Jamming and Classification of Drones Using Full-Duplex Radios and Deep Learning

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***Abstract*—The emerging full-duplex (FD) radio concept is set to double the spectral efficiency of commercial wireless networks, but it also has potential applications in the defense and security domains. In the form of multifunction military full-duplex radios (MFDRs), the FD capability could enable armed forces to conduct simultaneous electronic attacks, electronic support measures, and tactical communications. This paper demonstrates the feasibility of simultaneous jamming and reconnaissance of drones' remote control (RC) systems using a prototype MFDR. Alongside, we apply deep learning in the form of a convolutional neural network (CNN) for classifying the RC signals and analyze the effect of FD operation on the classification performance.**

I. Introduction

Recent advances in full-duplex (FD) radio research have enabled concurrently receiving and transmitting on the exact same frequencies. Such operation, as compared to the conventional half-duplex (HD) mode, improves the spectral efficiency of wireless communications and consequently enhances the network throughput in commercial systems [1]. In addition, FD radios can also reform the cyber battlefield by facilitating simultaneous combinations of electronic attacks, electronic support, and tactical communication [2], [3]. Several practical works have already demonstrated the feasibility of such concepts in laboratories [4]–[6]. We consider herein the application of the FD radio technology for countering the emerging threats caused by remotely operated aerial vehicles [7]–[9].

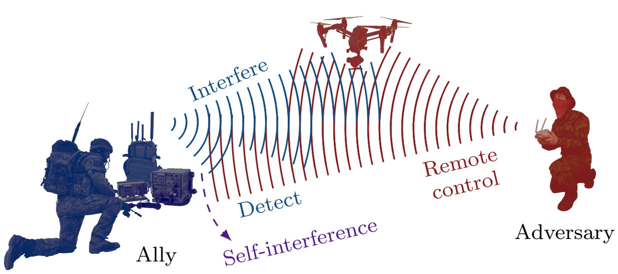

Fig. 1. Military full-duplex radios could be used to simultaneously detect and jam adversary drones' remote control systems, therefore benefiting from improved situational awareness and enhanced jamming techniques.

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The objectives of this work are to study the practical feasibility of simultaneously receiving and jamming the remote control (RC) signals of unmanned aerial vehicles/systems (UAV/Ss)—referred to as 'drones' herein—using FD radio technology and then to classify the intercepted signals using machine learning. The challenge is illustrated in Fig. 1. The RC signals received and classified during simultaneous jamming could be used to, e.g., locate the adversary or tailor the jamming waveform against the specific UAS. We propose the application of deep learning in the form of convolutional neural networks (CNNs) for the accurate classification of different RC protocols. Through measured and simulated results, we demonstrate the CNN model's feasibility to identify commercial drone RC signals in HD and FD modes.

II. Signal Detection and Classification

Deep learning has recently enjoyed significant success in various research areas that focus on feature extraction from raw input data [10], [11] and these advances have not gone unnoticed in the wireless communications research. Methods based on CNNs have been proposed for modulation recognition [12], wireless signals' classification [13], transmitter fingerprinting [14], radar classification [15] and, also, drone classification from radar micro-Doppler signatures [16], to name but a few. However, to the best of our knowledge, studies into drone RC signal classification have not been reported.

A. Architecture

Several radio-frequency (RF) signal representation and preprocessing methods have been proposed for deep learning-based signal classification purposes. These include simply using the complex-sampled time series of the signal without any preprocessing [17], the amplitude and phase difference representation [18], and the spectrogram-based method [18]. When considering the time-series representation, the wide bandwidth of the 2.4 GHz unlicensed radio band, in which many commercial drones operate, renders high computational complexity and can also degrade the overall classification accuracy [19]. In addition, time-series signal representation in deep learning methods for signal classification has been shown to have negative impacts on the overall classification accuracy for signals with frequency offsets, which could complicate the classification of the frequency-hopping signals at hand [19].

