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A Radio Frequency Fingerprinting-Based Aircraft Identification Method Using ADS-B Transmissions

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Abstract: The automatic dependent surveillance broadcast (ADS-B) system is one of the key components of the next generation air transportation system (NextGen). ADS-B messages are transmitted in unencrypted plain text. This, however, causes significant security vulnerabilities, leaving the system open to various types of wireless attacks. In particular, the attacks can be intensified by simple hardware, like a software-defined radio (SDR). In order to provide high security against such attacks, radio frequency fingerprinting (RFF) approaches offer reasonable solutions. In this study, an RFF method is proposed for aircraft identification based on ADS-B transmissions. Initially, 3480 ADS-B samples were collected by an SDR from eight aircrafts. The power spectral density (PSD) features were then extracted from the filtered and normalized samples. Furthermore, the support vector machine (SVM) with three kernels (linear, polynomial, and radial basis function) was used to identify the aircraft. Moreover, the classification accuracy was demonstrated via varying channel signal-to-noise ratio (SNR) levels (10–30 dB). With a minimum accuracy of 92% achieved at lower SNR levels (10 dB), the proposed method based on SVM with a polynomial kernel offers an acceptable performance. The promising performance achieved with even a small dataset also suggests that the proposed method is implementable in real-world applications.

Keywords: automatic dependent surveillance-broadcast; deep learning; radio frequency fingerprinting; wireless security

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1. Introduction

Due to the unprecedented growth in the number of passengers traveling via commercial aviation, it is expected by the Federal Aviation Administration (FAA) that the airspace will be more crowded in the near future [1]. In order to balance aviation growth with flight safety, the FAA launched the Next Generation Air Transportation System (NextGen) project [2]. The project aims at transforming the radar network-based Air Traffic Control (ATC) system into a satellite-based navigation system. One of the key components of the NextGen system is known as the Automatic Dependent Surveillance Broadcast (ADS-B) system. The main responsibility of the ADS-B system is to enhance crowded airspace safety. In a typical ADS-B system infrastructure, simple and low-cost radio stations are used for surveillance. This considerably enables the reduction of the operating and maintenance costs of the ATC system. Currently, most commercial aircrafts are equipped with the ADS-B system [3].

The ADS-B system automatically broadcasts the Civil Aviation Organization (ICAO) address (a unique identifier of the aircraft) and status data (position, speed, altitude, rate of descent or climb, and others) of the aircraft. ADS-B messages are sent in unencrypted plain text. This, in fact, causes significant security vulnerabilities to various types of wireless attacks, such as eavesdropping, jamming, message injection (spoofing), message deletion, and message modification (integrity) [4]. Therefore, many solutions have been proposed to secure ADS-B communications. These security solutions can be grouped into two main categories as follows: (a) broadcast authentication and (b) location verification [5]. It is important to note that the recent developments of securing communication protocols in wireless sensor networks offer great research opportunities to enhance broadcast authentication solutions for ADS-B security.

The main purpose of broadcast authentication solutions is to ensure that the messages transmitted from an authenticated source are not manipulated during transmission. The broadcast authentication solutions can be categorized into two schemes: (a) cryptographic solutions and (b) non-cryptographic solutions. Cryptographic solutions are difficult to implement due to their incompatibility with the ADS-B infrastructure, where key distribution and management are the major requirements. However, in non-cryptographic solutions, the key distribution and management issues are avoided via exploiting radio frequency fingerprinting (RFF) and spread-spectrum approaches. Nevertheless, spread-spectrum approaches are also incompatible with the ADS-B infrastructure. They are very difficult to employ due to the limitations of the ADS-B protocol. On the other hand, RFF approaches can offer reasonable high security solutions against attacks [6].

In general, RFF is a wireless device authentication technique, used for physical layer security. In an RFF technique, there are three main stages: signal capturing, feature extraction, and the classification or identification of the devices. Typically, the unique fingerprints (features) in the electromagnetic waves emitted by wireless devices are used to distinguish the identification of wireless devices in order to avoid attacks on the wireless network. The unique features are extracted from imperfections in the analog components of wireless devices that occur during the manufacturing process. Until now, many RFF methods have been explored in the literature [7,8]. In order to evaluate these methods, various wireless devices have been used, e.g., Wi-Fi [9], Bluetooth [10–14], RFID [15], and internet-of-things (IoT) transmitters [16,17]. Moreover, RFF methods have also been used for aircraft identification based on ADS-B signals in several studies [18–24], where the efficiency of RFF in boosting the security of ADS-B systems has been proven.

On the other hand, attacks on ADS-B devices can be intensified using simple hardware, like software-defined radios (SDRs). As discussed in [25–28], it is very easy to launch such attacks for an attacker with an SDR. Therefore, due to the advent of SDR technology, it is essential to take precautions against attacks from low-cost and widely available SDRs. Here, RFF methods could be an efficient means to protect ADS-B devices against such attacks. Thus, in recent years, researchers have started to investigate the potential of the RFF in their work using ADS-B signals collected from SDRs [29–34]. However, large-scale datasets composed of ADS-B signals collected from a large number of transmitters are needed for their implementation. Thus, the feasibility of these methods remains challenging and questionable within realistic settings due to the requirement of higher computational resources. Moreover, although spectral fingerprints have been used in several studies for RFF of wireless devices in the literature [9], their usage with ADS-B signals has not been scrutinized thus far.

