OPPORTUNITIES AND CHALLENGES OF GLOBAL FLIGHT DATA ACQUISITION

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Abstract – *Receptors on-board satellites are being implemented to track civil aircrafts all around the world. This new scenario requires novel methods to process the signals in order to efficiently retrieve more updated and reliable position and status data of every aircraft. To reach the required performance, it is indeed needed to engage carefully chosen algorithms of data analysis and processing. Machine learning algorithms, in particular k-nearest neighbors and support vector machines, are employed to estimate the potential success in decodifying ADS-B messages in highly congested areas, and simulations are performed to obtain the training and testing signals. First, the ADS-B communication system is described; second, multivariate analysis and machine learning algorithms are studied. Finally, the results obtained from machine learning methods are compared and future studies are proposed.*

Keywords – Global flight tracking, machine learning, signal processing

1. INTRODUCTION

The disappearance in 2014 of the flight MH370 is still a matter of concern for the international community. Many efforts were engaged in order to enable a safer flight environment all over the world. Nevertheless, there still is a long road ahead.

One of the very first actions taken was the creation of the Focus Group on Aviation Applications of Cloud Computing for Flight Data Monitoring (FGAC) at the Telecommunication Standardization sector of the International Telecommunication Union (ITU). At the same time as the FGAC was looking at telecommunication standards for an aviation cloud for real-time monitoring of flight data[1], Working Party 5B (WP5B) of the Radiocommunication sector of ITU (ITU-R) was also addressing the issue. The role of the ITU-R is to ensure the rational, equitable, efficient and economical use of the radio-frequency spectrum by all radiocommunication services, including satellite services, and to carry out studies on the basis of which Recommendations are adopted[2]. In WP5B, the challenge was to identify a suitable frequency band that would be required to know the status of every civil aircraft.

Automatic dependent surveillance-broadcast (ADS-B) was conceived by the International Civil Aviation Organization (ICAO) as a terrestrial communication system. Making use of satelital global positioning data and other on-board navigation information, ADS-B continuously broadcasts an aircraft's position and status to ground stations and other aircrafts. For that reason, the frequency band was attributed to the terrestrial service exclusively. In addition to that, the secondary surveillance radar (SSR) and other non-ICAO systems coexist with the terrestrial ADS-B system in that particular frequency band.

Low earth orbit (LEO) satellites have been widely used

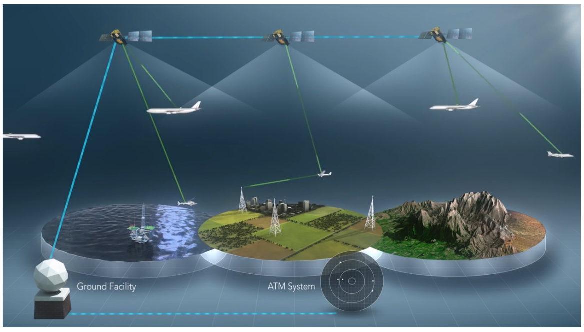


Fig. 1 – ADS-B coverage improved by a satellite network

for both voice and data communications for many years [4]. Based on this, WP5B conducted studies to evaluate the feasibility to receive ADS-B signals on-board LEO satellites, which would enhance coverage for aircraft that are suitably equipped, particularly in areas where terrestrial receivers cannot practically be deployed (such as oceanic, trans-polar and remote regions). Despite many issues being identified[5], it was shown that allowing the satellite reception of those signals is compatible with existing systems and would potentially solve the problem.

Following the information presented in WP5B Report (Document 5B/883-E Annex 1)[3], the administration members of the World Radiocommunication Conference 2015 (WRC-15), by Resolution 425, attributed the frequency band to the aeronautical mobile-satellite (Route) service (AMS(R)S) for the reception of ADS-B signals on board satellites.

