNR of the training data in AWGN channel of -10dB are shown in Fig. 2. In the -10 dB AWGN channel, only the case using training data with an SNR of -14 dB almost satisfies the 3GPP requirement, and the SNR gain of the optimal proposed algorithm compared to the conventional algorithm was 1.3 dB.

To demonstrate the performance gain by improving the input information from PDP to CDP, we compared the performance of the ML-based algorithm using PDP as an input, PDP-FNN, and the proposed algorithm, CDP-FNN. In the ML model for PDP-FNN, the number of input nodes is set to N_{SW}, but all other structures are the same as in the proposed algorithm, and a training dataset with an SNR of -10 dB was used. The superiority of CDP-FNN over PDP-FNN is confirmed from Fig. 3.

V. Conclusion

We proposed an efficient ML-based preamble detection for PRACH preamble ID and TA by leveraging appropriate ML methodology. The peak location was first identified through the conventional algorithm to construct an ML model that guarantees the same detection performance regardless of TA while keeping the number of parameters small. Subsequently, through data pre-processing using the peak location, the shape of the input data was made similar to that of the training data. In addition, by using CDP, which was first proposed in this paper, as input data, we could use the phase information of the input data. The power information and the phase-shift correction scheme for pre-processing for CDP were also shown mathematically. Through numerical experiments based on the 3GPP conformance test, we compared the performance of the conventional and proposed algorithms in an AWGN channel environment. Our results showed that the proposed algorithm using an SNR of -14 dB in the training dataset had an SNR gain of 1.4 dB compared to the conventional algorithm. Furthermore, to demonstrate the usefulness of CDP, we compared the performance of the proposed scheme (CDP-FNN) with that of the ML-based detection algorithm using the PDP as input data (PDP-FNN). Consequently, the CDP-FNN has an SNR gain of 0.9 dB compared to the PDP-FNN. In conclusion, the proposed scheme has been shown to possess a reasonable potential to be an efficient PRACH preamble detector in conjunction with the ML methodology.

References

[1] 3GPP TS 38.300 V17.5.0, "Technical Specification Group Radio Access Network; NR; NR and NG-RAN Overall Description; Stage 2 (Release 17)," June 2023.
[2] E. Dahlman, S. Parkvall, and J. Skold, "Random access," in *5G NR: The next generation wireless access technology,* 1$^{\text{th}}$ ed. Academic press, 2018.
[3] 3GPP TS 38.211 v17.2.0, *"5G NR physical channels and modulation,"* June 2022.
[4] D. Chu, "Polyphase codes with good periodic correlation properties," *IEEE Trans. Inf. Theory,* vol. 18, no. 4, pp. 531-532, July 1972.
[5] N. Modina, R. Ferrari, and M. Magarini, "A machine learning-based design of PRACH receiver in 5G," *Procedia Comput. Sci.,* vol. 151, pp. 1100-1107, 2019.
[6] S. S. Zehra, M. Magarini, R. Qureshi, S, M. N. Mustafa, and F. Farooq, "Procative approach for preamble detection in 5G-NR PRACH using supervised machine learning and ensemble model," *Sci. Rep.,* vol. 12, pp. 1-10, May 2022.
[7] H. Sun, A. O. Kaya, M. Macdonald, H. Viswanathan, and M. Hong, "Deep learning based preamble detection and TOA estimation," in *Proc. of 2019 IEEE Global Communications Conference (GLOBECOM),* pp 1-6, Waikoloa, HI, USA, Dec. 2019.
[8] H. S. Jang, H. Lee, T. Q. S. Quek, and H. Shin, "Deep learning based cellular random access framework," *IEEE Trans. Wirel. Commun.,* vol. 20, no. 11, pp. 7503-7518, Nov. 2021.
[9] S. Sharma and A. Athaiya, "Activation functions in neural networks," *Int. J. Appl. Sci. Eng.,* vol. 4, issue 12, pp. 310-316, April 2020.
[10] 3GPP TS 38.104 v 17.5.0, "Base station radio transmission and reception," Mar. 2022.