In this study, it is aimed at proposing a real-time implementable RFF-based aircraft identification method with a small dataset consisting of ADS-B signals. For this purpose, firstly, 3480 ADS-B samples were collected by a SDR from eight aircrafts. A moving average filter was then used to filter the samples, followed by the normalization process. Next, the power spectral density (PSD) features were extracted from the filtered and normalized samples. The support vector machine (SVM) with three main kernels (linear, polynomial, and radial basis function) was used for the identification of the aircraft at various channel signal-to-noise ratio (SNR) levels (10–30 dB). The results show that SVMs with a polynomial kernel classifier provided better classification performances at each SNR level. Overall, the classification performance results verify the applicability of the PSD features of the ADS-B signals in the RFF of aircrafts, even when a small-sized dataset is used. The main contributions can be summarized as follows:

- The applicability and efficiency of PSD features extracted from ADS-B signals in the RFF of aircrafts are evaluated for the first time in the literature.
- The proposed method is shown to achieve acceptable performance levels, even when a small dataset is used. Therefore, it is expected that the proposed method could operate effectively in real-world applications with low computational resources.

The structure of this paper is as follows: The relevant works presented in the literature are discussed in the next section. In Section 3, the ADS-B system is briefly overviewed. Then, in Section 4, the proposed RFF method is described. Next, experiments performed to assess the efficiency of the proposed method are presented in Section 5. Furthermore, the experimental results are discussed in Section 6. The paper is concluded in Section 7.

2. Related Work

In the literature, several RFF-based methods have been proposed using ADS-B signals collected by SDRs [29–34], as mentioned in the previous section. This section is devoted to discussing these methods in order to address the novelty of the work presented in this article.

In [29], an RFF-based method is proposed to identify an intrusion on a Mode S channel using features, such as a carrier phase and carrier frequency features, extracted from the signals transmitted from the aircraft. The performance is evaluated via a measurement campaign where a receiver consisting of an SDR running over a Raspberry Pi equipped with a modified digital video broadcasting terrestrial (DVB-T) dongle and an omnidirectional ADS-B antenna have been used to collect around 45 million messages from 2942 aircrafts. The evaluation has been carried out under various values of sliding window sizes and the k parameter in the k-Nearest Neighbors (KNN) algorithm.

In [30], an RFF method is proposed to recognize ADS-B signals for aircraft identification. The method is based on the use of convolutional neural network (CNN)-based models, namely AlexNet and GoogleNet, to classify the contour stellar images of ADS-B signals at different SNR levels (20–30 dB). For the evaluation of the proposed method, 2500 signals from five aircrafts have been collected by a SDR. The highest classification accuracy is obtained at around 95% when the SNR is greater than 28 dB.

Another method is proposed in [31] for the fingerprinting of ADS-B messages based on physical characteristics, such as the preamble phase and phase patterns. In order to identify the aircraft, a CNN classifier has been used. In data acquisition, multiple ground stations have been used. Each ground station consists of an SDR running over a Raspberry Pi 3. Thus, around 3 million messages from 274 aircrafts have been collected to be used in the performance evaluation. Experimental results show that aircraft identification can be achieved with an accuracy of 41.9%.

An RFF method for aircraft identification using a complex-valued CNN model is proposed in [32]. In order to evaluate its performance, the data from both ADS-B and VDL2 messages are collected from 50 aircrafts over multiple days by means of RTL-SDR hardware. The robustness of the model is assessed in terms of many aspects, such as various noise levels, different population sizes, hardware similarities, channel effects, and message injections. To test the effects of noise on the RFF performance, the messages collected from 50 aircrafts are exposed to a 10 dB SNR level. The accuracy of the proposed model is then found to be 44%.

A recurrent deep complex-valued network (RDCN) is proposed to fingerprint devices using raw I/Q data from Wi-Fi and ADS-B signals [33]. For its performance evaluation, ADS-B signals are captured using an SDR under various channel environments and SNR levels (2–5 dB). Experiments show that the RDCN network is able to achieve almost 100% accuracy at all SNR levels.

In [34], a baseline model inspired by AlexNet and a ResNet-50-1D model based on Residual Network (ResNet) are comprehensively investigated for RFF under various scenarios, including the effect of the channel, number of devices, SNR levels, and dataset size. The effects of different SNR levels (−13.3–15.3 dB) on the accuracy of the models are evaluated using a dataset of 120000 ADS-B transmissions, collected from 100 devices. The highest accuracy is found to be 92.5% by the baseline model, when the raw I/Q data of ADS-B signals is trained with a low SNR (−13.3–1.9 dB) and tested at a medium SNR level (5–2 dB).

Overall, relevant works are summarized in Table 1. As can be seen from the table, none of the works have considered the use of spectral fingerprints with the ADS-B signals. Furthermore, only the works presented in [30,32–34] investigate the effects of noise on the RFF performance. Additionally, instead of [30], large-scale datasets composed of ADS-B signals collected from a large number of transmitters (≥50 transmitters) are used to evaluate the RFF performance. However, the RFF method proposed in [30] is based on image recognition, which differs from the scope of our work. On the other hand, this work attempts to show that RFF-based aircraft identification using PSD fingerprints is possible, even with a small dataset containing ADS-B signals captured from eight transmitters under different SNR levels.

Table 1. A summary of relevant works.

Ref.	Feature/Information	Classifier/Process	Number of Transmitters	SNR	Accuracy
[29]	Carrier phase and frequency features	Sliding Window Size and KNN	2942	-	-
[30]	Contour stellar images	CNN	5	20–30 dB	~95%
[31]	Preamble phase and phase patterns	CNN	274	-	41.9%
[32]	Preamble and bit synchronization	Complex-valued CNN	50	10 dB	44%
[33]	Raw I/Q data	RDCN	100	2–5 dB	100%
[34]	Raw I/Q data	Baseline and ResNet-50-1D	100	−13.3–15.3 dB	92.5%

3. A Brief Overview of ADS-B System

The main components of the ADS-B system are depicted in Figure 1. As shown in the figure, the position of the aircraft is first determined by means of GPS. Using the ADS-B (Mode S) transponder on the aircraft, the position data along with the identity and status data are then broadcast. Both ADS-B ground stations and other aircrafts receive the broadcasts.

