Deep Learning for Aircraft Wake Vortex Identification

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Abstract. Aircraft wake vortex refers to a pair of closed vortices due to the air pressure difference between the upper and lower surfaces of the wing when the aircraft is flying. During the take-off and landing of the aircraft, the wake vortex of the preceding aircraft threatened the safety of the aircraft following its approach. Especially in the near-field phase, due to the low altitude of the aircraft, the wake vortex is more harmful under the influence of the ground effect. Therefore, the wake vortex of the front aircraft can not be ignored. In order to maintain air traffic safety and accelerate the smooth flow of air traffic, this paper used a YOLO v3 model based on the principle of deep learning to identify the wake vortex generated by the aircraft. Through laser radar scanning, data processing, and deep neural network simulation experiments, the results show that the model can achieve high confidence recognition of the aircraft wake vortex, and can provide air traffic controllers with auxiliary decision information in actual work to ensure aircraft safety.

1. Introduction
The wake vortex formed by the aircraft in flight will form a wake vortex field with weakening intensity under the influence of gravity, atmospheric turbulence, wind speed and atmospheric stability. In the early 1970s, the first aircraft crash which results of wake vortex was reported, when the aircraft crashed into the Boeing 747 (the largest civil aircraft at the time) and encountered a wake vortex[1]. On November 12, 2001, the crash of American Airlines Flight 587 was also due to the wake vortex[2].

In the near-field flight phase, the International Civil Aviation Organization (ICAO) and the Federal Aviation Administration (FAA) are in order to prevent the aircraft from entering the forward wake vortex region, resulting in pitching, rolling, and stalling, meteorological conditions (instrument meteorological condition, visual meteorological condition), means of control (procedural control, radar control), use of runway conditions (single runway, parallel or crossover runway) have developed a relatively complete set of wake vortex spacing standards [3]. China's National Air Traffic Control Committee and the Civil Aviation Administration have also promulgated China's aircraft wake spacing standards based on ICAO standards, and have developed relevant operational specifications[4]. Based on the above problems, the identification of aircraft wake vortex has become a key issue in aviation research. At present, the research on wake vortex detection and identification of civil aviation aircraft mainly includes theoretical analysis, numerical simulation and radar test[5]. Among them, radar test has been recognized as one of the most effective tools for wake vortex detection and identification. At present, the detection tool for the aircraft wake is mainly Doppler lidar. In 2001, Holzapfel F et al. used Doppler lidar to conduct a number of airport wake vortex field detection experiments in Germany, and gave a method for estimating the vortex ring volume of the wake vortex[6]. In 2006, France's Thales used X-band radar to perform a wake vortex detection experiment on an airliner at an airport near Paris[7]. In 2008, Frederic et al. conducted an X-band laser radar wake vortex detection experiment at
the Paris airport in France to evaluate the wake vortex monitoring capability under various atmospheric conditions[8]. In recent years, with the hot research of artificial intelligence, deep learning (DL) has become a new method for lidar target recognition. The concept of Deep Learning was proposed by Hinton et al. in 2006. In addition, the convolutional neural network proposed by Lecun et al. is the first real multi-layer structure learning algorithm, which uses spatial relativity to reduce the number of parameters to improve training performance. Deep learning is a representation-based learning method in machine learning, which can simulate the neural structure of human brain. The concept of deep learning originates from the study of artificial neural networks. Artificial Neural Network (ANN) abstracts the human brain neuron network from the perspective of information processing, establishes a simple model, and forms different networks according to different connection modes, referred to as neural network or similar neural network. Therefore, in-depth learning is also called Deep Neural Networks (DNN), which is developed from the previous ANN model of artificial neural networks. With the development of deep learning, especially the excellent performance of convolutional neural network in image recognition, convolutional neural network is widely used in target recognition of lidar. Because the convolutional neural network mimics the human visual mechanism and can more fully express the image information, it is more suitable for practical applications. Therefore, based on the Doppler lidar detection principle, this paper proposes an algorithm based on deep learning theory and uses convolution. The neural network extracts the image characteristics of the tail vortex cloud image to identify the wake vortex, and verifies its effectiveness by accuracy and false alarm rate to assist the decision-making control in the configuration of the wake vortex interval.