That decision was the enabler that many companies were waiting for in order to implement reliable ADS-B receivers on board their new satellites and to provide a new service. However, the issues that arise upon the spatial signal reception have to be deeply studied to obtain the correct performance. The idea is depicted in

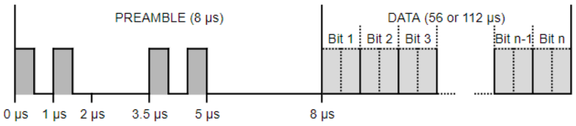


Fig. 2 – ADS-B Signal

Fig. 1.

Also, in 2015, ITU included the item 1.10 in the agenda of the World Radiocommunication Conference 2019 (WRC-19) with the subject "Studies on spectrum needs and regulatory provisions for the introduction and use of the Global Aeronautical Distress and Safety System" Moreover, the Conference Preparatory Meeting 2019 invited the ITU Radiocommunication Sector and Working Party 5B "[...] to conduct the relevant studies, taking into account information and requirements provided by ICAO for both the terrestrial and satellite components, including: a) quantification and characterization of radiocommunication requirements related to [Global Aeronautical Distress & Safety System] GADSS [...]"[10].

Due to the lack of a non-proprietary, unique and global system capable of providing accurate flight position and status data to air traffic controllers (ATC), in many parts of the globe, aircrafts have to maintain wider separation distances. Sometimes, changes in their routes due to weather or any other cause, have to be carefully coordinated relying only on voice communication between the pilot and the ATC. The consolidation of a global system capable of delivering accurate information in real time would change this situation, resulting in a safer and fuel efficient overall transportation system, reducing environmental impact caused by CO_2 emissions, while saving customers money.

Implementing space ADS-B technology by itself is not enough to prevent accidents. Additionally, to help with events similar to the MH370 disappearance, ADS-B equipment on board aircrafts must be tamper-proof, start automatically and be always on. Whether every aircraft in the world is precisely tracked, the time required to locate it, even in case of distress, can be reduced.

1.1 ADS-B system

ADS-B is a communication system for air traffic surveillance that operates at 1090 MHz. Using this technology, aircrafts routinely transmit identification and position information during flights. An ADS-B message consists of a preamble of $8\mu s$ and a data block of $112\mu s$. The message is Manchester-coded, meaning that each bit is represented with two states (high and/or low) that last half a bit time (see Fig. 2). Finally, the signal is modulated using on-off keying (OOK) and sent about six times per second, at random intervals.

There are two main ADS-B message types; squitter mode (S) of 64 bits and extended squitter (ES) of 120 bits long. ES ADS-B messages may contain information such as position, velocity, or status. The messages are broadcast with a random period to prevent aircraft from having synchronized transmissions. Depending on the aircraft category, the required transmission power ranges between $75W$ and $500W$. The vertically polarized ADS-B signals alternate between top and bottom mounted quarter-wave monopole antennas.

Air traffic services receive not only the SSR data, but also ADS-B messages that, due to their frequent update cycle, provide more accurate and timely surveillance information. In 2002, the American Federal Aviation Administration announced that 1090 MHz would be used in the next generation ATS for air carrier and private/commercial operators of high performance aircraft, wide-spreading the use of ADS-B. Many other airspace authorities have implemented, or plan to implement ADS-B mandates to enforce the use of ADS-B in civil flights in their airspace.

Although the deployment of ADS-B receptors is growing, ground stations are difficult to install and maintain in mid-ocean, desert and remote locations, resulting in uncovered zones.

1.2 Satellite ADS-B improvement

Using satellite receptors of ADS-B extends the coverage of the current terrestrial flight tracking system and has the potential to provide improved performance of aeronautical traffic control in areas where ground stations do not exist. Moreover, ADS-B is a non-proprietary technology which uses equipment widely implemented on most aircrafts and its use is already mandatory in many countries. The actual traffic procedures and limits may be improved, providing real-time and precise information of every civil aircraft in a particular airspace. This would enable the reduction of the aircraft separation distance, and pilots would be able to take different routes than planned due to weather or fuel economy reasons. Those changes would not only reduce time and fuel consumption, but also use crowded airspaces more effectively.