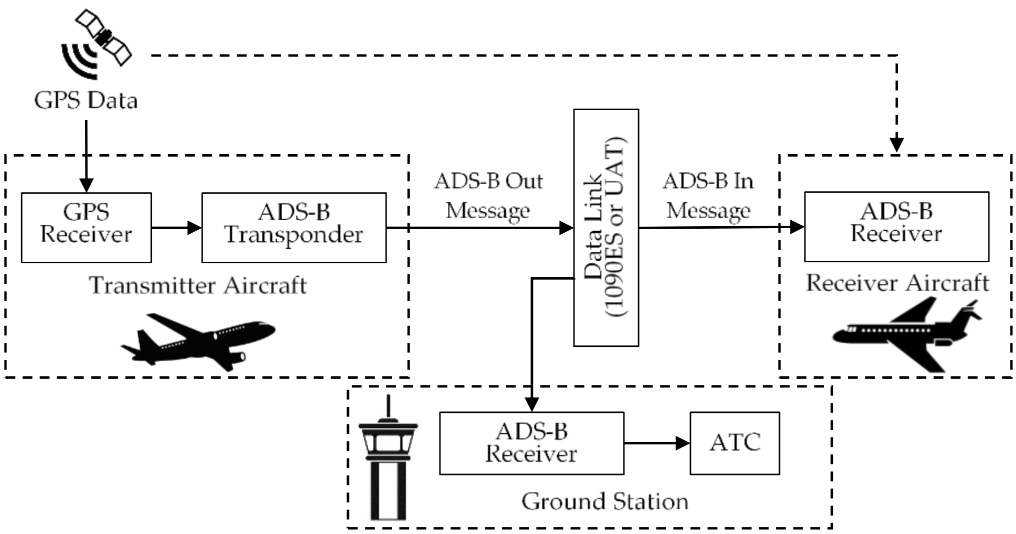


Figure 1. Main components and signal flow of the ADS-B system.

ADS-B has two forms, namely ADS-B Out (transmitter) and ADS-B In (receiver). ADS-B Out devices are used to transmit broadcasts to ADS-B receivers, whereas ADS-B In devices are used to receive broadcasts. The 1090 MHz Extended Squitter (1090ES) and the 987 MHz Universal Access Transceiver (UAT) are the data link standards for the ADS-B system. However, the ADS-B system uses the 1090ES protocol in commercial applications. In this study, we concentrate on the 1090ES data link.

A 1090ES message format is shown in Figure 2. A message structure consists of 8µsec preamble for synchronization and a 112-bit data block. The data block contains the downlink format (DF), transponder capability (CA), aircraft address, ADS-B data, and parity check sub blocks. The DF block is 5 bits long, which contains the type of message. The CA is 3 bits long and provides the communication capability of the transponder (additional identifier). The 24 bit aircraft address is a unique identifier assigned to each aircraft by the ICAO. The following ADS-B data is 56 bits long and contains the surveillance data, including identification, velocity, position, and urgency codes. A 24 bit parity check is the last field, which is used by receivers in order to validate the preceding message. It is also worth noting that the pulse position modulation scheme is used to transmit the ADS-B messages.

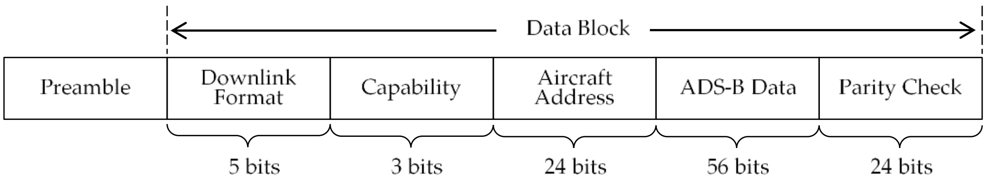


Figure 2. Message format of ADS-B 1090ES.

4. The Proposed Method

The proposed RFF-based aircraft identification method mainly involves ADS-B signal acquisition, data preprocessing, feature extraction, and classification stages. The overall process is illustrated in Figure 3. In the following sections, each stage is described in detail.

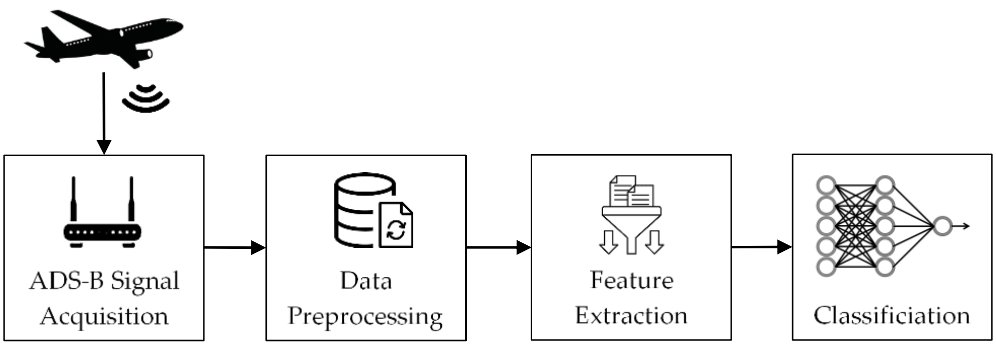


Figure 3. Operational diagram of the proposed RFF method (on the ground station).

4.1. ADS-B Signal Acquisition and Preprocessing

As shown in Figure 3, signal acquisition is the first phase of the proposed method, where SDR hardware is used to collect ADS-B transmissions. A direct-conversion architecture of a typical SDR receiver is shown in Figure 4.