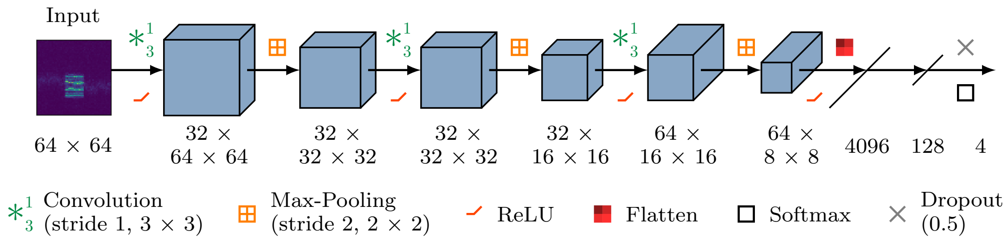


Fig. 2. The architecture of the convolutional neural network (CNN) used in this work for the spectrogram-based detection and classification of unmanned aerial vehicle (UAV) or 'drone' remote control (RC) signals after suppressing the self-interference (SI) caused by simultaneous same-band jamming.

The characteristics of typical drone RC systems, i.e., frequency hopping over a wide bandwidth, different channel frequencies, bandwidths and transmission times across different protocols, suit the spectrogram-based representation, as it is not sensitive to frequency offsets and phase shifts. In this work, we therefore rely on the spectrogram-based representation. In particular, the time-frequency evolution of the $80\,\mathrm{MHz}$ input signal is split into smaller spectrograms of size 64 × 64 pixels that are input to the CNN. Thus, the time and frequency coverage of the spectrograms is chosen to be $6.5\,\mathrm{ms}$ and $5\,\mathrm{MHz}$, respectively, in order for each of the different drone remote control signals analyzed in this paper to fit inside the spectrograms. The input is also normalized, as this enhances spectrogram-based classification accuracy [20].

The architecture of the proposed CNN model is outlined in Fig. 2. Similarly to efficient object recognition models [11], the spectrogram is passed through a stack of convolutional layers that have filters with very small receptive fields. To classify which of the categories (background interference and noise or one of the RC signals) the 64 × 64 spectrogram contains, it is passed through three consecutive convolutional layers, followed by two fully connected layers. In each of the convolutional layers, the convolution stride is 1 pixel and the receptive field is 3 × 3 pixels. The spatial padding of convolutional-layer inputs is such that the spatial resolution is preserved after the convolution. All convolutional layers are equipped with the rectified linear unit (ReLU) activation function that has been shown to speed up training in comparison to other activation functions [10]. Each convolutional layer is followed by a max-pooling layer for spatial pooling.

The two fully connected layers are followed by a softmax classifier that computes the probability of each class label over all classes. In order to prevent overfitting, dropout is used with a coefficient of 0.5 that has been shown to be close to optimal for a wide range of applications [21]. The model is implemented using open source TensorFlow machine learning framework [22] and Keras deep learning library [23].

B. Training

The CNN model was trained to classify between four categories: *'Noise'*, *'Taranis'*, *'Lightbridge'*, or *'Phantom 2'*. The data for training the model was recorded by connecting the RCs to a digital receiver one-by-one. The samples were recorded with different attenuation levels between the RC transmitter and the receiver in order to diversify the training dataset. During data collection, FD jamming and self-interference (SI) cancellation were not used. The noise class, unlike the three RC classes, was trained with an antenna at the $2.4\,\mathrm{GHz}$ band in order to capture authentic background transmissions. The noise samples were recorded in an urban environment iteratively through reinforced learning to minimize the false positive classification of the RCs.

Figure 3 gives examples of the time–frequency representations belonging to the classes that were used for training the CNN. The training dataset consists of 63,600 spectrograms, wherein 57,000 spectrograms represent the noise class and each remote controller is characterized by 2,200 spectrograms. The model was trained with a batch size of 128 using the Adam optimization algorithm, which updates the weights of the network adaptively to minimize classification errors [24].

