Detection of UAVs Based on Spectrum Monitoring and Deep Learning in Negative SNR Conditions

Fares B. Mehouachi, Qingjie Yang, Juan Galvis, Santiago Morales, Milosch Meriac, Felix Vega, and Chaouki Kasmi

Abstract – The detection and classification of unmanned aerial vehicles (UAVs) is a strategic task for several military and civilian applications. The use of UAV RF signatures along with convolutional neural networks (CNNs) has proven to be an accurate approach for classification in positive signal-to-noise ratio (SNR) conditions. This work investigates the RF-CNN approach in negative SNR environments. It presents, first, a noise-resilient detection method based on spectral entropy drop. It then investigates the role of temporal resolution in preserving classification accuracy without explicitly training the CNN for any specific noise levels. Tests on a public data set showed an increased classification accuracy from ∼32% to ∼60 for an SNR of –10 dB by just prioritizing time over frequency resolution.

1. Introduction

The democratization of unmanned aerial vehicles (UAVs) created an unprecedented need to monitor any misuse of this new technology. Privacy breaching [1], espionage attacks [2], and drug smuggling [3] are some notorious examples of illegal use of UAVs that have been reported. Despite the potential threats, UAVs provide practical and cost-effective solutions for several beneficial applications ranging from package delivery, maintenance operations [4], and agricultural management [5] to rescue missions [6]. Consequently, accurate real-time detection, classification, and identification of UAVs are fundamental to guaranteeing this technology's safe use and to protecting critical infrastructures. Multiple techniques have been proposed: RF analysis both in time and in frequency domains [7–10], MAC address identification [11], micro-Doppler–effect characterization [12], acoustic signature detection [13, 14], radar-based techniques [15, 16], and direct visual detection with high-resolution cameras [17, 18]. In practice, the small cross section of most UAVs and their ability to fly at low heights hinder their detection [16]. Despite these limitations, real-time spectrum monitoring using a combination of passive radio surveillance with convolutional neural networks (CNNs) turned out to be a suitable method to classify UAVs with high accuracy [7] even in the presence of moderately strong random noise [8]. For low and negative signal-to-noise ratios (SNRs), preserving the accuracy of CNN fingerprinting in real time requires the nontrivial knowledge of the a priori SNR in addition to training different networks for each specific level of noise [8]. The present work tackles the challenge of classifying RF signals with negative SNRs ranging from 0 to –10 dB. It addresses two aspects. The first relates to detecting weak signals drowned in noise. Spectral entropy is picked as a proxy indicator of relevant radio signals to analyze. The second aspect of this work relates to finding efficient strategies to preserve the classification accuracy for negative SNR. The effect of time and frequency resolutions on classification accuracy is investigated. This work shows that increasing the time resolution of spectrograms over frequency resolution enhances the accuracy of CNNs without the extra cost of training different networks for different noise levels [8]. The proposed approach has been tested and developed using a publicly available data set [19] composed of 17 UAV models.

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2. Time-Frequency CNN Classification

This section presents the two main steps involved in the RF passive monitoring solution. The first step is detecting the RF signal, around 2.4 GHz, for commercial UAVs. Bluetooth and WiFi signals are a significant source of interference and require filtering, as detailed in [7]. The second step consists of the CNN classification, initiated only when the detection is positive (entropy drop). A flowchart of these two steps is detailed in Figure 1.

