Spectral-Spatial Weak Signal Classification Using Deep Learning Techniques

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Abstract

Clear Air Turbulence (CAT) poses a significant hazard to aviation due to its unpredictable nature and difficulty in detection by conventional weather radar systems. Traditional techniques, like Pulse Pair Processing (PPP), often struggle with low signal-to-noise ratio (SNR) and CAT signals. While methods such as Reduced-Rank Multistage Wiener Filter (RR-MWF) and Dynamic Matrix Completion (DMC) have shown improvements in detection of Low SNR signals but they are not effective in classifying signals. This paper introduces a new neural network approach to improve radar target classification, particularly for CAT and low-SNR targets in cluttered and interfered environments. This method simplifies signal processing algorithms, enhancing radar detection performance and contributing to safer aviation operations.

1. Introduction

Turbulence is a common phenomenon that has contributed to several recent aircraft accidents. Clear Air Turbulence (CAT) consists of sudden swirls of air around an aircraft moving at high speeds, which often go unnoticed by weather radar systems. This happens when the different mass of air interacts with different velocities, pressure or temperature. Air flow passing from Irregular terrains , airflow above the cumulonimbus cloud through the vicinity of thunder storm scenario may also be the source of CAT [1]. The Federal Aviation Administration [2] defines CAT as "sudden severe turbulence occurring in cloudless regions that causes violent buffeting of aircraft. CAT is especially troublesome because it is often encountered unexpectedly and frequently without visual clues to warn pilots about the hazard.

In addition to directly causing accidents involving aircraft, CAT will interfere with radar echoes if it is not powerful enough to cause damage to the aircraft. This must be identified and eliminated in order to enhance weather radar data quality.Thus, it also has an indirect impact on how well radar detecting capabilities perform. Predicting the occurrence of CAT including its severity and intensity through weather radar is challenging task as a consequence, the pilot is unaware about this scenario. Flight SQ321 is one of the real example where aircraft cruising at 37000 ft altitude was affected by CAT .

The method used to characterize CAT involves thresholding vertical and horizontal acceleration and variance to classify it as normal, moderate, severe, or extreme. In rare cases, severe or extreme turbulence may result in loss of flight control or structural failures.

In [7], it was shown, that CAT SNR lesser than 10 dB is captured more effectively through Reduced-Rank Multistage Wiener Filter(RR-MWF) in comparison to the conventional weather radar signal proccessing method which is Pulse Pair Processing (PPP).

In [6], the work proposes a Dynamic Matrix Completion (DMC)-based approach which is an optimisation technique for use in the front-end of MIMO radar. The proposed approach suggests a Dynamic Singular Value thresholding technique which helps in eliminating the noise returns early in the processing chain.
The result shown was in terms of enhanced probability of detection, reduced false alarm rate, and ultimately, improved target tracking performance.

In [3], the author employs a neural network technique i.e, Faster Region based Convolutional neural network (R-CNN) for object detection in densely populated areas, noting that SNR limitations were not a concern. The study also highlights that the performance of the Single Shot Detector (SSD) surpasses that of the YOLOv5 model. However, the SSD may struggle to identify small objects in complex scenarios or when multiple sensors are integrated.

To the best of our knowledge, no existing work has explored the use of neural network techniques for detecting and classifying CAT or Low SNR targets in radar systems.

To address this , we propose utilizing the YOLOv5 model to detect small objects with low SNR from airborne weather radar data in environments characterized by complexity and poor resolution, particularly at long ranges.

As illustrated in Fig: 1 We propose use of a neural network technique to classify the CAT / Low SNR target signa-

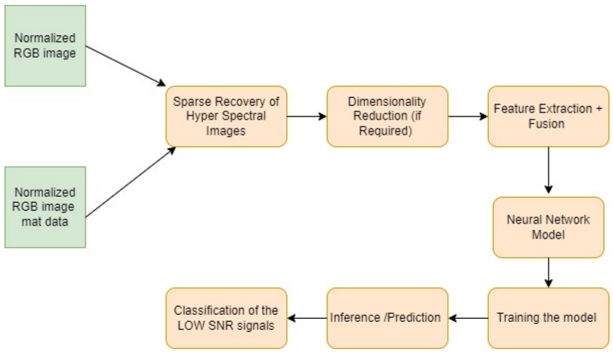

Figure 1. Block diagram

ture in the presence of clutter and interference, this strategy will help in the detection and classification of the desired signal. A probable flow chart that illustrates the work we do is what we are exhibiting.