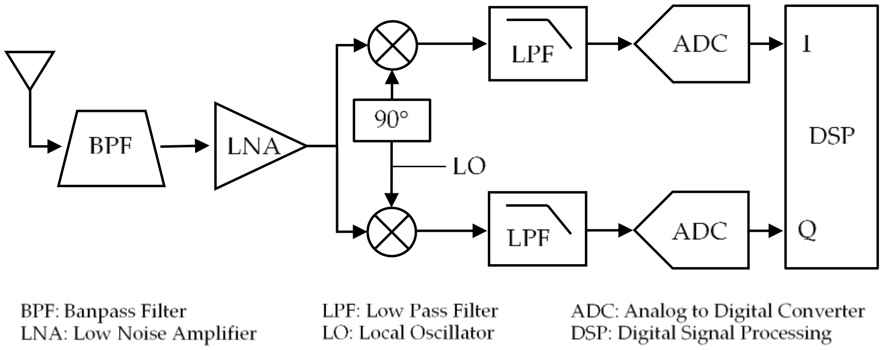


Figure 4. A direct-conversion architecture of a typical SDR receiver.

In a typical SDR receiver, the collected ADS-B signal ($x(t)$) is separated by the in-phase (I) channel ($\cos(2\pi f_c t)$) and the quadrature (Q) channel ($\sin(2\pi f_c t)$). Both have a center frequency (f_c) of the ADS-B signal being sampled, which equals 1090 MHz. After the sampling process, an analytic signal provided by the SDR can be expressed as

$$x[n] = I[n] + jQ[n]. \tag{1}$$

The analytic signal may contain several unique distinctive features, or so-called "RF fingerprints". Before extracting these features, various transformation or filtering techniques are employed to detect the signal of interest from the background. In this context, firstly, a moving average filter, which is the most common filter in DSP, is used to improve the SNR of the received signal. In general, the moving average filter produces each point in the output signal by averaging a number of points from the input signal. It can be mathematically represented by [35]

$$\overline{x}[j] = \frac{1}{NP}\sum_{k=0}^{NP-1} x[j+k], \tag{2}$$

where $\overline{x}[\,]$ is the output (filtered) signal, $x[\,]$ is the input signal provided in (1), and NP is the number of points used in the moving average. As we look into distinct features in the signals for a given hardware and sampling rate, which together represent the spectral characteristics of background noise, NP should be carefully determined. We have chosen the number of data points after a careful investigation of how distinctive features are unaffected by diverse values of data points on several records for both the targeted hardware and sampling rate. For the collected signals, the maximum value of NP is considered to be 40 in order to preserve the distinctive features of the signals. As an illustration, the input signal ($x[\,]$) and the output signal obtained after applying the moving average filter ($\overline{x}[\,]$) are shown in Figure 5a,b.

The next step in the filtering phase is data normalization. For this purpose, z-score normalization is used to complete the data preprocessing phase. A set of N normalized signals, each denoted by $\overline{x}_n$, can be normalized as [36]

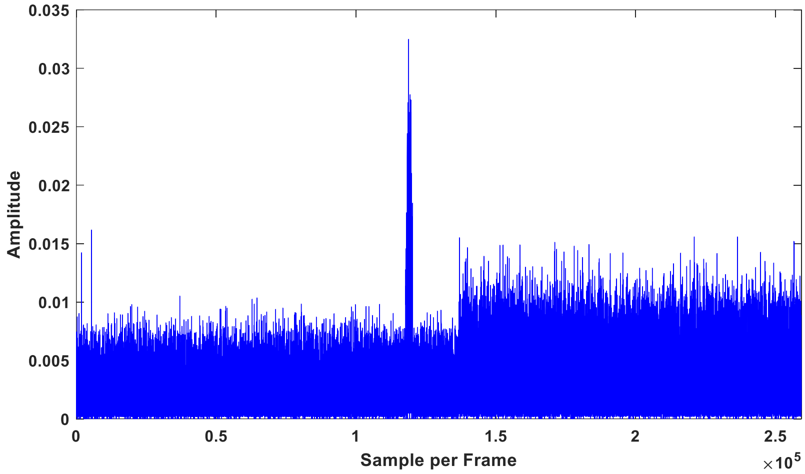
$$y_n = \frac{\overline{x}_n - E}{s}, \tag{3}$$

where E is the mean value of $\overline{x}_n$, which can be expressed as

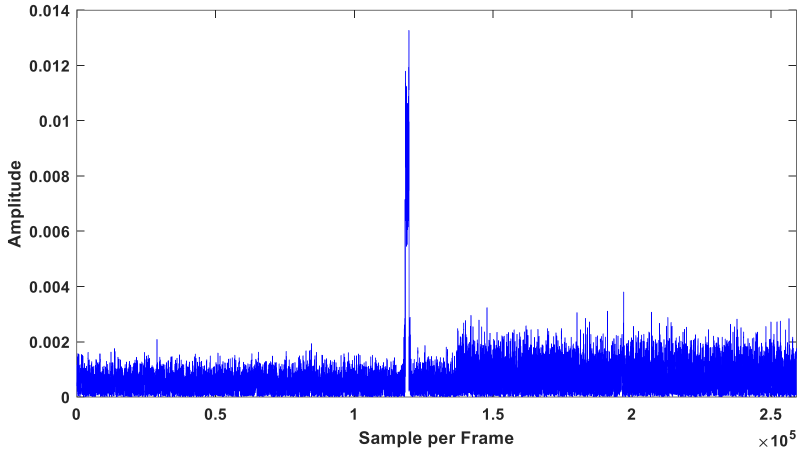
$$E = \frac{\sum_{n=1}^{N} \overline{x}_n}{N}, \tag{4}$$

and s is the standard deviation of $\overline{x}_n$, which can be calculated using

$$s = \sqrt{\frac{\sum(\overline{x}_n - E)^2}{N-1}}. \tag{5}$$



(**a**)



(**b**)

Figure 5. (**a**) A sample recording from ADS-B signals before and (**b**) after the filtering of the sample shown in (**a**).