2. Design of Data Acquisition Method

The main principle of lidar detection is to emit a laser beam of a specific wavelength to scan the target airspace, and receive the backscattered signal of the laser by atmospheric molecules or aerosol particles through the receiver, in the detection space, due to atmospheric molecules and aerosol particles. Brownian motion causes the captured scatter signal to produce Doppler broadening, while the overall average velocity of the particle results in Doppler shift of the atmospheric echo signal, and the Doppler shift and the detected wake vortex radial velocity. And the following relationship exists between the Doppler shift $\Delta f_D$ and the detected wake vortex radial velocity $V_R$:

$$\Delta f_D = 2f_0 \frac{V}{c} = \frac{2}{\lambda_0} V_R$$

This paper chooses the mode of transverse detection of wake vortex, i.e. Range-Height-Indication (RHI). As shown in Figure 1 below, the laser beam emitted by radar scans the cross section perpendicular to the flight direction of the aircraft. After processing, the velocity field of the wake vortex detected in the target airspace is obtained, and convolution is used. Meanwhile, the recognition of aircraft wake by lidar is realized by feature extraction layer processing method in the network.

![Lidar scanning wake vortex pattern](image)
3. Convolutional Neural Network and Its Detection Implementation

3.1. Convolutional Neural Network
In recent years, convolution neural network has been applied to the field of target recognition, and remarkable research results have been achieved. The convolution neural network is introduced into the target detection of aircraft wake vortices in atmospheric wind field, which provides a new idea and direction for the recognition of wake vortices detected by lidar[9]. Convolution Neural Networks (CNN) is a deep feedforward neural network widely used in computer vision and pattern classification. The training process of convolutional neural network is essentially a process of continuously learning and updating parameters. Training gives an initial random parameter and obtains the output value. When the output value differs from the standard value, the error is calculated, and then the back propagation algorithm is used. The parameters are updated layer by layer from the output layer to the opposite direction until the training accuracy is reached. With the continuous development of deep learning research at home and abroad, CNN has achieved great success in the fields of image recognition and target detection. In the aspect of lidar image recognition, convolutional neural network has its unique advantages[10]. Therefore, CNN is widely used in the field of target recognition of laser radar. Deep learning applications A wide range of target detection algorithms can be divided into two categories. The first category is based on regional nomination algorithms, also known as two-step target detection methods, such as Fast R-CNN, Faster R-CNN, Mask R-CNN, etc. These algorithms divide the process of target detection into two steps. First, the Region Proposal Network(RPN) is used to extract the candidate target information, and then the detection network is used to predict and identify the location and category of the candidate target. The second kind is the end-to-end algorithm, also known as the single-step target detection method, such as SSD, YOLO, YOLO 9000, YOLO V3. This kind of algorithm does not need RPN. It generates the location and category information of the target directly through the network and completes in one step. Therefore, the single-step target detection algorithm has faster detection speed. Because the end-to-end detection algorithm can complete the training quickly, it is hopeful to realize the function of real-time identification and early warning in aircraft wake vortex recognition. Therefore, this paper uses YOLO to realize the recognition of aircraft wake vortex.

3.2. Network Model Construction
YOLO v3 uses the newly designed Darknet53 residual network and combines the FPN network structure. After sampling on the two characteristic maps of the network, the corresponding feature maps are aggregated in the early stage of the network, and then the convolutional network is used to obtain the prediction result. Figure 2 shows YOLO v3 network structure diagram[11].

![YOLO v3 algorithm flow chart](image)

Figure 2. YOLO v3 algorithm flow chart

A convolutional neural network usually consists of an input layer, a convolutional layer, a pooling layer, and an output layer. The network inputs a two-dimensional image, and the convolution layer extracts and maps the detailed features of the image through the form of a sliding window; the pooling layer downsamples the input feature image, thereby reducing the computational complexity and extracting the main features on the one hand. The image feature information is extracted by convolving
each convolution kernel with the previous feature map, and then the feature map of the current layer is generated by the activation function, and the extracted feature maps are combined at a higher layer to obtain global features. By convolving the same feature map by setting different convolution kernels, different feature information is obtained, and the purpose of extracting features is achieved.

In this paper, according to the actual wake vortex identification situation, the network structure is adjusted, the network parameters are changed, and the appropriate convolution kernel and activation function parameters are selected to design a network model suitable for actual air traffic control requirements.

3.3. Network Settings
The network modular structure of YOLO v3 is shown in Figure 3. The network structure of YOLO v3 builds the network structure of YOLO improved algorithm based on Darknet-53 network, and realizes the detection of moving targets. Darknet-53 is similar to ResNet and is more powerful than Darknet-19, with a similar accuracy to ResNet-101 or ResNet-152, but at a faster rate[12].

