International Civil Aviation Organization

Twenty Eighth Meeting of the Communications/ Navigation and Surveillance Sub-group (CNS SG/28) of APANPIRG

Bangkok, Thailand, 01-05 July 2024

Agenda Item 6: Navigation
6.4 Other navigation related matters

INTRODUCTION OF THE DATA-DRIVEN GNSS INTERFERENCE DETECTION AND LOCALIZATION METHOD

(Presented by China)

SUMMARY

In recent years, China has dedicated significant efforts to researching data-driven methods for GNSS interference detection and source localization. These algorithms, based on this innovative approach, have been integrated into big data platforms and applied in real-world scenarios. This paper presents the practical performance and current status of these algorithms. Empirical data demonstrate that data-driven methods significantly enhance the efficiency of interference mitigation. Additionally, this paper outlines the key steps of the algorithms and the necessary theoretical foundation required to understand them.

1. INTRODUCTION

1.1 GNSS Interference Detection and Localization by Automatic Dependent Surveillance-Broadcast (ADS-B) Data was discussed several times in the ICAO APAC meetings. In the Fifth Meeting of the Mode S Downlinked Aircraft Parameters Working Group (Mode S DAPs WG/5), China presented IP/10 to introduce a GPS interference source identification and screening method in civil aviation operations. Using the changes in aircraft ADS-B report data, combined with the change rule of historical data and the principle of satellite navigation signal, the paper constructs an index of GPS interference, which can check and locate interference area and time sensitively.

1.2 In the Eighth Meeting of the Spectrum Review Working Group (SRWG/8), by IP/04, China presented the application of ADS-B downlink data in monitoring GNSS interference that affects aviation flights and locating the sources of interference. This technology has demonstrated impressive results in locating GNSS interference sources, resulting in a significant enhancement in the efficiency and accuracy of interference detection and localization.

1.3 Based on the Mode S DAPs WG/5 IP/10, this paper introduces an update of the data-driven GNSS interference detection and localization method. Firstly the new method proposes the detection the GNSS interference based on ADS-B multi-index features, and then the logistic regression algorithm is used to approximately detect and locate interference in an area. Finally, the method uses the Attention Mechanism Convolutional Network (AMCN) to accurately localize GNSS interference sources.

2. DISCUSSION

2.1 The ADS-B report, which is high-frequency and contains spatiotemporal data characteristics provides a new idea for interference detection. However, most existing methods for detecting GNSS interference sources based on ADS-B data rely on only one or two indexes from a single ADS-B report. The inherent uncertainty of the ADS-B data leads to a tendency for these detection methods to identify non-interfering as interfering. Since, we propose a new GNSS interference detection method based on ADS-B multi-index features, which reduces the impact of the uncertainty of the ADS-B data itself on GNSS interference detection through two improvements.

2.2 In the method, we extracted the Navigation Integrity Category (NIC), Navigation Accuracy Category for Position (NACp), Source Integrity Level (SIL), messages update interval, change rate of ground speed, change rate of position, track angle (TA), flight level (FL), and ADS-B equipment version were extracted as multi-index features. After conducting feature selection, the next step involves selecting a classifier to detect potential interference in the national data and categorize ADS-B reports as ‘interference’ or ‘non-interference’.

2.3 This classification also enables us to isolate theoretically interference-prone areas for subsequent localization of the source of interference. In summary, the desired classifier should meet the following criteria: ①This classifier is capable of handling discrete variables and outputting the result of binary classification. ②Is computationally fast, and it can handle big data because we are going to apply it to national data. In addition, we conducted a comprehensive comparison of different classifiers and the results indicated that the logistic regression achieves sufficient classification accuracy while also possessing the advantages of low computational complexity and fast computation speed.

2.4 To verify the effectiveness of multi-index in GNSS interference detection, we process the verification by learning from historical data and using logistic regression to identify the classification boundary between interference and non-interference data. The experimental dataset, this report uses flight data known to have interference, comprising a total of 7,725 messages from 17 flights. We select the first 5,000 data points and split them into a training set and a test set at a 7:3 ratio. The remaining 2,250 data points are used as a validation set to evaluate the classification performance of the methods. According to the verification result, the classification accuracy of the logistic regression is about 93.9% which can provide satisfactory performance for interference detection. Therefore, the logistic regression is considered the choice of the algorithm to approximately detect and locate interference in an area. After the logistic regression process, the interference ADS-B data is labeled as 1, while non-interference ADS-B data is labeled as 0 for further analysis.