4.2. Feature Extraction

In the proposed RFF method, it is necessary to extract the distinctive features (fingerprints) from the ADS-B signals to classify the authorized aircraft. Although various types of features have been proposed in the literature to be used in RFF, spectral fingerprints are still very useful for classifying wireless devices [9]. The methods of spectrum estimation can mainly be categorized into three main categories: non-parametric methods, parametric methods, and subspace methods. Among these methods, non-parametric methods are easy to use due to the fact that power spectral density can be directly estimated from the signal itself. One of the well-known non-parametric methods is the Welch method [37], which reduces noise in the estimated power spectrum in return for a lower frequency resolution. Therefore, the noise reduction provided by the Welch method is largely desired in practical applications.

On the other hand, there has been no published work on the use of spectral fingerprints with ADS-B signals. Thus, in the proposed method, the Welch method is applied to the PSD of the normalized signals, to then be used as fingerprints in the classification phase. Describing the Welch method mathematically is straightforward [38]. In the Welch method, the data sequences $y_j(n)$ are allowed to be overlapped, and a data window $w(n)$ is allowed to be applied. Here, $w(n)$ is the Hann windowing function, which can be expressed in the following form [39]:

$$w(n) = \frac{1}{2}\left(1 - \cos\left(\frac{2\pi n}{N-1}\right)\right), \tag{6}$$

where N is the length of window. Then, a set of modified periodograms is produced, which will be averaged. If successive sequences are offset by D points and each sequence is L points long, the jth sequence is expressed by

$$y_i(n) = y(n + iD),\ n = 0, \ldots,\ L - 1. \tag{7}$$

Thus, the quantity of overlap between $y_i(n)$ and $y_{i+1}(n)$ can be defined by $L - D$ points. In the case that K sequences cover the whole N data points, then

$$N = L + D(K - 1). \tag{8}$$

Next, the Welch estimate of PSD can be expressed in terms of $y(n)$ as follows:

$$\hat{P}_W\left(e^{j\omega}\right) = \frac{1}{KLU}\sum\nolimits_{i=0}^{K-1}\left|\sum\nolimits_{n=0}^{L-1} w(n)x(n + iD)e^{-jn\omega}\right|^2, \tag{9}$$

where U is constant, which can be defined by

$$U = \frac{1}{N}\sum\nolimits_{n=0}^{N-1}|w(n)|^2. \tag{10}$$

4.3. Classification

Today, continuous advancements in ML techniques offer efficient means to solve complex issues in various fields. Particularly, specialized ML techniques may increase the performance by learning the intricate hidden traits of the system. Essentially, ML uses real-world data to train an ML solution in order to capture the complex relationships between the input data (features) and the output values (labels).

It is important to note that ML techniques like deep and reinforcement learning often undergo testing, followed by rigorous training on gigantic quantities of data that are descriptive enough for the targeted system to properly construct a working model. This, in turn, enables the performance analysis of the trained and tested model. However, these methods may require significantly higher computational resources in comparison to conventional ML techniques [40]. Therefore, employing one of the conventional ML techniques or classifiers could be a reasonable choice to train relatively small quantities of data [41].

In the literature, the support vector machine (SVM) is considered one of the best known conventional ML classifiers due to its strong regularization properties, which refer to the generalization of the model to new data [42,43]. This has been shown to be an effective method for solving practical binary classification problems [44]. Moreover, in the development of an RFF method, using the SVM classifier provides acceptable classification accuracies with smaller datasets [10–14].

As outlined in the previous sections, this study proposes an RFF-based aircraft identification method using ADS-B transmissions. Our aim is to develop a method that operates effectively in real-world applications with limited computational resources and smaller datasets. To achieve this, a practical ML classifier is needed to classify ADS-B signals. Because each aircraft already transmits a unique ADS-B signal, the most practical classification approach is to determine whether a signal originates from the correct aircraft. Thus, binary classification (classifying whether a reported ADS-B signal belongs to its claimed source) can be employed for aircraft identification [45]. The SVM classifier offers advantages in binary classification and achieves higher accuracies when used in RFF implementations with smaller datasets. Therefore, we have selected it for the classification of ADS-B signals in the proposed method.

5. Experiments

Experiments were performed to assess the efficiency of the proposed method. In this section, firstly, the whole process followed to create the datasets used in the experiments is provided. Then, the results obtained from the experiments are discussed.

5.1. Dataset Description

Before creating the datasets, ADS-B signals were collected from the aircraft. As shown in Figure 6, ADS-B signals transmitted from the aircraft were captured through an Adalm-Pluto SDR (PlutoSDR), connected to a computer where MATLAB (communications toolbox support package for PlutoSDR) was used to process the received signals. In data acquisition, the signals sent from eight aircrafts at 1090 MHz were sampled at 12 MSPS. After the decoding process, the I/Q samples of each signal were generated. This was followed by the data preprocessing phase, where each sample was filtered and normalized as described in Section 4.1. In this way, a dataset consisting of eight aircrafts with 435 I/Q records of ADS-B signals for each was created.

