A Study on Deep Learning-Based Sampling Rate Estimation of Drone Signals

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Abstract— **This study presents a method for estimating the sampling rate of drone signals using Orthogonal Frequency Division Multiplexing (OFDM) and provides corresponding experimental results. The considered estimation approach utilizes the fast Fourier transform (FFT) Window Banks (FWB)-Convolutional Neural Network (CNN) model, which is based on the existing 1-D CNN. First, received signals from the DJI Mini 3 drone are captured at a sufficiently high sampling rate using a wideband receiver. Subsequently, the number of samples corresponding to the useful OFDM symbol duration is estimated using autocorrelation. At the same time, the FFT size of the drone signal is inferred employing the FWB-CNN model. The ratio of the estimated useful OFDM symbol duration to the estimate of FFT size indicates the relative sampling rate of the wideband receiver to that of the actual drone signal. Therefore, the sampling rate of the DJI Mini 3 drone signal is finally estimated by applying this ratio to the known sampling rate of the receiver. The FWB-CNN model is trained on OFDM signals generated by a computer simulator, where the signals have different bandwidths under noisy channels with various noise levels. Experimental evaluation results demonstrate that the sampling rate of drone signals can be accurately estimated.**

Keywords— CNN, drone, FFT, OFDM, sampling rate

I. Introduction

As drones become more commercially available, the number of users modifying or repurposing them for various purposes is also increasing. Some users even share how to attach remote-controlled drop devices to commercial drones to drop objects from the air. However, such modifications are not just for hobbyists. Armed groups in the Middle East have adopted these modifications and used drones as bomb-dropping platforms to carry out deadly attacks that spread fear and amplify propaganda. Moreover, the Russia–Ukraine War, which began in 2022, clearly showed the military value and tactical importance of drones. In particular, small civilian drones are highly effective in aerial reconnaissance and artillery engagements, and their use on the battlefield is rapidly increasing. However, countering small drones remains challenging, and the threat of drones continues in conflict zones [1][2]. Therefore, anti-drone solutions are being widely developed to counter drone threats. Drone detection is particularly important, and one practical approach is to capture and analyze the radio frequency (RF) signals transmitted by remotely operated drones.

DJI drones are expected to maintain the largest market share, accounting for approximately 70% of global sales by 2025. These drones utilize Orthogonal Frequency Division Multiplexing (OFDM) signals as the basis for wireless data transmission. Therefore, analyzing OFDM-based drone signals requires accurate estimation of fundamental parameters. This study presents a blind estimation method for the sampling rate of drone signals and verifies its performance through experimental evaluations. This estimation method utilizes the fast Fourier transform (FFT) Window Bank-Convolutional Neural Network (FWB-CNN) model [3][4].

In this study, a wideband receiver is used to acquire the DJI Mini 3 drone signal at a sufficiently high sampling rate. From the captured signal, the number of samples corresponding to the useful OFDM symbol duration is estimated, and the FFT size is selected using the FWB-CNN model. To train the model, a synthetic dataset containing OFDM signals using various bandwidths under noise conditions is generated. To evaluate the accuracy of this approach, real drone signals are captured using a wideband receiver, and the estimated sampling rate is compared with a reference value.

II. Methodology

This section details a blind estimation for the sampling rate of an OFDM signal. This method involves estimating the number of samples corresponding to the useful OFDM symbol duration at the receiver sampling rate and estimating the FFT size of the OFDM signal using the FWB-CNN model.

A. Estimation of the useful OFDM symbol duration

In this study, an autocorrelation-based approach is used to estimate the number of samples, N_s, corresponding to the useful OFDM symbol duration by utilizing the received signal, $r[n]$, at a sufficiently high sampling rate. This process can be expressed as:

$$R(k) = \sum_{k=0}^{n} \mathrm{r}[n-\tau] r^*[n] \tag{1}$$

Here, n represents the time index and τ is the time delay in samples. The OFDM signal structure includes a cyclic prefix (CP) at the beginning of each signal to mitigate inter-symbol interference (ISI). Since the CP replicates the latter part of the useful OFDM symbol, the auto-correlation function shows a distinct peak at $\tau = N_s$, which allows for the estimation of N_s.