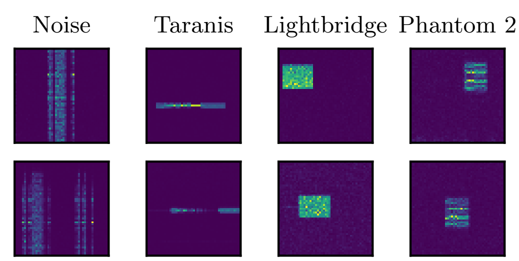


Fig. 3. Each spectrogram is 64 by 64 pixels, has a time duration of $6.5\,\mathrm{ms}$, and covers a frequency bandwidth of $5\,\mathrm{MHz}$. The 'Noise' class includes also co-channel interference, e.g., from WiFi/Bluetooth, and partial RC waveforms.

III. Experimental Setup

In order to verify the feasibility of simultaneous FD jamming and classification, we carried out experiments in a laboratory environment. The measurement setup simulates a scenario where an unauthorized drone is being remotely controlled and a prototype military full-duplex radio (MFDR) is used to simultaneously jam and intercept the RC link as shown in Fig. 4. All of the devices involved in the measurements are connected through coaxial cables instead of using antennas. This provides a controlled environment in which all sources of interference, besides the devices under test, are eliminated. Also, this ensures precise control and measurement of the power levels during the experiments and that the jammer does not cause any unlawful collateral interference to its vicinity.

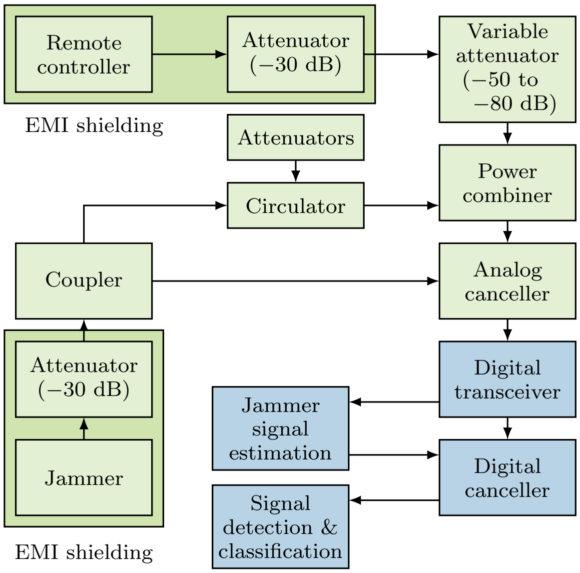


Fig. 4. The measurement setup, where both transmitters were enclosed in electromagnetic interference (EMI) shielding boxes to prevent wireless leakage from reaching the analog canceller and the digital transceiver.

A. Experimental Full-Duplex Transceiver

The MFDR prototype is built on top of a high-quality vector signal transceiver (PXIe-1073) that receives and records signals in a $80\,\mathrm{MHz}$ bandwidth ($120\,\mathrm{MHz}$ sampling rate) with duration of $50\,\mathrm{ms}$. A separate jammer with output power of $43\,\mathrm{dBm}$ is used to generate and transmit a $80\,\mathrm{MHz}$ wide linear chirp jamming signal that acts as SI for signal surveillance at the receiver. In order to suppress the jamming signal, SI cancellation is implemented in three stages. At the first stage, a circulator is used together with $30\,\mathrm{dB}$ of attenuation immediately after the jammer to imitate transmit–receive antenna isolation of approximately $60\,\mathrm{dB}$. Typically drone jammers, and in fact the jammer used in these measurements, use highly directional antennas. Therefore, taking into account the recent research in transmit–receive antenna isolation [25], it is plausible that such separation could be achieved. Passive isolation is followed by an active analog SI canceller [26] and, finally, the residual SI is suppressed digitally [27].