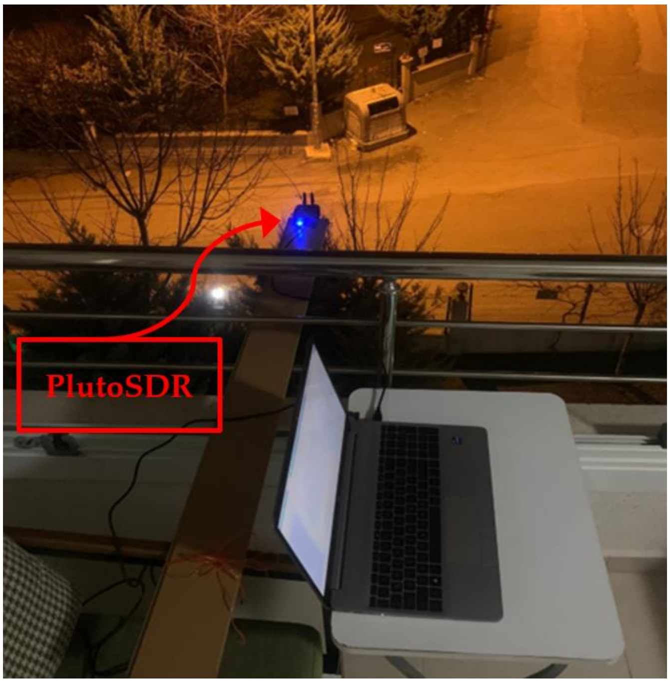


Figure 6. Data acquisition system.

On the other hand, to investigate the noise performance of the proposed method, noisy samples at different SNR levels were generated. Similar to previous works [10–14], different levels of channel noise captured during data collection were randomly added to the samples which were initially captured at high SNR as follows:

$$\mathrm{SNR} = 10\log\left(\frac{S}{N} - 1\right) \quad (11)$$

where S is the average energy of a noisy sample and N is the average energy of a sample. Hence, five different datasets were created with the following SNR levels: (a) 10 dB, (b) 15 dB, (c) 20 dB, (d) 25 dB, and (e) 30 dB. As an example, Figure 7 shows the samples of four different aircrafts at 30 dB SNR level.

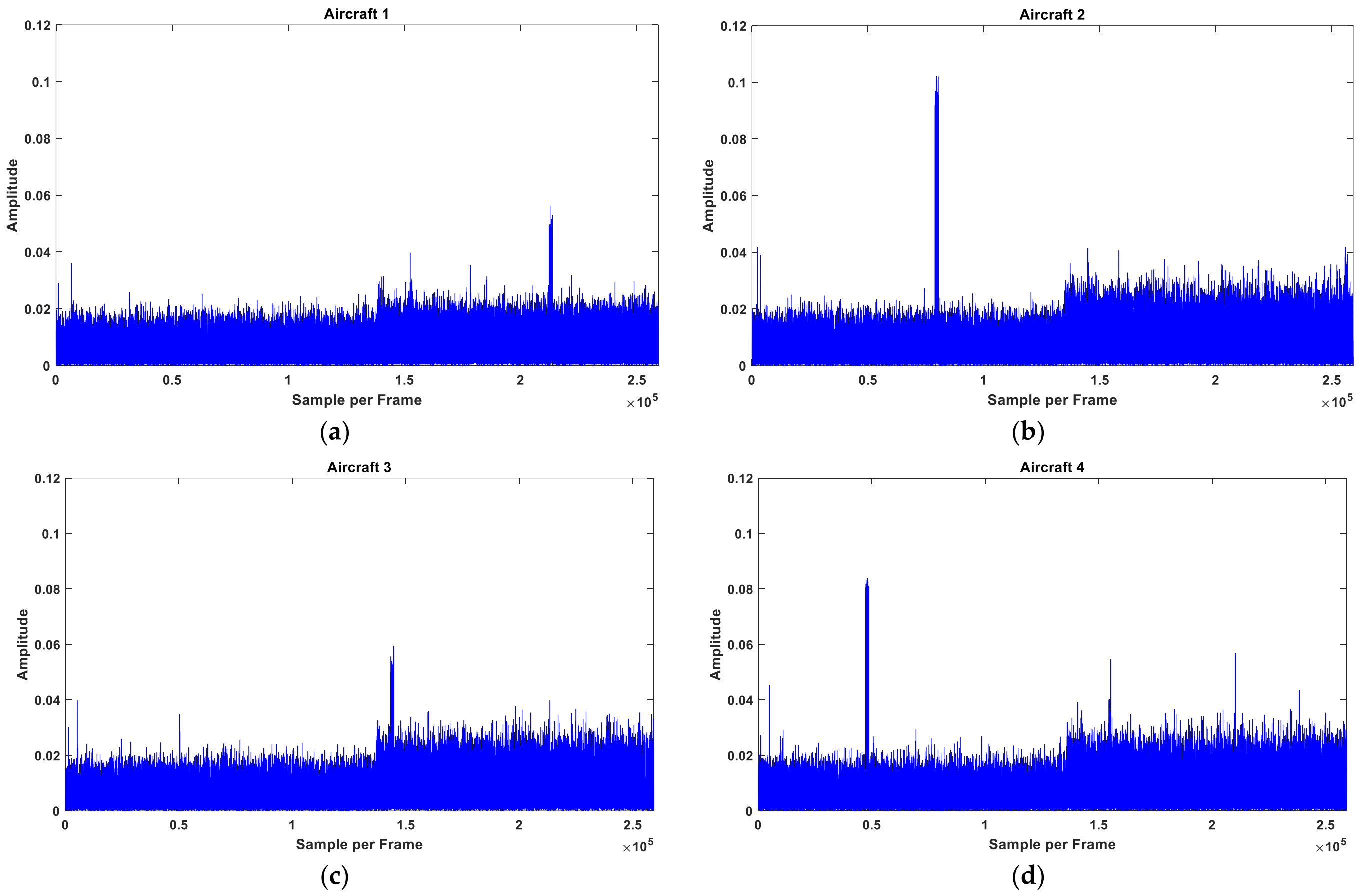


Figure 7. The samples of four aircrafts at 30 dB SNR level: (**a**) Aircraft 1; (**b**) Aircraft 2; (**c**) Aircraft 3; (**d**) Aircraft 4.