2.1 Signal Start Detection

The simplest spectrum sensing and detection approaches rely on energy-based criteria. However, for negative SNRs, most energy-based methods would fail because the noise would have significantly higher energy than the drone RF signal. Alternatively, UAV RF signals could be detected via spectral entropy, which is more robust to noise [20]. For a recorded time series $x(t)$, the definition of entropy is based on the time-frequency transformation $x(t) \rightarrow S(t,f)$. After

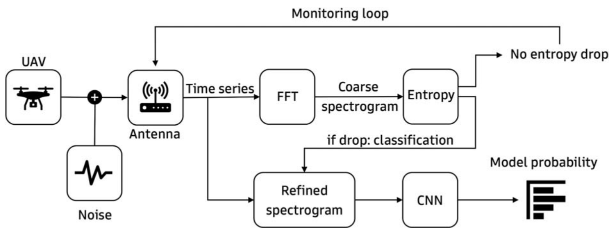

Figure 1. Overview diagram of the RF-CNN process.

normalization of the spectrogram, the spectral entropy $H(t)$ is

$$\begin{cases} P(t,f) = \frac{S(t,f)}{\iint dtdfS(t,f)}, \\ H(t) = -\int dfP(t,f)\log_2(P(t,f)) \end{cases} \tag{1}$$

Such a method is resilient even in unfavorable SNR conditions, as illustrated in Figure 2.

Estimating the spectral entropy requires the computation of a spectrogram, which could be implemented efficiently with a coarse resolution. Once the presence of a potential UAV is suspected, the time signal is trimmed and windowed. A higher-resolution time-frequency transformation is performed, and the model classification is carried away (Figure 1). The incorporation of machine learning algorithms for the classification task has been studied extensively through several approaches, such as deep belief networks [21], CNNs [17, 22], residual networks [23], and support vector machines [24]. The CNNs was used in visual detection of drones [25] and showed consistently superior accuracy for spectrogram classification [8, 22]. Therefore, it is selected as the primary classification method in this work.

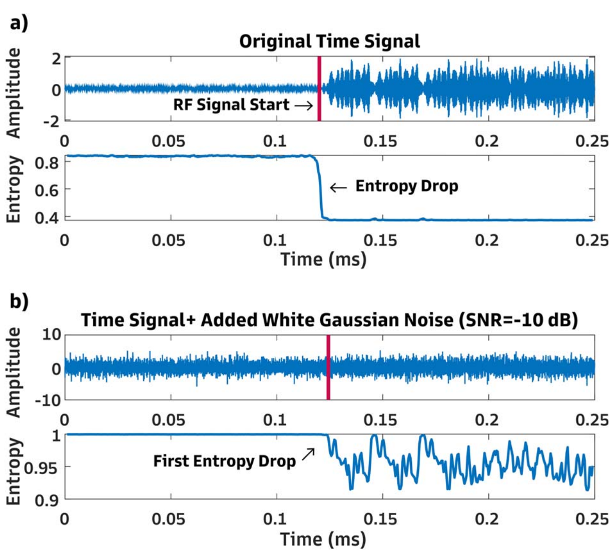

Figure 2. Spectral entropy drop as a noise-resilient detector of the RF signal. (a) An RF time signal from the database [19] and its spectral entropy below. The entropy drop indicates the beginning of the UAV RF signal. (b) The same time series from (a) with added white Gaussian noise. The original time signal is drowned in noise, yet the entropy drop criterion performs relatively well.