The step-by-step full description is given in the following steps as illustrated in Fig: 1

1. **Data Collection and Loading**. Multiple.mat files with associated RGB images and hyperspectral data is collected. Make sure the RGB images are in a 3D array format (e.g., 32x32x3) and the hyperspectral data is in a 3D array format (e.g., 32x32xY), where Y might be [16 / 32 / 64 / 128 / 256] band.
2. **Data Preprocessing:** RGB images and hyperspectral data normalization, as well as dimensionality reduction if data sets include redundant information.
3. **Feature Extraction**: Using the neural network (NN) technique, extract spatial features from RGB images and spectral features from hyperspectral data. To generate a complete feature set, combine the extracted spatial and spectral information.
4. Develop the neural network model and use fused spectral-spatial features to train it.
5. We can use a new data set to test and refine the model once it has been trained. Classifying the various signal kinds in the hyperspectral images is the task of the trained model.

While RGB images can be used for cloud and clutter classification with YOLOv5 model , we enhance classification capabilities by employing a geometric model. This model converts RGB or any other input images from various spectral bands into HSI(Hue, Saturation and Intensity) format [].

As in fig 6 and fig 7, we can see that the RGB image reconstructed from HSI images is capturing more information about the target compare to original RGB images. With this hypothesis we can say that HSI/HSI-RGB images will be more effective in classification of targets, especially when SNR is very low. HSI can classify target more effectively than RGB in scenarios where color and lighting is more critical , it means that target can be distinguished due to it hue and saturation components.

In the case of CAT, when the input is a hyperspectral image, the designed model will convert the hyperspectral data based on various spectral bands, resulting in different saturation and hue compared to RGB images. This approach enhances the classification of CAT, even when its signal-to-noise ratio (SNR) is not particularly strong.

2. Simlation Results

To accomplish the task of classification of the weather or clutter. The set of images consisting of weather only, weather with clutter are obtained from the .mat files which consists of I-Q samples from radar. We then labeled the available images manually using the image label python package. The main classification labels are weather and clutter. Then we trained the YOLOV5s model, which uses CNN as backbone for classification tasks. For training, the 70% of available labeled images were used and remaining for testing.

In fig 2, we can observe that weak weather signal has been detected in the presence of strong clutter. In fig 3, only the clutter is identified. Likewise. in fig 4, the model successfully detects the weather in the absence of clutter. Further more, when the model is tested with 2sided weather , it differentiate with clutter.

To improve the effectiveness of classification, By using the algorithm presented in [4] and [5], we converted RGB weather and clutter images to HSI and vice versa. RGB to HSI is essential for improving the detection and classification of targets in various applications. The HSI color space provides enhanced color discrimination, simplifies color detection, and offers robustness against illumination changes, ultimately leading to improved classification accuracy. This makes HSI a preferred choice in fields such as computer vision, remote sensing, and image processing.

3. Conclusion

In this work, we demonstrated the detection of turbulence with low SNR or signals mixed with various types of clutter, which poses significant challenges. Detecting such phenomena is crucial, as it not only contributes to aircraft accidents but also distorts the radar's transmitted beam, ultimately degrading detection performance. Unlike traditional filtering techniques, we propose a neural network-based approach to classify and detect CAT or low-SNR target signatures represented as RGB images in the presence of clutter and interference.

We trained labeled RGB radar echo images using the YOLOv5 model. To enhance performance, we explored

