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FIX ABSTRACT

**ABSTRACT** – GPS Spoofing has become more common, as the ease to implement such an attack increases. All USAF assets rely on GPS data for navigation and timing, and are vulnerable to spoofing attacks. A data focused approach would provide a flexible, lightweight solution that could be easily implemented on a variety of systems. Machine learning techniques provide a promising way to develop such a system. Logistic regression, naïve Bayes, and random forests classifiers were trained on simulated spoofing data to detect a spoofing attack. All of these methods showed promise when given appropriate training data, and random forests proved to be the best solution with high recall, even outperforming a deep learning method implemented in previous research. Future work is needed to test the approach with more subtle spoofing attacks.

1. Introduction

The proliferation of Software-Defined Radio (SDR) and other Commercial Off-the-Shelf (COTS) systems has led to increased vulnerability of United States Air Force (USAF) systems through the spoofing of Global Positioning System (GPS) signals. USAF assets (drones, airplanes, ground systems) rely on GPS signals to coordinate timing and for navigation. While military GPS signals are encrypted and more difficult to spoof, many systems also use civilian GPS messages. The MIL-STD-1553 avionics bus coordinates traffic between systems on USAF assets. It times messages between a bus controller (BC) and the different components (GPS, INS, Flight Computer), or remote terminals (RTs). The most effective lightweight solution to counter GPS spoofing would be in a bus monitor for MIL-STD-1553 that can parse the messages between the avionics and detect GPS spoofing, using a machine learning approach.

This research strives to answer the following questions: Can a supervised machine learning algorithm classify MIL-STD-1553 messages as spoofed based on observations from the bus? The central hypothesis is that a machine learning algorithm can correctly classify MIL-STD-1553 messages with statistical significance using bus traffic from other avionics components as features, 17 in total. It is also likely that a more drastic spoofing attack, one with more deviation in position from true position, will be easier to detect and have higher accuracy. The features collected in the data are: GPS Latitude, GPS Longitude, GPS Altitude, Velocity-North, Velocity-East, Velocity-Down, Attitude-Roll, Attitude-Pitch, Attitude-Yaw, Barometer-Altitude, IMU-Delta Theta (DT)-North, IMU-DT-East, IMU-DT-Down, IMU-Delta Velocity (DV)-North, IMU-DV-East, IMU-DV-Down. The Inertial Measurement Unit (IMU) data will likely have the most significance in classifying when compared to the GPS data .The research objective is to develop a classification model that can correctly classify spoofed GPS messages on the MIL-STD-1553 bus with recall of 90% or greater. Recall will be the main measure of success, since false negatives will result in navigation errors while a false positive will simply result in further verification and monitoring of system data.

The data used in this project has been procured from a set of real flight data curated by the Autonomy and Navigation Technology (ANT) center. That flight data was used in tandem with the ANT Center’s Fly program, which generates simulated sensor readings with error from the flight data. The data was collected from 4 flights, totaling over 8 hours of data and over 5 million observations. The spoof was implemented when combining the various sensor readings from Fly into a single Comma Separated Value (CSV) format, altering the GPS readings to simulate the attack. The spoof occurred in minute intervals, and the class (spoofed or unspoofed) was recorded alongside the rest of the data.

1. Related Work

A number of papers have been published on the application of machine learning to anomaly detection in time-based systems. All of these models address a simple binary classification problem, distinguishing between normal system behavior and anomalous system behavior [3]. Marvin attempted a deep learning approach to detect spoofing with mixed results, likely due to issues with the data and the additional complexities of a neural network application [5]. Genereux, et al. has used the timing of messages over the 1553 bus to detect anomalies and intrusion using a simple histogram approach [7]. Similarly, message timing data has been used to detect an attack in a variety of cyber-physical systems [6]. Other work includes the use of Support Vector Machines to detect GPS spoofing using information from the signal characteristics and a supervised approach [8]. More generalized research includes the use of Markov models and relative probabilities to detect anomalies in time series data [1], and applications of deep learning to detect ADS-B spoofing [4] and network intrusion [2]. The aforementioned research is representative of the applicability of machine learning methods to this problem and other anomalous behavior in time series data. This project differs mostly in the data that is being used, messages from the MIL-STD-1553 bus. The advantage of using 1553 data is that developing a simple bus monitor with the trained detection algorithm would provide a lightweight solution that can be implemented on any USAF asset.

1. Methodology

The flight data that was collected in the original dataset is very similar to the data that would be collected directly from the MIL-STD-1553 bus, but was instead collected using the ANT Center’s Scorpion system. As such, it was used with the Fly program to generate sensor data to ensure reproducibility. All data was recorded using the WGS-84 coordinate system. The flight data and sensor readings were recorded in log files which were then parsed and combined in a CSV file. Since the flight data was recorded every millisecond, it was downsampled, based on timestamp, to match the observation per second output from Fly. As a result, each observation in the final dataset represents one second of flight time. In between the combination of log files into the singular CSV, the spoofing attack was implemented. The attacks vary in their drift from the true position, the largest of interest is a drift rate of 5 meters per second in a single axis, although larger drift rates, up to 1000 meters per second, were tested as well. A future attack to be implemented will shift the position readings in time. Once the data was recorded, it was separated into its 18 features, 3 of which were susceptible to the attack; GPS-Latitude, GPS-Longitude, and GPS-Altitude. Finally, every feature in every observation was normalized to represent a value between 0 and 1 to assist the model and exacerbate smaller changes in feature values.