Furthermore, the autocorrelation-based estimate depends on the ratio of the FFT size of the OFDM signal and the sampling rates of the receiver and transmitter. For example, suppose the FFT size of an OFDM signal is 1,024 samples and the receiver's sampling rate is three times that of the transmitter. In that case, the autocorrelation-based estimate will be approximately 3,072 samples.

B. Estimation of the FFT Size

In this study, the FFT size estimation of OFDM signals is based on a one-dimensional CNN model, specifically the FWB-CNN method in [3]. The FWB is a preprocessing step and generates input data for the 1-D CNN model as follows: Let M be the number of candidate FFT sizes and $N_i, i = 1, \cdots M$, the i-th candidate. The received OFDM signal is resampled according to the ratio of N_i to N_s. Assuming the wideband receiver uses a sufficiently high sampling rate, this effectively downsamples the original signal. Then, an FFT of fixed size N_K is performed on this resampled signal.

After FWB preprocessing, a 1-D CNN model is trained and used to estimate the FFT size of the OFDM signal. Unlike conventional methods in [4], which input both the in-phase (I) and quadrature (Q) components of the FWB output to the CNN, this study uses only the magnitude spectrum obtained by taking the absolute value of the FWB output. This magnitude spectrum is normalized by its maximum value and used as the CNN input, thereby mitigating performance degradation that may occur due to phase mismatch between the received and training signals. Additionally, the training dataset contains OFDM signals of various bandwidths, reflecting realistic scenarios for signal acquisition.

Fig. 1 shows the 1-D CNN training data structure. The subcarrier ratio represents the ratio of the occupied bandwidth of the signal to the total bandwidth corresponding to the FFT size, facilitating the generation of OFDM signals across various bandwidths. Oversampling is performed based on the ratio of N_S/N_i, and the input segment to the CNN represents a set of FFT results corresponding to each candidate FFT size. Table I summarizes the dataset details used for training the 1D CNN. This study considers five candidate FFT sizes – 128, 256, 512, 1024, and 2048 – with the FWB FFT size denoted as N_K fixed at 4096. Table I summarizes the dataset details used for training the 1D CNN. The training parameters employed for the 1D CNN include a batch size of 256, 100 epochs, an initial learning rate of 0.01, and a learning rate decay every 10 epochs [3].

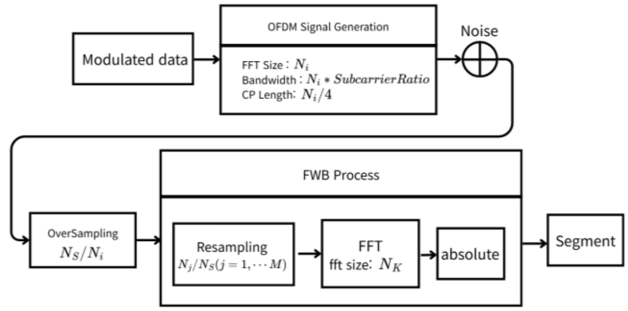

Fig. 1. CNN Model Training Data Structure

TABLE I. 1-D CNN TRAINING DATASET

Modulation	QPSK
Subcarrier Ratio	50, 60, 70%
FFT Size	128, 256, 512, 1024, 2048
CP Length	1/4*FFT Size
SNR Range	5, 10, 20, 30 [dB]
Training Segments	122,880 [Segments]

III. EXPERIMENTAL RESULTS

In this section, we capture the signal from DJI Mini 3 drone at a sufficiently high sampling rate and verify the estimation results for the number of samples corresponding to the useful OFDM symbol duration and the FFT size of the drone signal. The OFDM signal parameters and the signal capture environment for the DJI Mini 3 drone are detailed in Table II.