![Figure 3. YOLO v3 network modular structure](image)

As shown in Figure 3, the DBL block is the basic component of YOLO v3, namely the convolutional layer BN layer Leaky relu, corresponding to the Darknet conv2 d_BN_Leaky in the code. For YOLO v3, the convolutional layer, the BN layer, and the loss layer are inseparable parts that together constitute the smallest component. The n in the Resn block represents a number, and there are res1, res2, ..., res8, etc., indicating how many res_units are contained in this res_block. This is a large component of YOLO v3, YOLO v3 began to draw on ResNet's residual structure, using this structure can make the network structure deeper. The concat block is a tensor splicing that stitches up the upper layer of the darknet and one of the subsequent layers. The splicing operation is different from the operation of the residual layer add block superposition. The splicing expands the tensor dimension, and the add block just adds directly without causing a change in the tensor dimension.

The entire YOLO v3_body contains 252 layers, which are organized as shown in Table 1 below:

| Total              | 252 |
|--------------------|-----|
| Add                | 23  |
| BatchNormalization | 72  |
| Concatenate        | 2   |
| Conv2D             | 75  |
| InputLayer         | 1   |
| LeakyReLU          | 72  |
| UpSampling2D       | 2   |
| ZeroPadding2D      | 5   |
The network features in this article: 1) Multi-scale target prediction. There are 3 scales, and each anchor scale predicts 3 anchor frames. A total of 9 anchor frames can be obtained by K-means clustering. The YOLO v3 model is much more complex than the previous version, and you can weigh the speed and accuracy by changing the size of the model structure. (2) Adopting a better basic network structure Darknet53 residual network. (3) Classification loss The Softmax loss function is replaced by a binary cross entropy loss function. Since Softmax only assigns one target category to each border, and for open data such data sets, the target may have overlapping category labels, so Softmax is not suitable for multi-label classification; Softmax will select the category with the highest score to determine that the current box belongs to the category, while in reality one target may belong to multiple category labels; Softmax can be replaced by multiple independent logistic classifiers, and the accuracy will not decrease.

4. Experiment and analysis

4.1. Border Prediction
Like YOLO, the YOLO v3 algorithm divides the input image into a grid. When there is a center point of a target in the grid, the grid predicts the target. During training and testing, each grid predicts B bounding boxes, each of which has (x, y, w, h, c) 5 prediction parameters here (x, y) is the information of the bounding box, (x, y) is the center point position of the object, w and h are the width and height of the bounding box, respectively, and c is the confidence of the target. The difference is that the YOLO v3 algorithm uses the offset of x and y as the linear transformation of the length and width of the border. The expression is as shown in equation (2), which effectively improves the problem that the boundary of the moving target is not accurate due to the fixed frame size of the YOLO algorithm.

\[
\begin{align*}
\hat{G}_x &= P_x t_x (P) + P_x \\
\hat{G}_y &= P_y t_y (P) + P_y \\
\hat{G}_w &= P_w e^{x_w} (P) \\
\hat{G}_h &= P_h e^{x_h} (P)
\end{align*}
\]

\(\hat{G}_x, \hat{G}_y, \hat{G}_w, \hat{G}_h\) A is the position coordinate of the real frame on the feature map. The estimated value \(P_x, P_y\) is the center point of the preset anchor frame on the feature map. The coordinate \(P_w, P_h\) is the width and height of the preset anchor frame on the feature map. The relevant information value of the e-learning target is \(t_x, t_y, t_w, t_h\).

The solution of the border information \((x, y, w, h)\) is given by equation (3):

\[
\begin{align*}
b_x &= \sigma(t_x) + c_x \\
b_y &= \sigma(t_y) + c_y \\
b_w &= P_w e^{x_w} \\
b_h &= P_h e^{x_h}
\end{align*}
\]

The final frame information value is \(b_x, b_y, b_w, b_h\), and the network learning target information value is \(t_x, t_y, t_w, t_h, c_x, c_y\), is the coordinate offset of the grid \(P_w, P_h\) is the side length of the preset anchor border.

The confidence score can be expressed as formula (4):

\[
Pr(object) \times IoU_{\text{pred}}^{\text{truth}}, \quad Pr(object) \in (0,1)
\]
Pr(object) reflects the confidence of the target in the current bounding box, and \( \text{IoU}^{\text{truth}}_{\text{pred}} \) reflects the accuracy of the current bounding box's predicted target position. If there is no object in the bounding box, then \( \Pr (\text{object}) = 0 \), if there is an object, then \( \Pr (\text{object}) = 1 \).