Three different classical classification methods attempted to discern spoofing attacks: random forests, k-nearest neighbors, and support vector machines. More specifically, the random forests classifier consisted of 100 trees, and k-nearest neighbors used 5 neighbors. Six advanced classification methods were also evaluated with the dataset: two different basic multilayer perceptrons (MLP), a convolutional neural network (CNN), a multivariate long-short term memory (MLSTM) model, an MLSTM with dropout, an MLSTM with convolution, and a previous students MLSTM Fully Convolutional Network (FCN). These models were evaluated with tensors ranging from 3 timesteps to 1000 timesteps, and similarly variable batch sizes, with the potential for larger batches with less timesteps and the necessity of smaller batches with more timesteps in the tensors. While small drift rates are of greater interest, because they will be more difficult to detect, the performance of the models warranted testing with larger drift rates, of 100m/s and even 1000m/s. All of these instances used an 80/20 split for train/test data. The models were trained and tested on the same drift rate in latitude for a single flight, and also for all flights combined. There was equal representation of both spoofed and unspoofed observations across the data, as well as in the training and testing data.

After the models trained, they were tested on the remaining data and collected results. For the classical models, the results were compiled in the form of precision, recall, and F1 score. Recall is the primary measure of success in this application, since a false positive is preferable to a false negative, but precision and F1 score also provide meaningful metrics in assessing the models. The classical models serve as a baseline to the advanced methods, as well as a proof of concept and validity. An effective model is measured by a recall rate of more than 90%. The advanced methods, given their poor performance with the existing dataset, were only evaluated using loss and accuracy. Since the classification is binary, the loss function used for training and evaluation was binary crossentropy. Similar to recall, an accuracy of more than 90% would indicate an effective model.

1. Results

The results verify the practicality of a supervised machine learning approach to the problem, and show promise, particularly in the use of a random forests or k-nearest neighbors classifier. They also emphasize that an altered dataset or better adapted models may be needed to make use of advanced machine learning techniques. importance of having quality training data, as unseen attacks provided the greatest obstacle for the models. As shown in Table 1, the random forests classifier performed perfectly in each scenario, while logistic regression and naïve Bayes performance deteriorated as the attacks became more subtle. Logistic regression and naïve Bayes also performed mediocrely when trained and tested on all attacks.

**Table 1: Individual Attack Scenarios**



LCV = Logistic Regression with Cross-Validation, GNB = Gaussian Naïve Bayes, RFC = Random Forests Classifier

More interestingly, all of the models underperform in the face of an unseen attack, highlighted in Table 2. Surprisingly, the models perform worse when the fixed point attack is withheld than they do when the most subtle attack is withheld. However, the trend of lower model performance with more subtle drift rates holds for the remaining attacks.

**Table 2: Unseen Testing Attack Scenarios**



LCV = Logistic Regression with Cross-Validation, GNB = Gaussian Naïve Bayes, RFC = Random Forests Classifier

When compared to the deep learning model on the same data set and scenarios, it is interesting to note that the random forests classifier outperforms the multivariate long-short term fully convolutional network, shown in Table 3. While the increase in model recall is marginal, it is worth noting that the computational requirements for the classical machine learning model are far lower than that of the deep learning model, and it may provide a more flexible solution. Moreover, the random forests classifier may outperform the deep learning model more drastically when faced with more advanced spoofing attacks.

**Table 3: Deep Learning Model Comparison**



RFC = Random Forests Classifier, MLSTM = Multivariate Long-Short Term Fully Convolutional Network

1. Conclusion & Future Work

The results obtained show the promise of a supervised machine learning approach, implemented in a MIL-STD-1553 bus monitor, in detecting a GPS spoofing attack. The random forests classifier had perfect results when trained using proper data. These results also emphasize the importance in obtaining accurate, realistically spoofed data in implementing such a solution. There are potentially severe limitations of the models when attempting to identify an unseen spoofing attack. The data also proves that a less drastic spoofing attack is harder for the models to detect, as there is less contrast in the readings to determine anomalous behavior. Moreover, a classical machine learning model seems to provide better intuition at less cost than a deep learning model. However, further testing is necessary to verify this outcome. Using a measure of a recall rate of at least 90%, the random forests classifier succeeds in every scenario except when the fixed position attack is not represented in the training data, and for less extreme cases even the naïve Bayes classifier is successful in detecting a spoofing attack.

Future work must be conducted in order to verify these results. Specifically, much more advanced and subtle spoofing attacks must be implemented in the training and test data. The attacks implemented in the data used are much simpler than would be realistically employed. Also, the data should reflect a response by the aircraft’s flightpath as a result of spoofed navigation data. The data used in this research does not reflect any deviation in the aircraft’s flightpath with the presence of conflicting GPS data, but in a real attack the aircraft should begin following the spoofed route. With more realistic data, the same method can be applied and should reproduce these results. Another area of interest is in testing different machine learning models, potentially support vector machines for example. Support vector machines were excluded in this research in favor of random forests, because random forests are less computationally intensive and yield similar results.

1. References

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