2. CHALLENGES

The frequency band used by ADS-B is shared with other ICAO and non-ICAO standardized aeronautical applications. This means that signals such as replies to SSR interrogations, distance measurement equipments (DME) and tactical air navigation system (TACAN) may interfere with an ADS-B message. For that reason, it is needed to distinguishing these (undesired) signals from ADS-B messages.

Moreover, due to the altitude of LEO satellites, the coverage area of a satellite receiver is notably larger than a terrestrial one. In the world's most congested zones, satellites will be receiving messages from a high number of planes at the same time, making message collision a source of great interference. An example of that situa-

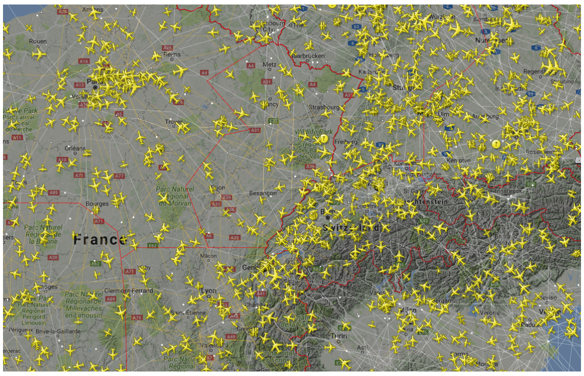


Fig. 3 – Snapshot of approximately 1400 aircrafts in western Europe zone, Sunday, July 29. Source: FlightRadar24.com

tion is shown in Fig. 3.
The above-mentioned problem appears due to increased coverage, and so the received signal needs to be treated to separate, as much as possible, messages broadcasted from different aircrafts. In order to achieve that, it is necessary to conduct different signal processing analysis from many perspectives, using as many methods as possible.

3. DATA RETRIEVAL AND PROCESSING

3.1 Multivariate analysis

It is possible to receive signals from more than one aircraft at the same time applying multivariate data analysis methods. These statistical techniques can be used to analyze data that arises from more than one variable. Generally speaking, said techniques can be used to uncover the latent structure (dimensions) of a set of variables, which in this case, indicates that it would be possible to know how multiple messages are added to the received signal. However, for this practical problem, the main objective is not to know how the radiofrequency channel affected the message, but to decode the message hidden in the sum of signals (i.e., to de-garble the message). For this case, the technique employed is the independent component analysis (ICA).

3.1.1 Independent component analysis

Looking at previous results, it can be seen that many messages are interfered with other (also useful) messages. This situation is similar to the cocktail party problem[15] where it is desirable to isolate one speaker within a crowd. It would be even better to be able to isolate every source and decode process them independently. Independent component analysis attempts to decompose a multivariate signal into independent non-Gaussian signals.
The next analysis needed is to determine whether it is possible to separate these contributing sources from the received total signal. When the statistical independence assumption is correct, blind ICA separation of a mixed signal gives very good results [6].
The independent components are found based on the statistical properties of the signals; by minimizing the statistical dependence of the estimated signal factors (components) and using the kurtosis or any approximation of negentropy, the independence of the components can be measured, which, by hypothesis, should not be Gaussian.
It is important to consider that, in theory, if N messages are present, at least N observations (e.g. receiving antennas) are needed to recover the independent signals. This derives into a practical problem on board the satellite, due to the complexity of the antenna deployment. This consist of a major problem if only one satellite receptor is considered. Even if many antennas or receptors are installed in one satellite, the received signals will be highly correlated and the methods will not be able to deliver good results.

3.2 Data classification

As the previous attempts are not practical using only one satellite receptor, another tool needs to be developed to obtain useful information. A testbed is needed to make all the trials and evaluate the performances of the methods studied. In the following sections the deployed simulator is explained, and then two algorithms are evaluated and its performance is quantified.

