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Classification of RF Transmitters in the Presence of Multipath Effects using CNN-LSTM

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***Abstract*—Radio frequency (RF) communication systems are the backbone of many intelligent transport and aerospace operations, ensuring safety, connectivity, and efficiency. Accurate classification of RF transmitters is vital to achieve safe and reliable functioning in various operational contexts. One challenge in RF classification lies in data drifting, which is particularly prevalent due to atmospheric and multipath effects. This paper provides a convolutional neural network based long short-term memory (CNN-LSTM) framework to classify the RF emitters in drift environments. We first simulate popular-used RF transmitters and capture the RF signatures, while considering both power amplifier dynamic imperfections and the multipath effects through wireless channel models for data drifting. To mitigate data drift, we extract the scattering coefficient and approximate entropy, and incorporate them with the in-phase quadrature (I/Q) signals as the input to the CNN-LSTM classifier. This adaptive approach enables the model to adjust to environmental variations, ensuring sustained accuracy. Simulation results show the accuracy performance of the proposed CNN-LSTM classifier, which achieves an overall 91.11% in the presence of different multipath effects, bolstering the resilience and precision of realistic classification systems over state of the art ensemble voting approaches.**

***Index Terms*—Radio-frequency emitter classification, Convolutional neural network, Long Short-Term Memory.**

I. Introduction

Radio frequency (RF) communication systems are the backbone of transport and aviation operations, ensuring safety, connectivity, and efficiency. These systems utilize electromagnetic waves within the RF spectrum to establish connections between platforms, such as air traffic control communications, providing pilots with vital instructions, weather updates, and route adjustments (e.g., take-off, landing, and navigation [1]). Classification of RF transmitters holds critical importance in aircraft security applications [2] and maintenance operations [3]. The ability to accurately identify and classify RF emitters helps distinguish between authorized and unauthorized communication sources. This aids in detecting potential threats such as unauthorized transmissions or attempts to interfere with communication systems. For instance, if an unidentified RF transmitter is detected near an airport or within restricted airspace, swift action can be taken to ensure airspace security. As such, accurate classification of RF transmitters is vital for enhancing security and supporting maintenance efforts, ultimately contributing to the safe and reliable functioning of aircraft in various operational contexts.

TABLE I: Classifier Accuracy of RF Emitters using different current Algorithms

Methods	Accuracy	Precision	Recall	F1 Score	F2 Score
Voting Classifier	0.8925	0.8929	0.8925	0.8924	0.8924
Random Forest	0.8915	0.8922	0.8915	0.8915	0.8914
XGBoost	0.8850	0.8853	0.8850	0.8849	0.8849
Gradient XGBoost	0.8840	0.8849	0.8840	0.8841	0.8839
SVM	0.7265	0.7298	0.7265	0.7255	0.7254
Decision Tree	0.6330	0.6541	0.6330	0.6317	0.6300
Logistic Regression	0.6255	0.6276	0.6255	0.6257	0.6254
KNN	0.5960	0.5994	0.5960	0.5927	0.5935
Naive Bayes	0.4565	0.4523	0.4565	0.4380	0.4452
Adaboost	0.3245	0.2400	0.3245	0.2267	0.2675

A. Literature Review

Specific emitter identification, established in the 1960s [4], aims to discern emitters via their unique radio frequency (RF) signatures, undergoing comprehensive investigation in cognitive radio, military communication, and cellular networks [5]. This identification hinges on unintentional modulation traits, encompassing steady-state and transient features [6]. Table I shows the accuracy of existing algorithms in aircraft RF device identification, including ensemble methods such as the voting classifier, which we will compare our results to.

1) Steady-State Features: The derivation of RF fingerprints from stable features typically falls into two primary categories: frequency-domain and time-domain algorithms. Frequency-domain techniques, such as integral bi-spectra and Hilbert-Huang Transform (HHT) time-frequency-spectrum analysis [7], [8], primarily detect spectral differences. However, they often fall short in capturing RF fingerprints rooted in signal non-linearity, especially in low signal-to-noise ratios (SNRs), affecting identification performance. Conversely, time-domain algorithms like phase space difference and singular value decomposition encounter challenges in determining suitable embedding dimensions and time delays, particularly in diverse wireless communication scenarios [6]–[9].