The autocorrelation results of the captured DJI Mini 3 drone signal are shown in Fig. 2. As shown in Fig. 2, the correlation peaks arising from the structural characteristics of the OFDM signal are clearly identified, allowing for estimating the useful OFDM symbol duration as 2667 samples. This estimate is consistent with the product of the FFT size of the OFDM signal used by the DJI Mini 3 drone and the ratio of the receiver and transmitter sampling rates.

TABLE II . DJI MINI 3 DRONE'S OFDM PARAMETERS AND CAPTURE ENVIRONMENT

DJI Mini 3 Drone's OFDM Parameters	
Modulation	QPSK
FFT Size	1024
Sampling Rate	15.36MHz
Signal Capture Environment	
Equipment	Signal Hound BB60D
Captured Sampling Rate	40MHz
Center Frequency	2.4GHz

Also, after capturing the DJI Mini 3 signal, we extracted the signal bearing interval using the energy threshold method to estimate the OFDM FFT size. A total of 53 intervals were extracted, and the first $N_i, i = 1, \cdots M$, samples from each interval were used to estimate the FFT size. The FFT size estimation results shown in Fig. 3 confirm that the estimated OFDM FFT size is 1024, which precisely matches the drone's actual FFT size.

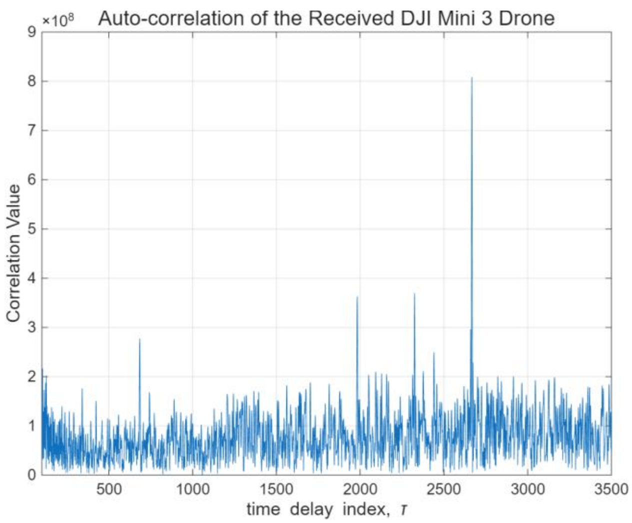

Fig. 2. Autocorrelation of the Received DJI Mini 3 Drone Signal

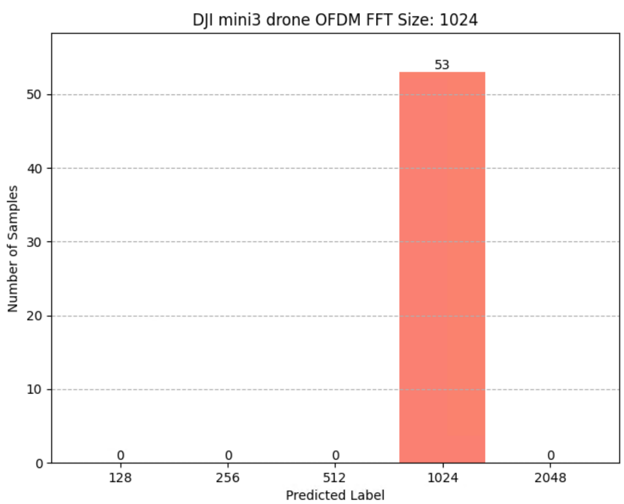

Fig. 3. OFDM FFT Size Estimation Performance for the DJI Mini 3 Drone

IV. Conclusion

This study extended an existing technique for blindly estimating the sampling rate of an OFDM signal by applying it to the DJI Mini 3 drone. This methodology successfully estimated both the number of samples corresponding to the useful OFDM symbol duration and the FFT size of the OFDM signal with high accuracy. Consequently, the sampling rate of the DJI Mini 3 drone was accurately determined.

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