3.2.1 Simulator

The first step is to build a test bed to be able to explore every possible scenario and situation. The main variable to study is the signal received on board the satellite. The simulator was built considering a LEO satellite orbiting above an area with an aircraft density similar to the one found in the most congested areas. The aircrafts were individually placed at random locations in the satellite coverage.
Then, the received signal was built adding all the aircrafts' transmissions (generated by the signal generator) and affected individually by the particular channel gain and stochastic propagation effects[11]. The model comprises the main effects found in the communication channel and fits well enough to study the possible solutions.

3.3 Machine learning classification

After having the signal available at the satellite, two different pattern recognition algorithm were tested; k-nearest neighbours (kNN) and support vector machine (SVM). The aim was to be able to identify if, at a certain moment, the received signal contained or not a decodable message. At this stage, the content of the message was not being considered, but whether it was feasible or not it's demodulation. In the machine learning model (Fig. 4), this simulator is the message generator as it creates the signal $\tilde{x}$ and also the supervisor as it labels

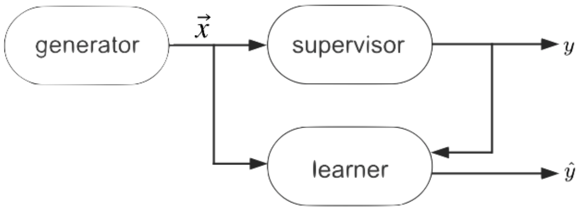


Fig. 4 – Learning model

the data (y signal). If it is known how the signal is being generated, it is possible to create a label that contains the desired result of the ideal classificator. For this problem the labels state whether is possible or not to decode a certain message based on the level of interference or signal power. In other words, two classes were defined based on whether the message could be decodified or not. This mainly depends on the received power of that message, e.g. a received power above the receiver's sensitivity and on if there were collisions between messages with comparable power.

Actually, the $\vec{x}$ signal used as input to the learning algorithms is a multidimensional signal composed of features extracted from $\tilde{x}$. Finally, $\vec{x}$ is expected to maximize the distance between samples of different classes. If the features are carefully chosen, that could be accomplished[7].

Once the vector $\vec{x}$ and the labels y were properly conditioned, they were introduced into a k-nearest neighbors classifier and a support vector machine. The performance was recorded with the error probability P_e as the key indicator and time/computational consumption as a secondary one.

Both algorithms need specific parameters depending on the chosen structure and many techniques are usually employed to tune them. In k-fold cross-validation, used in this study, part of the original samples are used as training data, and the remaining subset of samples to test the model. The partition of the samples is randomly chosen and this process is repeated k times. In order to obtain a single estimation, the k results are averaged. Using this method, all observations are used for both training and validation, and each one only once for validation. k is an unfixed parameter, and usually 5-fold cross-validation is used.[8].

3.3.1 k-nearest neighbors

The kNN search is a generalization of the optimization problem of finding the closest point to a given one in a determined set. This algorithm classifies the point by counting from which class are the k-nearest training points in the feature space (see Fig. 5). Choosing different k values sets different boundaries, as shown in Fig. 6a and 6b.

The training phase of the algorithm consists of storing vectors in a multidimensional feature space, labeling them with classes. Then, in the classification phase, an unlabeled vector is assigned to the class which is most frequent among the k closest training samples to that point.