B. Remote Control Systems

Three different drone RC systems were used separately to provide the signals-of-interest in the measurements. The RCs were *FrSky Taranis X9D Plus*, *DJI Phantom 2*, and *DJI Phantom 3 Advanced*. Each of these RC systems makes full use of the $2.4\,\mathrm{GHz}$ industrial, scientific, and medical (ISM) band through frequency hopping. The remote controllers' output powers adhere to the $20\,\mathrm{dBm}$ limit of the ISM band. In order to emulate different remote controller signal strengths (or link distances), a variable attenuator was used between the remote controller and the receiving front-end. The remote controller signal was attenuated in the range of $-80\,\mathrm{dB}$ to $-110\,\mathrm{dB}$ with $5\,\mathrm{dB}$ steps.

The RC systems exhibited the following characteristics during our experiments. *FrSky Taranis X9D Plus* hops among 47 frequency channels with $1.5\,\mathrm{MHz}$ spacing between the center frequencies of adjacent channels and has a dwell time of $9\,\mathrm{ms}$, which is the time interval between each transmitted packet. The packet transmission time itself is actually lesser, $4.75\,\mathrm{ms}$. *DJI Phantom 2* hops among 36 frequency channels with dwell time of $7\,\mathrm{ms}$, packet transmission duration of $1.6\,\mathrm{ms}$, and has a spacing of $2\,\mathrm{MHz}$ between adjacent channels' center frequencies. *DJI Phantom 3 Advanced* uses *DJI Lightbridge* protocol with 34 different channels, spacing of approximately $2\,\mathrm{MHz}$, dwell time of $14\,\mathrm{ms}$, and transmission duration of $2.15\,\mathrm{ms}$. In principle, the differences in these parameters and modulation bandwidths is what enables the CNN model to classify between the protocols based on the spectrograms.

IV. Experimental Results

In this paper, we focus mainly on the classification results, acknowledging that both analog and digital SI cancellation stages contribute $40\,\mathrm{dB}$ to $45\,\mathrm{dB}$ of SI suppression [27]. The classification of *'Phantom 2'* RC signals is illustrated in Fig. 5. Without any SI, the packets are easily detected by the model, unlike when relying only on passive isolation as then the model is completely blinded. After analog cancellation, the model is already able to detect signals of interest in certain frequency ranges because of the canceller's frequency selectivity. After digital cancellation, the RC signals are accurately detected regardless of the used channel and the results resemble the situation without SI.