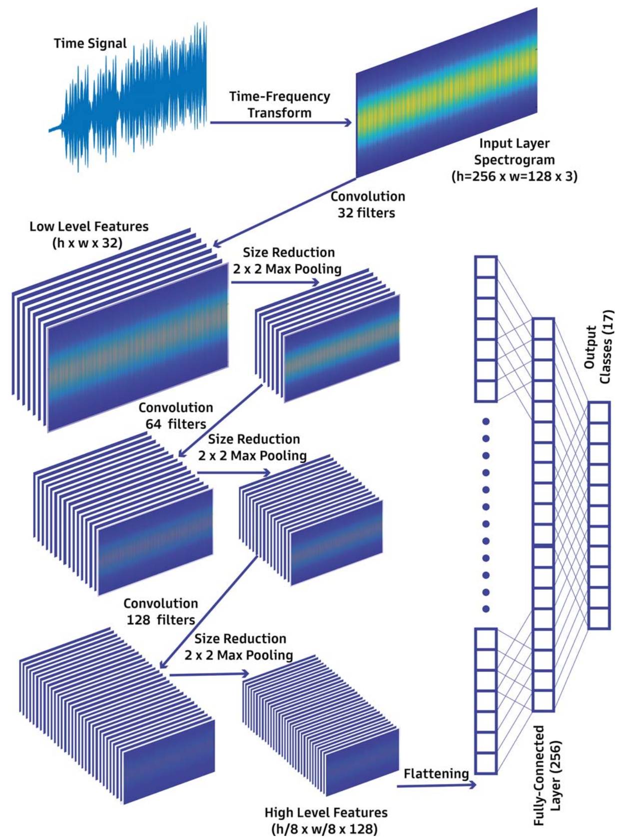

Figure 3. The architecture of the CNN used for RF signal classification. Three convolutional layers apply 32, 64, and 128 filters of 3×3 pixels. The max-pooling reduces the sizes of the features by applying a local 2×2 maximum function. The final features are flattened and run through a fully connected layer before applying a SoftMax function. The final output consists of probabilities of being in one of the 17 classes of the database's UAVs. The database [19] has $\sim$17,000 UAV RF signals ($\sim$128 Gb) from 17 models in the 2.4 GHz band. The data were split 90% for training and 10% for validation. Stochastic gradient descent with momentum [27] was used for training with a constant learning rate of 0.001, a minibatch size of 32, and 50 epochs. Batch normalization and 5% dropout are applied at each hidden layer to accelerate the training and enhance generalization.

2.2 CNN Architecture

CNN is a class of hierarchical neural networks that could be trained for recognition, classification, and segmentation tasks on images. It conducts local feature extraction through convolutional operators. CNNs have demonstrated a remarkable ability to classify and distinguish visual objects with an accuracy level that surpasses human abilities and most computer vision algorithms [26]. The UAV-generated spectrograms are treated as images and are classified using a CNN. Similar architecture to [8] is used in this work, as detailed in Figure 3. The height and width of the input spectrograms (h, w) are related to the frequency and time resolutions, respectively.

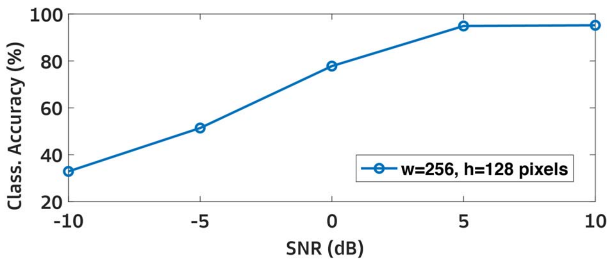

Figure 4. Degradation of the classification accuracy of UAV RF signals for negative SNRs.

The illustrated architecture performs relatively well even in low-SNR conditions. However, its accuracy degrades rapidly for negative SNRs, that is, when the noise has similar or higher energy than the RF signal, as illustrated in Figure 4.

Negative SNR scenarios are realistic when the UAV detection is performed at the kilometer scale. Such a decrease in the accuracy limits the range of the monitoring solution intrinsically. Training the CNN with negative SNR levels is a possible strategy; however, this requires training for different levels of noise separately [7]. Mixing disparate SNR levels in the training database leads to learning failure and poor assimilation of the training database. The following section investigates a different solution to handle the unfavorable SNR conditions by modifying the time-frequency spectrograms and quantifying the impact on classification accuracy.

3. Impact of Time and Frequency Resolutions on Classification Accuracy

Generating time-frequency representations of the RF signals or simply spectrograms consists of performing several Fourier transforms of windowed and tapered portions of the recorded time signal. There is, naturally, a limiting trade-off between time and frequency resolutions, and it is not possible to have high values for both. The time and frequency resolutions dictate the shape of the generated spectrogram (pixel numbers). In the context of adverse SNR conditions, the effects of both these parameters are explored.