5.2. Implementation

As described previously, the proposed RFF method relies on extracting and utilizing the distinctive features, also known as fingerprints, of ADS-B signals for aircraft classification. As detailed in Section 4.2, the PSD of each signal sample was estimated for use in fingerprinting. Before applying the Welch method to the PSD of the normalized signals, the length of the window and the number of overlapped points were chosen to be 2048 and 1024, respectively. Following this, the unique features extracted from the PSD were labeled with the corresponding ICAO code of the originating aircraft. Following the discussion provided in Section 4.3, SVM with three kernels, namely linear, polynomial, and radial basis function (RBF), was employed for the binary classification of the aircrafts. To achieve this, different SVM models were trained, where each model treats the targeted aircraft as a single class, while the remaining seven aircrafts collectively represent the other class. Simply, SVM models were created to predict whether the ADS-B signal originated from the targeted aircraft. Thus, based on the literature focusing on binary classification with SVM, 90% of the sample was used for training, while 10% of the sample was used for testing. On the other hand, a significant concern is the potential for overfitting, which can lead to poor generalization due to the limited size of the dataset. This means that the model might perform well on the data it was trained on, but fail to accurately classify new, unseen data. While the literature on SVM binary classification suggests that 435 records per aircraft might be sufficient, we acknowledge the potential risks in our case. As an attempt to mitigate this risk, we have implemented 10-fold cross-validation.

For the implementation, MATLAB tools were used. The configuration parameters are listed in Table 2.

Table 2. The configuration parameters used in the implementation.

Parameter	Value
Kernel Scale Parameter	Auto
Standardize	True
Box Constraint	1
Polynomial Kernel Function	Auto
Optimization Solver	Iterative Single Data Algorithm (ISDA)
Cache Size	1000
ClipAlphas	True
Nu (v parameter for one-class learning)	0.5
NumPrint	1000
OutlierFraction, Verbose	0
RemoveDuplicates	False

5.3. Results

The classification accuracies of SVM with polynomial, linear, and RBF kernels at different SNR levels are listed in Table 3, Table 4, and Table 5, respectively. As can be seen from Table 3, the overall classification accuracy of SVM with a polynomial kernel classifier is 92.07%, 93.16%, 93.53%, 93.73%, and 93.91% at 10 dB, 15 dB, 20 dB, 25 dB, and 30 dB SNR, respectively. From Table 4, it can be observed that the overall classification accuracy of SVM with a linear kernel classifier is 91.27%, 92.12%, 92.18%, 92.19%, and 93.33% at 10 dB, 15 dB, 20 dB, 25 dB, and 30 dB SNR, respectively. Furthermore, it can be seen from Table 5 that the overall classification accuracy of SVM with an RBF classifier is 90.14%, 90.64%, 90.58%, 90.63%, and 90.85% at 10 dB, 15 dB, 20 dB, 25 dB, and 30 dB SNR, respectively.

Table 3. The classification accuracies (%) under different SNR levels (SVM with polynomial kernel).

SNR (dB)	Aircraft 1	Aircraft 2	Aircraft 3	Aircraft 4	Aircraft 5	Aircraft 6	Aircraft 7	Aircraft 8	Overall
10	99.23	88.97	88.37	90.54	90.78	90.54	91.58	96.56	92.07
15	99.47	90.14	89.71	91.24	92.28	91.68	93.36	97.39	93.16
20	99.35	90.74	90.09	91.77	92.56	91.91	94.20	97.64	93.53
25	99.31	90.91	90.46	92.26	92.60	92.27	94.27	97.79	93.73
30	99.46	91.24	90.76	92.02	93.05	92.41	94.43	97.92	93.91

Table 4. The classification accuracies (%) under different SNR levels (SVM with linear kernel).

SNR (dB)	Aircraft 1	Aircraft 2	Aircraft 3	Aircraft 4	Aircraft 5	Aircraft 6	Aircraft 7	Aircraft 8	Overall
10	99.28	87.97	87.603	89.49	89.68	90.01	90.73	95.41	91.27
15	99.08	88.70	88.02	90.06	91.09	91.06	92.55	96.43	92.12
20	98.65	88.83	88.259	90.05	91.24	91.36	92.69	96.39	92.18
25	98.57	88.87	88.417	90.06	91.29	91.12	92.72	96.42	92.19
30	98.70	88.93	88.724	90.26	91.46	91.44	92.73	96.38	93.33

Table 5. The classification accuracies (%) under different SNR levels (SVM with RBF).

SNR (dB)	Aircraft 1	Aircraft 2	Aircraft 3	Aircraft 4	Aircraft 5	Aircraft 6	Aircraft 7	Aircraft 8	Overall
10	97.41	87.61	87.50	89.13	87.98	88.65	89.20	93.63	90.14
15	97.81	87.79	87.53	89.50	88.63	89.30	90.09	94.47	90.64
20	97.55	87.84	87.58	89.70	88.65	89.29	89.86	94.16	90.58
25	97.31	88.03	87.62	89.89	88.79	89.48	89.76	94.14	90.63
30	97.43	88.38	87.60	90.11	89.19	89.82	90.02	94.28	90.85

The overall accuracy results are shown in Figure 8. It is clear that SVM with a polynomial kernel classifier provided better classification performance, while SVM with an RBF kernel classifier provided relatively lower classification performances at every SNR level. This is an interesting result, since RBF is known as one of the most popular SVM kernels in the literature due to its efficiency in classification tasks.