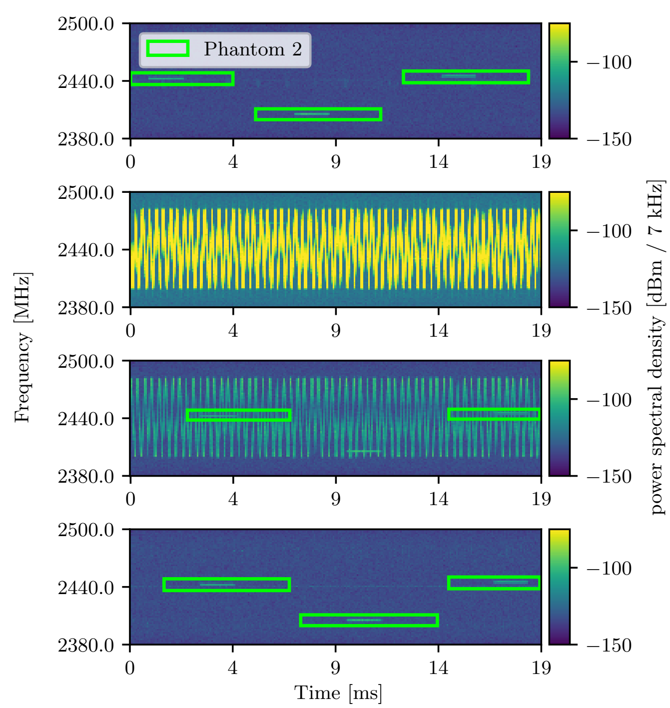
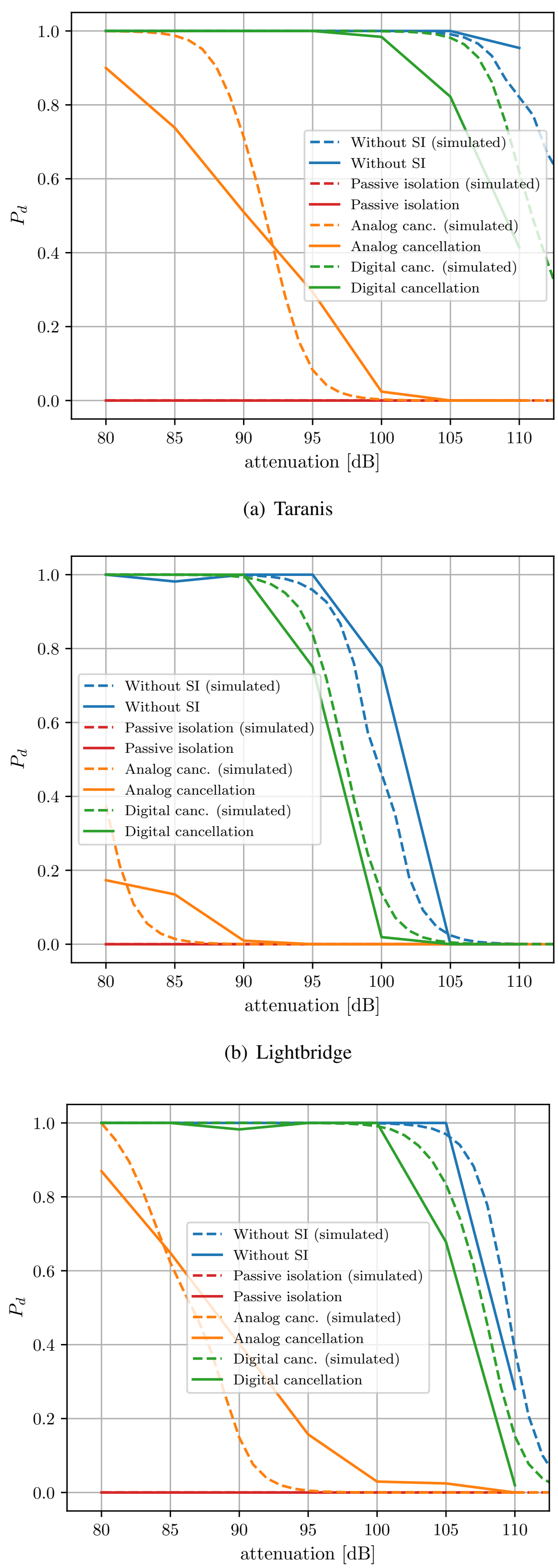


Fig. 5. Top–down: Example signal classification (a) without SI, (b) with SI and only passive isolation, (c) after analog SI cancellation, and (d) after digital SI cancellation. The bounding boxes indicate classification.



(a) Taranis

(b) Lightbridge

(c) Phantom 2

Fig. 6. Remote controller signal detection probability without SI, with SI and only passive isolation, after analog cancellation, and after digital cancellation.