3.1 Frequency Resolution

To better understand the impact of the frequency resolution, the validation accuracy is estimated for various shapes of spectrograms. The frequency step in the time-frequency transform is changed, while the width of the spectrogram, which corresponds to the time axis, remains unmodified. The same data set splitting from the previous section is used between training and validation. Training is done uniquely with noise-free data. The validation data set (10% of the whole data) is augmented with random noise corresponding to the various studied SNR levels. The CNN input layer is changed and adjusted to match the dimensions of the analyzed spectrograms. The results are reported in Figure 5. The frequency resolution has a

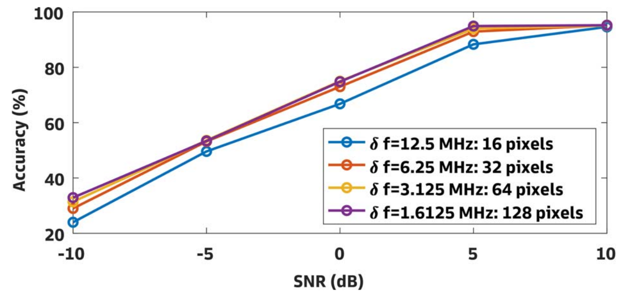

Figure 5. The marginal impact of the frequency resolution on the accuracy levels of the CNN for negative SNRs. The curves correspond to different δf and height (h) inputs into the CNN.

marginal impact on the accuracy of the CNN below a threshold of $\delta f = 6.25$ MHz. Such a result is unexpected given the importance of frequency resolution in several detection applications based on the micro-Doppler effect [12]. The value of $\delta f = 6.25$ MHz seems to capture most of the classification capacity of the frequency variable and is used in the remainder of this work. To further understand the optimal shape of the CNN input, the above analysis is repeated for the time resolution.

3.2 Time Resolution

The same analysis from the previous paragraph is carried out on different time resolutions while keeping the frequency resolution constant at 6.25 MHz (i.e., 32 pixels). The width of the CNN input is adapted to match the various time resolutions. The results are reported in Figure 6.

The time resolution has a pronounced effect on the accuracy of the CNN in negative SNR conditions. At an SNR of -10 dB, the accuracy has nearly tripled between the largest and smallest time resolutions: $\delta t = 2$ s and $\delta t = 0.125$s. These results confirm the possibility of preserving the accuracy of the UAV CNN classification without training for noisy spectrograms or an augmented database. This improvement is possible by simply adjusting the time resolution. Decreasing further the resolution δt improves the classification but seems to yield diminishing returns starting from $\delta t = 0.25$ s. To avoid increased computational cost due to large spectrograms, a

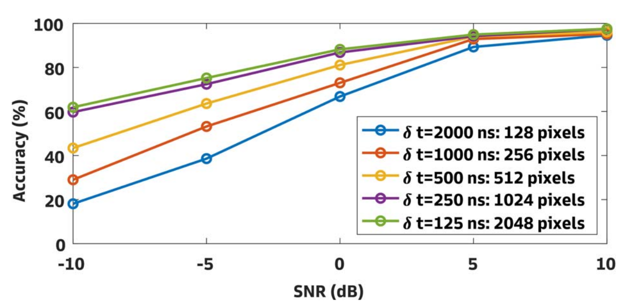

Figure 6. Impact of the time resolution on the accuracy levels of the CNN for negative SNRs. The curves correspond to different δt and width (w) inputs into the CNN.