Recent research explores distinctive hard-device properties for RF fingerprinting. Notably, the utilization of power amplifier (PA) non-linearities for RF fingerprinting [10] and the extraction of the PA's frequency representation for RF device classification [11]. Challenges arise due to heavy SNR reliance, impractical in some scenarios [10] , and the lack of a comprehensive analysis regarding the impact of PA non-linearity. Additionally, imperfections in RF oscillators and front-end non-linearity features have been examined, including unique methods to involve in-phase and quadrature (I/Q) modulation properties [12]–[16], DC offset, gain imbalance, and carrier frequency offset into a 2D image using the differential constellation trace figure (DCTF) method, achieving high accuracy for SNRs above $15dB$ [2]. Integration of silicon-based physical unclonable functions (PUFs) with RF fingerprints for robust wireless device authentication has also been explored [17], [18]. Other statistical approaches, such as non-parametric features for ZigBee device identification [19] and RF-DNA-based features for ultra-wideband noise radar device identification [20], exhibit high individual accuracies. These methods, however, all neglect explicit data drift handling strategies, which could limit performance over time in dynamic operational scenarios.

2) Transient Features: The transient-based approach involves detecting unique features in radio turn-on transients [21]–[24]. This includes FFT-based Fisher features for wireless node identification [25], Hilbert-Huang transforms for time-frequency-energy distribution features, energy envelope features for Bluetooth device identification [26], and wavelet-based approach, e.g., as dual-tree complex wavelet transform (DT-CWT) [27], dynamic wavelet RFID tag [28]–[30], WD-based Bayes micro UAV detection [31]. Numerous other approaches such as Frequency domain analysis using k-NN classification for UMTS RACH preambles [32], Permutation entropy for capturing signal envelope changes [33], Multi-Fingerprint and Multi-Classifier Fusion (MFMCF) for WiFi AP localization enhancement [34], and Permutation and Dispersion Entropy (PE and DE) for IoT device identification, offer specific characteristics and potential applications in RF fingerprinting. Though effective in capturing distinctive features, these methods might face challenges in adapting to changing operational environments and handling data drift.

3) Machine Learning Classifiers: After RF Fingerprint extraction, machine learning methods using different neural network architectures play pivotal roles in device classification. Feedforward Neural Networks (FNN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Generative Adversarial Networks (GANs) offer versatile solutions for complex problems across domains like high-dimensional data, and time series analysis. Specifically, CNN-based RF fingerprinting approaches aim to classify wireless devices based on their unique RF characteristics [35]–[40], and RNN-based methods can capture long term erosion of the antenna fingerprint [41]. These methodologies collectively contribute to advancing RF fingerprinting techniques, offering valuable insights into their capabilities and potential applica-

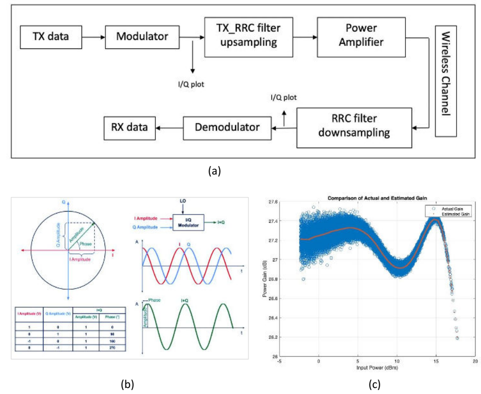

Fig. 1: RF communication system: (a) overall (b) the I/Q signals (c) the nonlinear gain of power amplifier

tions, but often fall short in classifying RF emitters in the presence of multipath propagation, necessitating robust models capable of handling data drift originating from wireless channel effects.

B. Contributions

To address this critical gap, our study focuses on developing a novel CNN-LSTM-Parallel model, incorporating approximate entropy and a unique scattering coefficient approach to tackle data drift and wireless channel effects. This innovative approach aims to create a model resilient to data drift, to ensure applicability in dynamic operational power amplifier and channel environments, contributing to the evolution of RF-based device recognition methods.