The IOU value is calculated according to the ratio of the predicted bounding box and the real bounding box data, and the conditional probability of predicting a common class \( C \) object, each grid only predicting the class \( C \) object, \( \Pr (\text{Class} / \text{object}) \), \( i = 1, 2, ..., C \). Each grid predicts the position of the B bounding boxes. That is, the B bounding boxes share a set of conditional class probabilities \( \Pr (\text{Class} / \text{object}) \), \( i = 1, 2, ..., C \). Based on the calculated \( \Pr (\text{Class} / \text{object}) \), the class-related confidence within a bounding box can be calculated during the test, as in formula (5):

\[
\Pr (\text{Class} / \text{object}) \times \Pr (\text{object}) \times \text{IoU}^{\text{truth}}_{\text{pred}} = \Pr (\text{Class}) \times \text{IoU}^{\text{truth}}_{\text{pred}} \tag{5}
\]

\( \Pr (\text{Class} / \text{object}) \) is the category information for each grid prediction, and \( \Pr (\text{object}) \times \text{IoU}^{\text{truth}}_{\text{pred}} \) is the confidence level for each bounding box prediction. Equation (5) can get the probability that the predicted border belongs to a certain class, and the accuracy information of the border prediction can also be obtained.

At the time of inspection, the classification confidence of each category bounding box is equal to the product of the confidence of each target bounding box and the category information for each grid prediction. After obtaining the classification confidence of each border, by selecting a reasonable threshold, the lower bounding box is removed, and the remaining borders are normalized to obtain the final detection result.

### 4.2. Loss Function

During the training process, YOLO uses the mean square and error as the loss function. It consists of three parts: coordinate error, IOU error and classification error, as shown in equation (6):

\[
\text{Loss} = \sum_{i=0}^{S^2} \text{coodErr} + \text{iouErr} + \text{clsErr}
\tag{6}
\]

Taking into account the contribution rate and relative error of each loss, the loss of the YOLO v3 algorithm during the training process is calculated as (7):

\[
\lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} Z_{ij}^{\text{obj}} \left[ (x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right] + \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} Z_{ij}^{\text{obj}} \left[ (\sqrt{w_i} - \sqrt{\hat{w}_i})^2 + (\sqrt{h_i} - \sqrt{\hat{h}_i})^2 \right] \\
+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} Z_{ij}^{\text{obj}} \left( C_i - \hat{C}_i \right)^2 + \lambda_{\text{obj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} Z_{ij}^{\text{obj}} \left( C_i - \hat{C}_i \right)^2 \\
+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} Z_{ij}^{\text{obj}} \left| p_i(C) - \hat{p}_i(C) \right|^2
\tag{7}
\]

Where \( \hat{x}_i, \hat{y}_i, \hat{w}_i, \hat{h}_i, \hat{C}_i, \hat{p}_i(C) \) is the predicted value and \( x_i, y_i, w_i, c_i, p_i(C) \) is the training mark value. \( Z_{ij}^{\text{obj}} \) indicates that the object falls within the jth bounding box of the lattice i.

If there is no target in a cell, the classification error is not back-propagated; in the B bounding box, the back-propagation of the coordinate error is performed only for the predicted value with the highest IOU, and the rest are not performed.

### 4.3. Experiment result

In the depth learning of images, in order to enrich the image training set, better extract image features, generalize the model, and usually enhance the sample image data[13]. This experiment uses rotation
processing, multi-scale scaling and changing contrast and three kinds of algorithms to enhance the training data, increase the amount of data in the training data set, and enable the trained model to learn more pixel information of the image, thereby improving the model. Classification performance and generalization ability[14]. This paper trains 5,000 samples, 4,600 training sets, 400 test machines, and a total of 1000 training sessions. The learning rate (LR) controls the learning progress of the model. If the learning rate is set too small, the network convergence will be slow and the learning efficiency will be significantly reduced. If the learning rate is set too large, the parameter update will be intensified, causing the network to converge to the local The best, or the loss value, starts to increase directly. Therefore, after many experiments, the basic learning rate is set to 0.001, the momentum coefficient is 0.9, and the attenuation coefficient is 0.005. Some experimental results of the tail vortex identification test are shown in Figure 4.

![Figure 4. Part of experimental results — identification of the wake vortex by YOLO v3](image)

The experimental results show that when a wake vortex is detected, the network model displays ‘Deteted’ and gives a predicted value. Its accuracy rate reaches to 94.46%, and the recall rate is 91.27%. In order to effectively identify and avoid the danger of aircraft wake vortex, a YOLO v3 based
algorithm is proposed, which can predict the target from multiple scales. The experimental results show that the proposed algorithm can accurately identify the wake vortex detected by the lidar and accurately predict the frame return to the target, which effectively improves the airport capacity. The algorithm can better detect the wake vortex of the approaching stage and provide technical support for the new civil aviation technology.

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