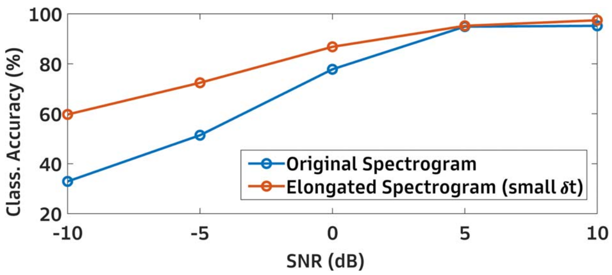

Figure 7. CNN accuracy improvement by resolution modification of the input spectrograms. The blue curve is the initial accuracy from Figure 4. The red curve corresponds to the accuracy after fine-tuning the time-frequency resolution and adopting time-elongated spectrograms ($\delta f = 6.25$ MHz, $\delta t = 0.25$ s).

time resolution of $\delta t = 0.25$ s is chosen to compromise performance and accuracy. Fine-tuning the time and frequency resolutions of UAVs spectrograms can enhance the accuracy of CNN classification without any a priori knowledge about the SNR level or any redundant training with noise-augmented data sets. This article's improvements for negative SNRs are summarized in Figure 7. A detailed example of an improved classification of an UAV RF signal is illustrated in Figure 8.

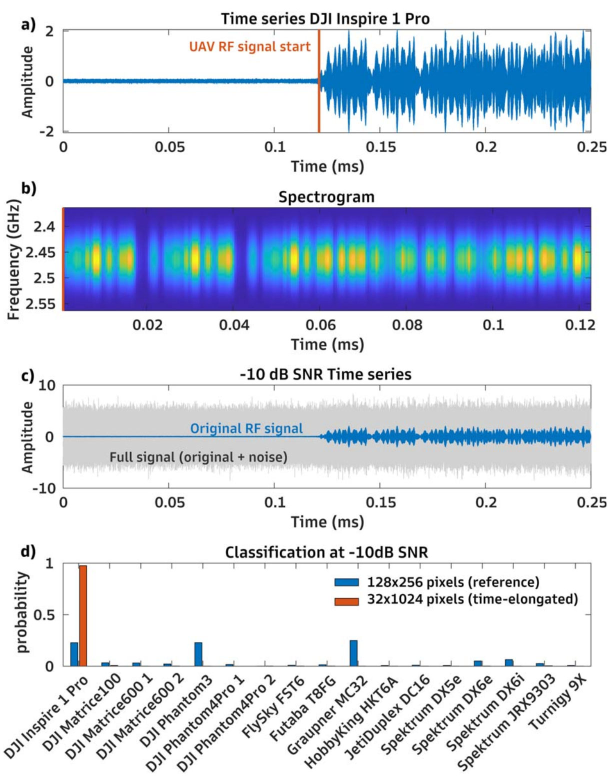

Figure 8. Noise resiliency of time-elongated spectrogram for detecting DJI Inspire 1 Pro UAV. (a) Time series. (b) Corresponding spectrogram (128×256 pixels). (c) Noise contamination (gray) of the original signal (blue) at an SNR of -10 dB. (d) Classification results: model probabilities using spectrograms with different time and frequency resolutions. Enhancing the temporal resolution preserves accuracy. The reference spectrogram (128×256 pixels) yields an incorrect classification.

4. Discussion and Conclusion

This article tackled the issue of UAV detection and classification in adverse SNR conditions up to -10 dB. Spectral entropy of intercepted RF signals was preferentially used to detect potential UAVs. Once an intrusion is suspected, the time-frequency signature of the RF signal is classified using a CNN. The accuracy of CNN classification deteriorates with negative SNRs. However, increasing the time resolution turned out to be a computationally effective and straightforward solution to preserve the UAV classification accuracy for adverse SNRs. Validation tests showed an enhanced classification accuracy from $\sim$32% to $\sim$60% for a negative SNR of -10 dB. Unexpectedly, frequency resolution had a marginal impact in adverse SNR conditions. The marked effect of the time resolution relative to the frequency suggests that increasing the operational range of RF monitoring solutions is possible by fine-tuning and adjusting the time-frequency representation. Finally, it is essential to notice that fine-tuning the time resolution did not fully preserve the accuracy capabilities of the CNN. As such, it might be necessary to investigate complementary strategies to recover a higher accuracy beyond the 90% threshold. This article requires additional validation with multipath and fading effects, testing different CNN architectures, and further training with more extensive RF databases.

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