To be specific, In Section II, we first construct the RF communication models for 12 different aircraft transmitters, where the data drift is considered as the change of the data statistical distribution involved by the change of wireless channel multipath and power amplifier. In Section III, we elaborate our classification method by (i) selecting the I/Q signals with their unique approximated entropy and scattering coefficients as the input feature, and (ii) the design of parallel CNN-LSTM for classification. In Section IV, the classification accuracy (achieved 91.11%) is illustrated with the comparison to the state-of-the-art algorithm (listed in Table I). We finally conclude this work in Section V.

II. RF Communication Model

The base-band RF communication model consists of a pair of transmitter (Tx) and receiver (Rx), modulator and demodulators, Root-raised-cosine (RRC) filtering upsampling and downsampling, which is shown in Fig. 1. In this setup, a random bit sequence is initially transformed into complex symbols using the modulator, e.g., pulse-amplitude modulation (PAM), quadrature amplitude modulation (QAM), orthogonal frequency-division multiplexing (OFDM), etc. Then, RRC pulse shaping filters are applied for upsampling purposes. The base-band signal next passes through a nonlinear power

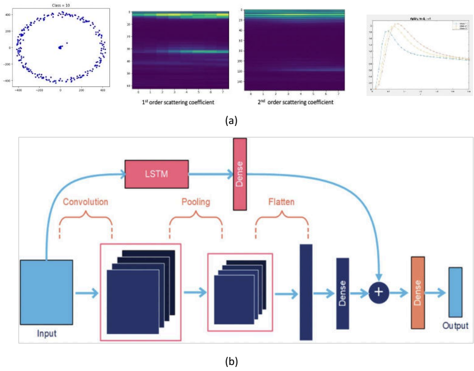

Fig. 2: CNN-LSTM based RF emitter Classification: (a) constructed features (i.e., I/Q, scattering coefficient, and approximated entropy) served as the input to the classifier; (b) the architecture of CNN-LSTM classifier.

amplifier (PA), and a wireless communication channel. In Rx, the received signal goes through the downsampling and demodulating modules to recover the transmitted signals.

Our aim is primarily on the received I/Q signals, which serve as the input for RF feature extraction and further Rf emitter classification. Here, one challenge of the machine learning-based classifier lies in the data drifting phenomenon, which is referred to as the change over time in the statistical properties of the training data. This phenomenon can lead to reduced accuracy or performance deviations from the model's intended design. The causes of data drift often revolve around the outdated or non-representative nature of the training data or the model's inability to accommodate evolving data patterns.

In the context of wireless communications, the data drifting is induced by (i) the changes of positions Tx-Rx, and (ii) the changes of the multi-path fading pattern of the wireless channels (e.g., in urban of rural places). These affect both the line-of-sight (LoS) path and the variance of the non-LoS (NLoS) paths in the widely used Rician channel models [40].

III. Entropy Assisted CNN-LSTM Classifier

A. RF Feature Extraction

For the RF emitter classifier, our approach involves utilizing Raw I/Q samples obtained directly from the RF communication link. These raw samples capture the unprocessed characteristics of the received signal, preserving its original complexity and nuances. Then, we calculate the approximate entropy to extract relevant features from the signal. Additionally, we employ a signal decomposition technique known as the wavelet scattering transform. This allows us to compute the first and second-order scattering coefficients of the RF signal. By combining these steps, we aim to enhance the accuracy and effectiveness of our RF emitter classification process, leveraging the inherent information in the raw I/Q samples for improved signal characterization and identification.

1) Raw I/Q samples: In RF communication, I/Q samples capture signal traits in amplitude and phase at discrete time points, forming a 2D complex representation, seen Fig. 1(b). The in-phase element signifies amplitude changes, while the Quadrature element signifies phase changes. Using Raw I/Q samples preserves the unprocessed signal nature, holding key data like modulation, timing, and frequency attributes. This aids in RF emitter classification by extracting vital features without pre-processing or demodulation.