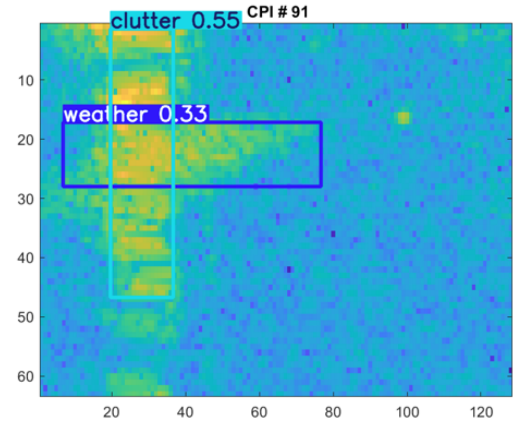

Figure 2. Weather_Clutter

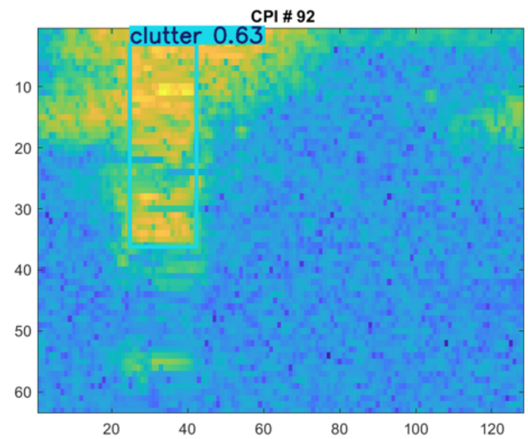

Figure 3. clutter only

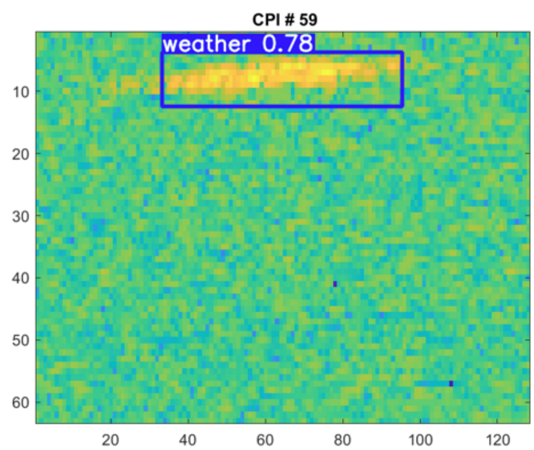

Figure 4. weather only

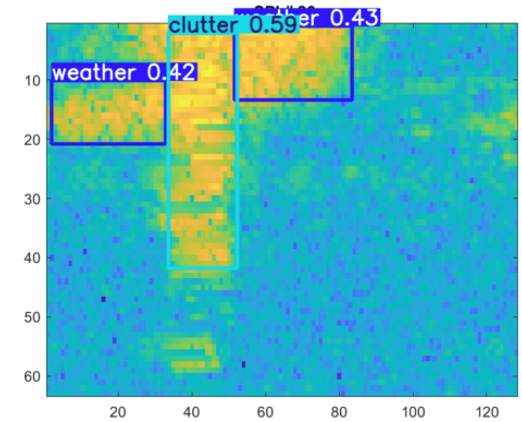

Figure 5. 2sided weather

converting RGB images to HSI using a geometric model, as true HSI data was unavailable. Our observations suggest that HSI images offer improved classification of weather and clutter. As future work, we propose training and classifying HSI images using the same model and comparing results. Additionally, if true CAT data captured through airborne equipment becomes available, it could be utilized for training and classification, enabling further comparative analysis.

References

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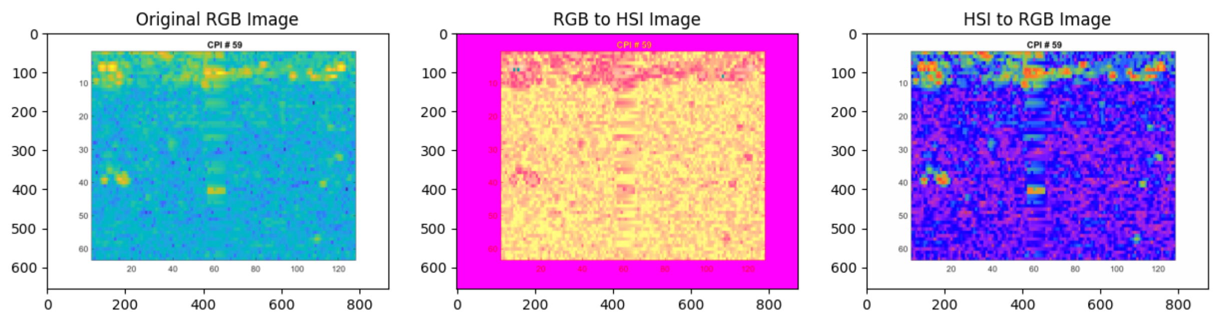

Figure 6. RGB - HSI and vice versa

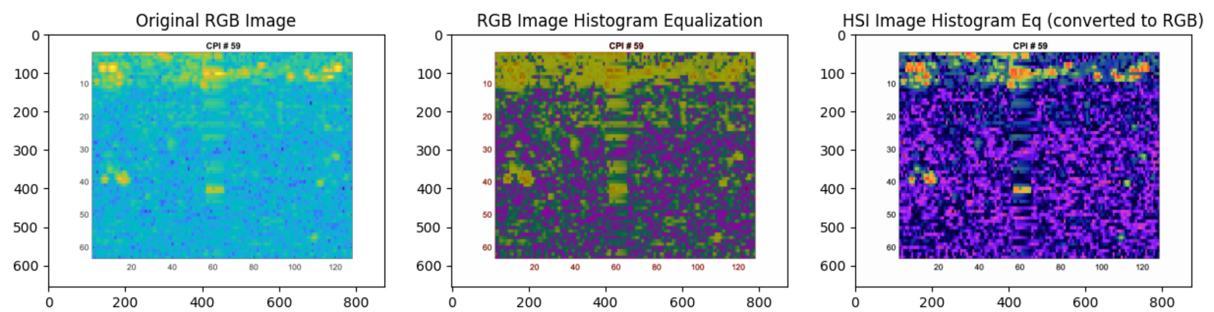

Figure 7. Histogram of HSI and RGB spectrum