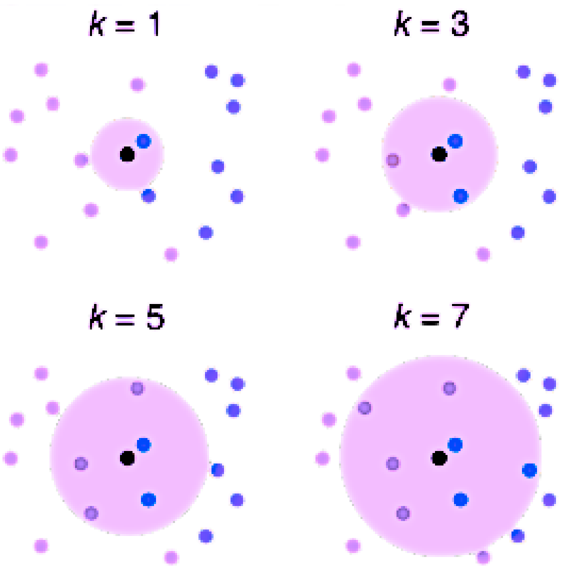
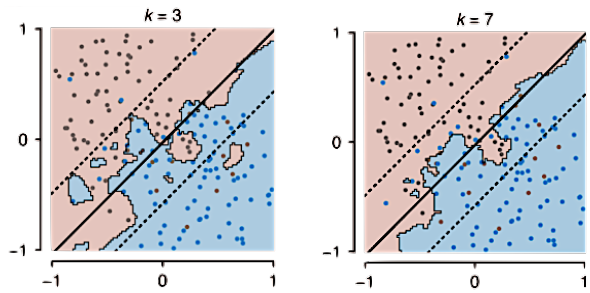


Fig. 5 – Example of finding k near neighbors.



(a) Boundary using 3 neighbors. **(b)** Boundary using 7 neighbors.

Fig. 6 – Effect of choosing different k.

Depending on the problem, and specially on the nature of the data, larger values of k can reduce the effect of the noise on the classification, but it could cause wrong predictions between less distinct classes. It is helpful to choose an odd k if it is a binary classification problem, in order to prevent ties[9].

For multi-class kNN classification exists an upper bound error rate:

$$R^* \leq R_{kNN} \leq R^* \left(\frac{2 - MR^*}{M - 1} \right) \quad (1)$$

where R^* is the Bayes error rate, R_{kNN} is the kNN error rate, and M is the number of classes in the problem.

The only parameter that has to be chosen for this method is k, i.e. the number of neighbors considered.

As previously detailed, to choose the optimal k (the one that committed fewer errors), k-fold cross-validation method was employed. $AP_e = 0.059$ was obtained for $k = 11$.

The contour for this method is shown in Fig. 7.

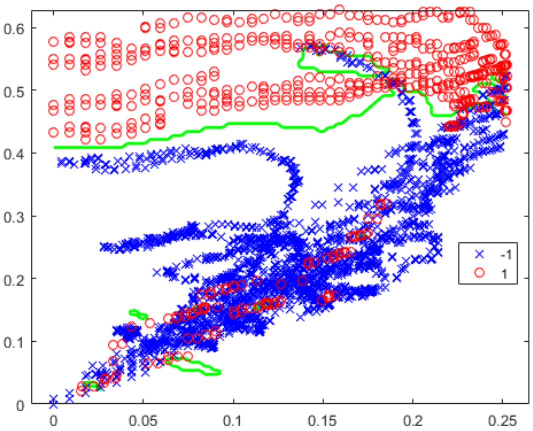


Fig. 7 – 11NN Classification results.

3.3.2 Support vector machine

SVM[13] is a method to find the boundary with the widest margin between all possible cases (Fig. 8b). Considering the case of $\mathbb{R}^2$, when the classes are linearly separable, a straight line can be drawn that perfectly separates the classes, with the margin being the perpendicular distance between the closest points to the line from each class, as seen in Fig. 8a. If the dimension of the sample is greater than three, the separating line becomes an hyperplane. The closest samples to the margin, or the ones that violate it are called support vectors and are the only samples that are considered to define the separating hyperplane[14].