2) Approximate Entropy Computation: Approximate Entropy (ApEn) is a statistical metric to assess the regularity and predictability of sequential RF signals. ApEn gauges the similarity between neighbouring data points within a time series, providing insights into the level of non-linearity and predictability present in the signals. ApEn is particularly valuable because it requires only 500 to 1000 data points for computation and is resistant to noise. Its parameters, such as the embedding dimension (denoted as m) and the tolerance threshold (denoted as r), enable the fine-tuning given specific characteristics of the data. Through training a classifier on a dataset comprising known RF sources and their corresponding ApEn values, the classifier can learn to identify and classify new, unseen RF signals based on their ApEn values.

The steps to calculate ApEn is provided in the following. For a given $m \in \mathbb{N}^+$ and time series of length N, i.e., $u_1, u_2, \cdots, u_N$, the step 1 is to form the vector sequences $\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_{N-m+1}$ as:

$$\mathbf{x}_i = [u_i, u_{i+1}, \cdots, u_{i+m-1}]. \tag{1}$$

Step 2 is to calculate the distances between vector $\mathbf{x}_i$ and $\mathbf{x}_j$:

$$d_{ij} = \max_{k \in \{0m \cdots, m-1\}} |u_{i+k} - u_{j+k}|. \tag{2}$$

Step 3 is to calculate the degree of self-similarity by a given tolerance r as:

$$C_i^m(r) = \frac{\text{Number of } j \ (d_{ij} \leq r, j \leq N-m+1)}{N-m+1}. \tag{3}$$

Step 4 is to compute the average over i of the natural logarithms of $C_i^m(r)$, denoted as $\phi^m(r)$, i.e.,

$$\phi^m(r) = (N-m+1)^{-1} \cdot \sum_{i=1}^{N-m+1} \ln C_i^m(r). \tag{4}$$

Step 5 is to calculate the approximated entropy:

$$ApEn(m, r, N) = \phi^m(r) - \phi^{m+1}(r). \tag{5}$$

3) Scattering Coefficients: Scattering coefficients are a set of features obtained through wavelet scattering transform, which plays a significant role in capturing the unique characteristics of RF signals by providing hierarchical representations of the signal's time-frequency structure, capturing both low and high-frequency information. By extracting scattering coefficients from the RF signal's wavelet scattering transform, we can create a feature vector that encapsulates essential information about the signal's behaviour. These coefficients are robust to variations and distortions, making them well-suited for identifying RF emitters under different conditions and variations due to channel effects. They serve as discriminative features that can be fed into a classifier, enabling the system to learn and differentiate between different RF emitters based on their scattering coefficient patterns.

In this study, we are using Kymatio Python library, which is designed to perform the wavelet scattering transform, a translation-invariant signal representation technique. The library implements scattering transforms as convolutional networks, where the wavelet filters, are predefined and not learned during the process. Fig. 2(a) displays the first and second-order scattering coefficients extracted from the input sample. In this study, the utilization of these 1st and 2nd order scattering coefficients is significant. These coefficients encapsulate essential information about the signal's characteristics and variations. By analyzing these coefficients, we can effectively detect data drift, which refers to changes in the signal properties due to various factors such as channel effects. The first-order scattering coefficients capture the signal's basic features, while the second-order coefficients provide insights into more complex variations. Incorporating both sets of coefficients allow us to create a robust RF emitter classifier that can accurately differentiate between different RF transmitters, even in the presence of data drift caused by channel effects or other factors. This comprehensive approach enhances the model's capability to identify and classify RF signals, improving its performance in real-world scenarios.

B. CNN-LSTM based Classifier Architecture

In this part, we elaborate on our design of the CNN-LSTM based classifier, which incorporates both CNN layers for feature extraction from input data and LSTM layers for sequence prediction [42]. Typically utilized for tasks like recognizing activities, labelling images, and annotating videos, CNN-LSTM models excel in visual time series prediction challenges and the generation of textual annotations from sequences of images [42]. In the context of Rf identification with data drifting, CNN provides the process of 2D I/Q data, and the LSTM expresses the sequential drift induced by time-varying channel scattering and multi-path. As such, by amalgamating both architectures, the CNN-LSTM model effectively learns spatial and temporal patterns from RF signals, adapting to noise and fading complexities.