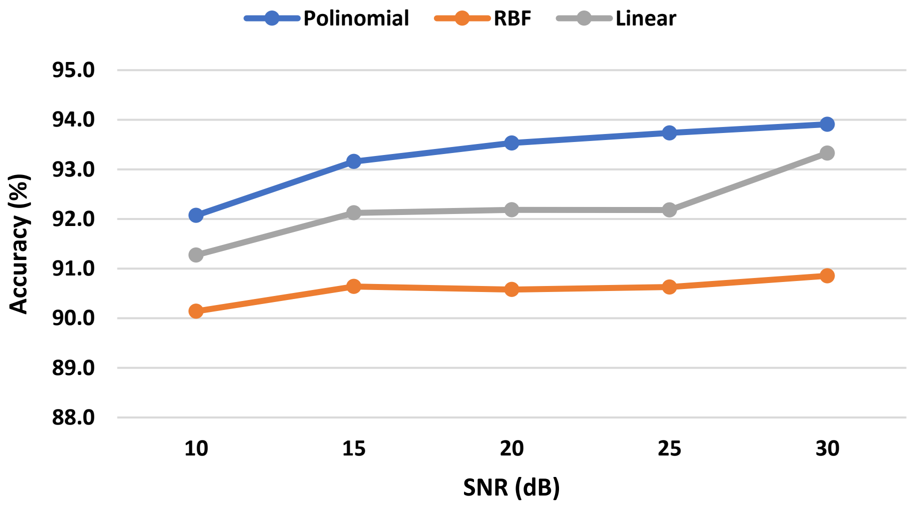


Figure 8. Overall classification accuracies of SVM with polynomial, linear, and RBF kernels at different SNR levels.

Moreover, the results achieved from the experiments reveal that SVM with an RBF kernel has a strong tolerance to noise. As shown in Table 5, it is obvious that there is only an increase of 0.7% in the classification performance when the overall accuracies obtained at 10 dB (minimum) and 30 dB (maximum) SNR levels are considered. However, when the overall accuracies of SVM with polynomial and linear kernels are examined for the same SNR levels, an increase of around 2% in the classification performance can be clearly observed.

As a summary, the minimum classification accuracy of 90.14% achieved from the experiments suggests that the proposed RFF method can use the PSD of the ADS-B signals as features to classify the aircraft. This has implications for the applicability of the proposed method in practice at various SNR levels. Nevertheless, it is worth noting that using SVM with a polynomial kernel could be a better choice to classify the aircraft due to its higher classification performance on the created dataset when compared to SVM with linear and RBF kernel functions.

6. Discussion

As mentioned in [6], RFF provides high security at the expense of higher implementation costs in general. The implementation cost increases, especially when there is a large amount of data collected from many transmitters. This may also adversely affect the real-time implementation of an RFF method, which leads to a significant concern in practice, owing to the requirement of higher computational resources. In this context, this study aims at proposing a real-time implementable RFF method for aircraft identification using a small dataset consisting of ADS-B signals. The results obtained from the experiments conducted to evaluate the efficiency of the proposed method under different SNR levels verify that the proposed method based on SVM with a polynomial kernel can work well to classify aircrafts, even with a small dataset.

To quantify the efficiency of the proposed method, its performance can be compared with the existing RFF methods that utilize ADS-B signals collected by SDRs under different SNRs [32–34]. As summarized in Table 1, the accuracy of the model proposed in [32] is found to be 44% at the 10 dB SNR level. Obviously, with more than 90% classification accuracy, the proposed method provides a better performance at the same SNR level, despite the small dataset size. The method presented in [33] provides almost 100% accuracy for the SNR levels between 2 dB and 5 dB. Moreover, in [34], the highest accuracy is found to be 92.5% when the I/Q samples of ADS-B signals are trained with a low SNR (−13.3–1.9 dB) and tested at a medium SNR level (5–2 dB). However, the results achieved from this study are incomparable with the results obtained in [34] because of the inconsistent SNR levels. Furthermore, the methods proposed in [33,34] are based on DL models, where the size of the datasets is significantly higher than the size of the dataset created in this study. Nevertheless, with around 92% accuracy achieved at 10 dB SNR, the proposed method offers a promising and acceptable performance, even when a small dataset is used. Therefore, it is believed that the proposed model could operate effectively in real-world applications with low computational resources.

On the other hand, there is still room to improve the classification accuracy of the proposed model, especially at lower SNRs (≤10 dB) by employing or developing an efficient classifier. For this purpose, using DL approaches based on CNNs could be a feasible option, due to their efficiency in classification tasks [46]. However, to provide an implementable RFF method in real-world settings, the CNN-based model (as a classifier) needs to be simple and efficient, even with a small dataset size. Currently, the authors are already working on the development of such simple CNN-based models to be used in various fields [47,48].

7. Conclusions

In this study, an RFF-based aircraft identification method is proposed. The proposed method utilizes the PSD of ADS-B signals as a distinctive feature for RFF implementation. The SVM with three kernels (polynomial, linear, and RBF kernels) is used to identify aircrafts at different SNR levels (10–30 dB). According to the results obtained from the experiments, a higher classification performance is achieved using SVM with a polynomial kernel classifier. More precisely, the overall classification accuracy of SVM with a polynomial kernel classifier is found to be 92.07%, 93.16%, 93.53%, 93.73%, and 93.91% at 10 dB, 15 dB, 20 dB, 25 dB, and 30 dB SNR, respectively.

The results obtained from the experiments also show that SVM with an RBF kernel exhibits strong noise tolerance, with only a 0.7% increase in classification performance at 10 dB and 30 dB SNR levels, in comparison to SVM with a polynomial and linear kernel. Nevertheless, a classification accuracy of 90.14% achieved from the experiments verifies that the PSD of the ADS-B signals can be used as features to classify the aircraft in RFF implementation. Furthermore, it is shown that RFF-based aircraft identification is possible, even with a small dataset containing ADS-B signals, collected by a low-cost and widely available SDR. As a future work, our purpose is to propose an RFF method based on DL approaches. Our intention is to develop a simple CNN-based classifier for the identification of aircrafts at lower SNRs (≤10 dB).

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