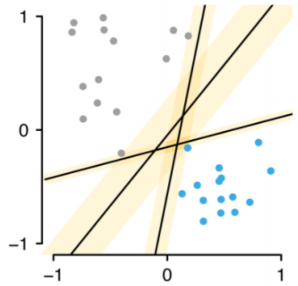
When the classes are linearly separable, the wider the margin, the confidence in the classification is higher because it indicates that the classes are less similar. Usually, it is difficult to obtain samples or data sets that are linearly separable and any separating hyperplane will not be useful. It is said that the margin is violated by a sample whether it is beyond the separating hyperplane as shown in Fig 8c with arrows marked as '1'. Also, the case where the samples are on the correct side, but are inside the margins has to be considered and an example is marked with the arrow and '2' in Fig. 8c.

To take into account violations, penalty is considered proportional to the distance between each violating sample and the corresponding margin. Then, the problem is reduced to the minimization of the risk:

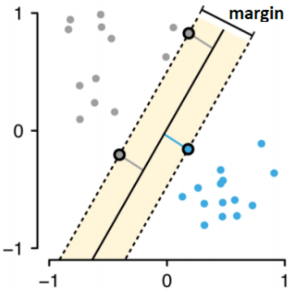
$$1/\rho + C \sum \xi_i \tag{2}$$

where ρ is the margin width, ξ_i is the penalty paid of the ith violating sample and C is a parameter that enables to tune the trade-off between the width of the margin and the amount of violating samples.

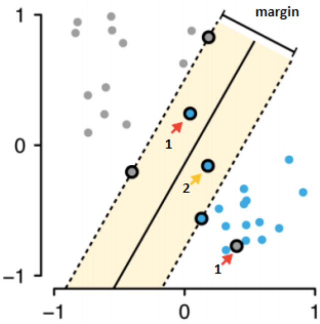
If C is large, there will be fewer training errors, meaning that fewer samples from the training set will be misclassified. This is known as overfitting, and when it occurs, as shown by the dashed line in Fig. 9, classes are perfectly separated, but the separation is greatly influenced by noise, potentially leading to greater classification errors.



(a) Linearly separable classes.



(b) Maximum margin.



(c) Margin violation and misclassification.

Fig. 8 – SVM using a linear classifier

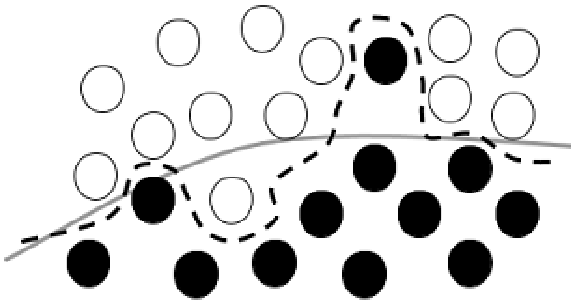


Fig. 9 – Overfitted samples

On the contrary, when C is small, there will be more misclassified samples, but the margin will be greater, as shown by the grey continuous line in Fig. 9. To improve the final result of the algorithm this parameter has to be chosen using cross-validation[12].

For this method, two main parameters had to be set; C of eq. *(2)* and the kernel used. A Gaussian kernel was chosen for the present case. The only additional parameter required by the kernel was σ or the bandwidth.

Using k-fold cross-validation $C = 11 \times 10^5$ and $\sigma = 0.0433$ were found to be optimal. Training the SVM classifier with those parameters, the performance regarding the error probability was $P_e = 0.049$.

Furthermore, despite that the training phase took an important amount of time, the classification of every new sample could be done very quickly or with little computational effort.

The contour for this method is shown in Fig. 10.

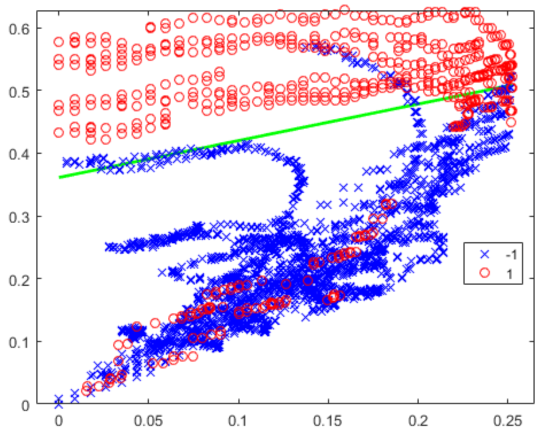


Fig. 10 – SVM Classification results.