Here, different from the cascaded connection of CNN and LSTM modules, we adopt the parallel architecture, which is shown in Fig. 2(b). The CNN-LSTM parallel model offers specific advantages over the sequential counterpart in addressing the challenges of RF emitter classification under conditions of low SNR and severe multipath fading. In the parallel model, the input data is simultaneously processed by both the CNN and LSTM components. This allows the CNN to focus on spatial feature extraction and noise reduction, while the LSTM captures temporal dependencies induced by fading. The parallel architecture enables concurrent processing, thus saving time and enhancing computational efficiency. In scenarios with fading and noise, where both spatial and temporal patterns are crucial, CNN-LSTM parallel model's simultaneous handling of these aspects can provide better accuracy and robustness compared to the sequential model, making it suited for this case.

As shown in Fig. 2(b), the parallel CNN-LSTM consists of a CNN component with two Conv-1d layers, each followed by ReLU activation and max-pooling operations for spatial feature extraction. Subsequently, a Flatten layer and a Linear layer with an output feature size of 128 are used to capture hierarchical patterns. The LSTM component includes an LSTM layer with specified hidden size, number of layers, and batch-first setting. A linear layer is employed to reduce the LSTM output to a dimension of 128. Finally, the model's outputs from the CNN and LSTM pathways are concatenated along the second dimension, and another linear layer is applied to produce the final classification results. The model is trained by cross-entropy loss criterion and updated through Adam optimizer with a learning rate of 0.001. This architecture allows the model to simultaneously extract spatial and temporal information from RF signals, enhancing its ability to classify RF emitters in the presence of noise and fading effects.

IV. Experimental Results

A. Dataset

In this experiment, two datasets are used to evaluate the proposed parallel CNN-LSTM classifier. The first dataset is generously provided by industrial sponsor. The data set collects data from 12 Midland handheld radio devices in 10 days, with carrier frequency as $462.6375MHz$ and sampling rate as $2GSPS$. This data is stored in TFRecords format which enables efficient input/output operations, parallel processing, and seamless integration with TensorFlow pipelines. In this dataset, we use data from day-1 to day-9 for training, and the data from day-10 for testing.

The second dataset is gathered through a simulated RF emitter version crafted elaborated in Section II. For this dataset, 12 Rf transmitters are created, with the baseband OFDM data (number of sub-carriers 456) in the same sampling rate as $2GSPS$. Here, 12 PAs are modelled via the memory polynomial method, trained by the labelled input and output power. For each emitter $k \in \mathbb{N}^{+}$, the output power $y^k_{MP}(n)$ is fitted by polynomial of the input power $x(n)$, i.e.,

$$y^k_{MP}(n) = \sum_{p=1}^{P}\sum_{q=1}^{Q} a^k_{pq} x(n-q)|x(n-q)|^{p-1} \tag{6}$$

where a^k_{pq} is fitting coefficients, P is the order of nonlinearity, and Q is the order of the memory. The wireless channel is the Rician-based model with 5-10 NLoS paths to simulate the data-drifting. The SNR is selected as $9dB$-$29dB$.