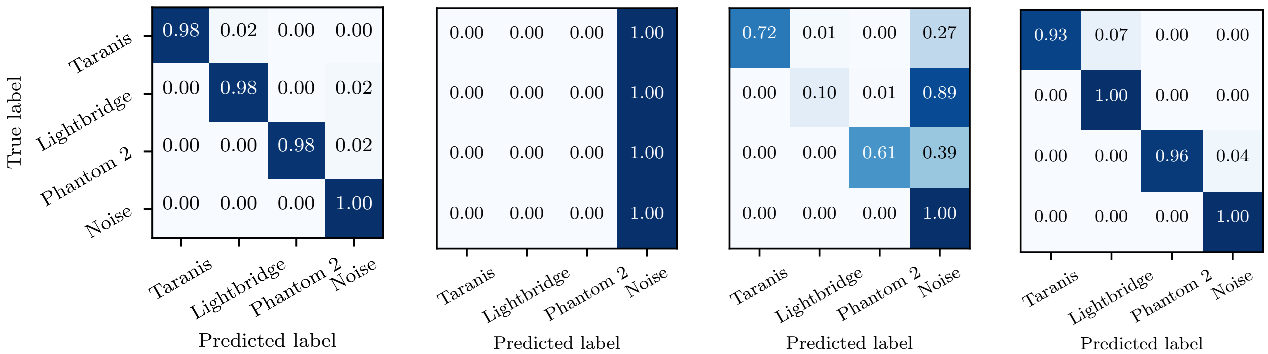
Figure 6 illustrates the measured and reference simulated signal detection probabilities P_d after each of the SI cancellation stages. The model is incapable of detecting any of the RC signals without active SI cancellation. Depending on the remote controller, the CNN is more or less successful in classifying the RC signals after analog cancellation at good signal-to-noise ratios (SNRs). However, digital interference cancellation substantially improves the detection probability and allows to detect the RC signals already at poor SNRs. Nevertheless, when compared to the results without SI from FD jamming, the probability of detection is slightly (2–$5\,\mathrm{dB}$) hampered by FD operation.

In general, the simulated and measured results are fairly similar, except for the analog cancellation stage. The simulations were carried out using a frequency-swept signal so that its power was constant and matched to the average measured power of the SI at the respective stage. However, because the analog canceller exhibits considerable frequency selectivity, the residual SI after the analog cancellation stage does not have constant power over the whole frequency band. Thus, in frequency ranges with more effective SI cancellation, the empirical probability of detection is better than in simulations and vice versa. This results in the more gentle slope of detection probability over the measured attenuation range.

The classification accuracy of the CNN model is tabulated in Fig. 7. The confusion matrices are calculated using the combined measurements that were carried out with attenuation values of $80\,\mathrm{dB}$ to $90\,\mathrm{dB}$ in order to emphasize the effect of residual SI rather than poor SNR. Similarly to the results presented in Figs. 5 and 6, the cases without SI limit the accuracy that can be achieved by using the FD operation mode. However, the results in Fig. 7 also illustrate the robustness of the CNN-based classification model. Regardless of the SI level, the false alarm or incorrect classification rate remains low. This is partly because the measurements were done in a laboratory environment without the presence of other signals, in addition to the residual SI, that could trigger false alarms.

V. Conclusion

In this work, we have demonstrated the feasibility of combining simultaneous jamming and reconnaissance of drone remote control (RC) signals using full-duplex (FD) radio technology and deep learning. We have proposed a convolutional neural network (CNN) based signal classification method that utilizes time–frequency domain data to classify drone RC signals that typically hop in frequency over a wide bandwidth. We have analyzed the impact of residual self-interference (SI) at different stages of the FD radio on the performance of the CNN model through measurements and simulations. Both measured and simulated results indicate that residual SI degrades the classification accuracy and probability of detection to some extent. Nevertheless, given that the classification in the FD operation mode comes at almost no cost to the jamming efficiency, the FD mode can be highly advantageous compared to conventional half-duplex (HD) operation, where jamming needs to be ceased during reconnaissance.



(a) Without self-interference (b) Only passive isolation (c) After analog cancellation (d) After digital cancellation

Fig. 7. The measured classification accuracy of the convolutional neural network model under good signal-to-noise ratio conditions (combined measurements made with attenuation values $80\,\mathrm{dB}$ to $90\,\mathrm{dB}$). The model is capable of discerning with high accuracy between frequency-swept interference (or residual thereof) and the different drone remote control signals. The combination of analog and digital self-interference cancellation enables the model to achieve classification accuracy similar to that without any interference.

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