3.3.3 *Performance comparison*

The performance driven by the error probability P_e as the key indicator and time/computational requirement as the secondary were used to evaluate the two studied methods. Results are condensed in Table 1.

Table 1 – kNN vs. SVM

Method / Indicator	kNN	SVM
P_e	0.059	0.049
Classification	Slow	Very fast
Training CPU Usage	Low	High

From Table 1, it can be seen that kNN performs better during training time, but relatively to SVM, the classification process takes more time to complete. On the other hand, SVM requires higher CPU usage during the training phase, but it is able to classify new samples significantly faster than kNN.

4. RESULTS

Under the hypothesis stated, it was shown that kNN and SVM can determine whether a message can be decoded from the received signal, performing with little difference. It is clear that SVM is about 1% better than kNN. Under that circumstance, other indicators have to be analyzed in order to define which method will be better.

One of the most important indicators is the time or computational resources that are needed to classify a new sample. In that case, the SVM will perform better. Nevertheless, if kNN is manipulated in order to obtain a single and simpler boundary, the process can be approximated by a simple function. But, in many cases that method is not applicable, especially when the dimension of the samples (i.e. the amount of features used) is increased.

Despite that the training time for SVM is important, this phase can be done offline, and once the system is trained, the classification process will be very fast.

Nonetheless, during this study only one kernel was used to test SVM. The results show that a simpler kernel can be used, improving the performance of the method.

5. FUTURE WORK

It is considered for future work to model more phenomena that affect the signal, e.g. doppler shift and phase shift. Also, different strategies of pattern recognition and feature extraction could be considered to know which method fits better to this problem.

Moreover, as the classificators studied only are able to distinguish whether a decodable message is present in the signal or not, a solution to the problem presented at multivariate or ICA could be addressed in order to find a solution. If that is achievable, then the reliability of the algorithm should be tested to validate its potential use in a satellite.

Finally, experimental tests are needed in order to evaluate the performance of the algorithm. In future studies, the algorithms will be tested with a real signal at satellite receivers.

6. CONCLUSIONS

The conducted studies present a different way to deal with the, already known, problem of receiving ADS-B messages in congested airspaces. Machine learning and pattern recognition are novel analysis methods that can increase the amount of messages that a receiver could decode in an efficient manner. This new technique can contribute to international recommendations and standards to improve them, not only in a particular assumption, but also in the way that parameters are chosen.

The approach found is the stepping stone to building a robust satellite receptor of ADS-B messages. It is clear that the challenges lead to the investigation of novel methods to process the signal in order to obtain clean and reliable data, using as little energy as possible. If that is achieved, new real-time aircraft position and status data can be obtained for all the aviation stakeholders.

If the addition of this method makes the system more efficient, the lifespan of the satellites will be improved due to reduction in energy consumption. Consuming less energy not only impacts on the battery depth of discharge, but also makes the satellite cheaper due to smaller electronic parts. Therefore, using machine learning techniques could potentially reduce the overall cost of satellite missions carrying ADS-B receivers.

Improved flight tracking systems will be used in the future to provide more secure, energy and time efficient and convenient flights all around the world. Issues regarding aircraft flow as separation, conflict resolution, approaches, planning, weather avoiding, etc. will be improved to enhance safety, and provide additional capacity. Furthermore, fuel consumption and CO_2 emissions will be reduced since more efficient routes into busy airports will be provided, thus cutting down holding time spent in the air and on the ground. It is shown that despite the difficulties, having available enhanced data that is provided by already-installed equipments, will transform the industry to become more efficient and secure, which yields a smart transportation system.

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