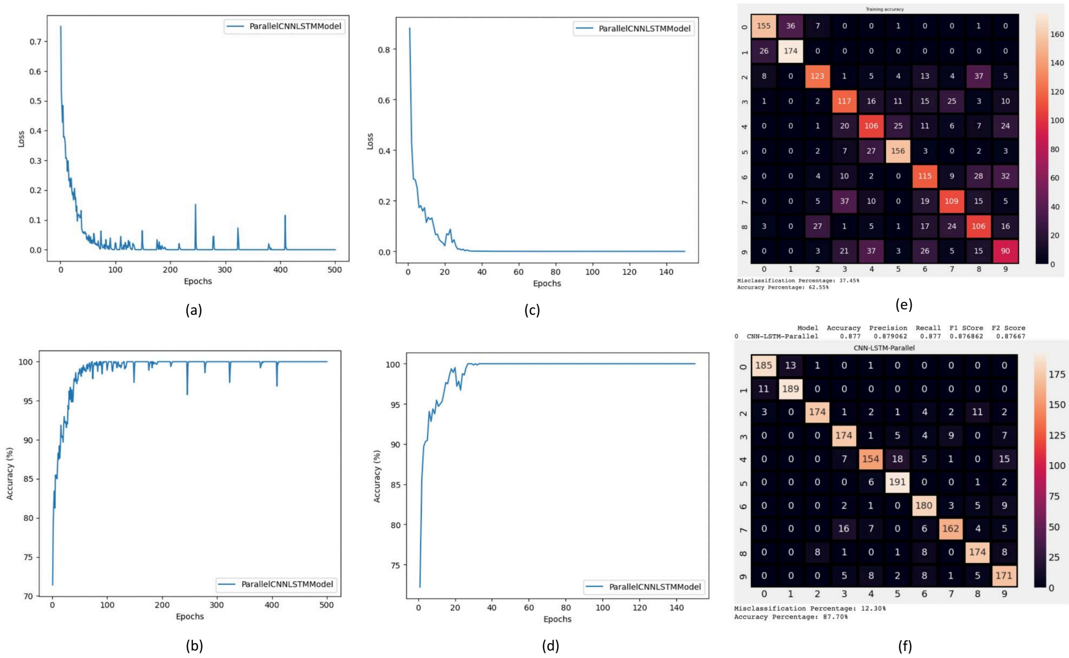

Fig. 3: Classification accuracy performance. (a)-(d) Loss v.s. epochs of our proposed parallel CNN-LSTM classifier: (a)-(b) training and testing via simulation data; (c)-(d) training and testing via real aviation transmitter dataset. (e)-(f) classification accuracy comparison with ensemble Voting algorithm (who has the best performance given Table 1): (e) Voting algorithm; (f) proposed CNN-LSTM based classification.

Raw I/Q samples are obtained from individual RF emitters. Then, the subsequent step is to extract features from I/Q data (in Section III. A). The input of the CNN-LSTM classifier is the combined I/Q signals and extracted features.

B. Classification Accuracy

The training and testing performance of the proposed parallel CNN-LSTM classifier is evaluated using data characterized by low SNR and severe multi-path effects. The outcomes are visually depicted in Fig. 3. Notably, the Parallel CNN-LSTM model demonstrates superior performance, achieving significant improvements in just 500 training epochs for both simulation data set and real dataset. Subsequently, the model's capabilities are evaluated on real transmitter dataset and the corresponding results achieve a test accuracy of 91.11%.

Fig. 3 provides the classification accuracy comparison between the proposed parallel CNN-LSTM classifier and the ensemble Voting classifier. Recall from Table I that Voting has the best performance in classifying RF emitters when the channel model is ideal without drifting. However, when multi-path and low SNR-induced data drifting is increased, the classification accuracy degradation of the Voting classifier can be seen in Fig. 3(a). This is because, in the scenario with low SNR and severe multipath fading, the quality and reliability of the received signals diminish. This further leads to increased noise and signal distortion, making it harder for to discern meaningful patterns and features from the data.

By comparison, the Parallel CNN-LSTM model demonstrates superior performance of classification accuracy, which is shown in Fig. 3(b). This attributes (i) the extracted RF features that are capable of expressing the distinct RF devices; (ii) the capability of CNN to learn the high-dimensional features from I/Q samples, and more importantly (iii) the LSTM to adapt the time-varying channel and data drifting.

V. Conclusion

We demonstrated the effectiveness of the proposed parallel CNN-LSTM framework in classifying RF emitters within aircraft communication systems. By addressing the challenge of data drifting in RF classification, exacerbated by atmospheric and multipath effects, the research incorporates stable metrics like the scattering coefficient and approximate entropy of each sample as the combined input to I/Q signals to classifier. This adaptive strategy ensures the model's resilience to environmental variations, maintaining accuracy in RF emitter classification (achieved 91.11%), which is significantly improved over state of the art. The research therefore underscores the significance of advanced statistical methods in reinforcing the precision and robustness of RF emitter classification systems. Such enhanced accuracy substantially bolsters aircraft security by validating the authenticity of incoming RF signals, crucial for the dependable and secure functioning of aviation systems.

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