2.5 Based on the ADS-B report interference classification result, the further objective is to establish a novel approach to explore and fully leverage the intrinsic relationship between the location of the source of GNSS interference and variations in ADS-B data. To achieve this purpose, we propose a novel framework named Attention Mechanism Convolutional Network (AMCN). This framework uses convolutional neural networks to initially extract the local features of aviation data from individual aircraft, then utilizes an attention network to generate a comprehensive representation of the global features of ADS-B data from multiple aircraft that have been impacted by interference events. This framework assumes that each interference accident is caused by fix and unique interference source.

2.6 In this AMCN framework, we first extract the information of interference classified ADS-B data of variable length by using time sliding windows based on the number of timestamps in the ADS-B data. The extracted data is then processed using a convolutional operation by a one-dimension Convolutional Neural Network (1D CNN) to extract the temporal and spatial features of the interference sample which is essential for training the spatial feature extraction model. Secondly, the actual geographic relationships of the slid interference classified ADS-B report are used to construct sequence data, which is the input of an encoding layer in the attention network. The attention mechanism mines the correlation between each sliding and the location of the interference source. Finally, the learned features are input into the classifier through global pooling, and the results are used to update all weight coefficients of the AMCN framework. Figure 1 represents the schematic diagram of the AMCN framework. Our method of transforming a localization problem into a classification problem using the relative location of the interference sources and the affected flights, and subsequently inverting the classification back to specific locations.

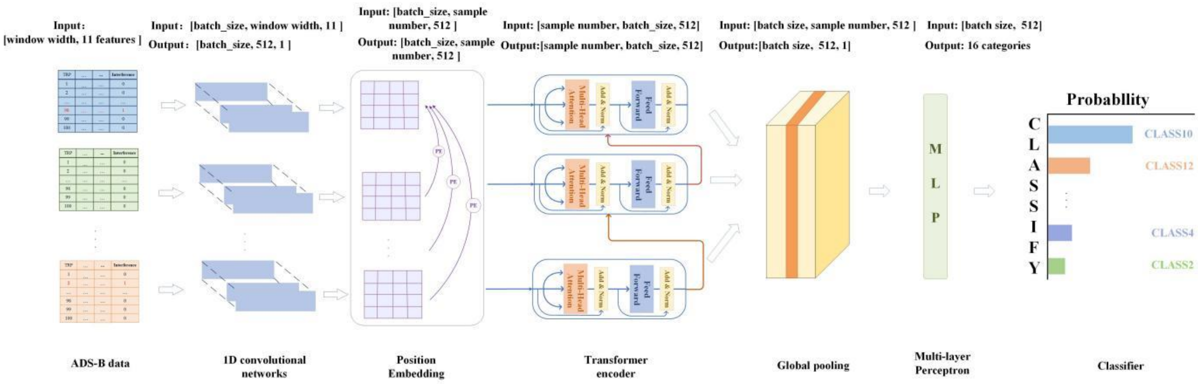

Fig 1: The Framework of AMCN

2.7 To verify the performance of the Framework of AMCN, we compare our method with several baseline methods by the indicators of classification accuracy and localization accuracy. For the comparison of classification accuracy, AMCN has the best empirical results among these methods. This is due to its use of relative position methods for classification, which enables a more rational application of various classification models to the problem, and the serial structure of CNN and attention network allows comprehensive analysis of the local and global features of the data. For localization accuracy, AMCN has a more stable performance on different interference sources than other current models. This is because the AMCN reduces the uncertainty of the prediction results through mutual confirmation in its input construction, making its prediction accuracy more stable. In addition, the AMCN also achieves consistent results on the validation set and demonstrates the generalizability in addressing the problem of interference source localization. Based on the actual GNSS interference events verification of Lanzhou and Guangzhou FIR, the distances between the actual investigation positions and the AMCN predicted positions are less than 10km which can significantly reduce the workload of manual investigation.

2.8 GNSS interference is a pressing issue in both navigation and surveillance fields that requires more serious attention and resolution. Currently, data-driven GNSS interference detection and localization methods can effectively enhance the efficiency of related investigations. CAAC will continue to verify and optimize this method to further improve the accuracy of interference detection and localization, thereby increasing the efficiency of further investigation.

3. ACTION BY THE MEETING

3.1 The meeting is invited to:

a) note the information contained in this paper; and

b) discuss any relevant matter as appropriate.

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