Intelligent Antenna Attitude Parameters Measurement Based on Deep Learning SSD Model

Abstract: Due to the consideration of safety, non-contact measurement methods are becoming more acceptable. However, massive measurement will bring high labor-cost and low working efficiency. To address these limitations, this paper introduces a deep learning model for the antenna attitude parameter measurement, which can be divided into an antenna location phase and a calculation phase of the attitude parameter. In the first phase, a single shot multibox detector (SSD) is applied to automatically recognize and discover the antenna from pictures taken by drones. In the second phase, the located antennas' feature lines are extracted and their attitude parameters are then calculated mathematically. Experiments show that the proposed algorithms outperform existing related works in efficiency and accuracy, and therefore can be effectively used in engineering applications.

Keywords: deep learning; drone; object detection; SSD algorithm; visual measurement; antenna attitude parameters

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1 Introduction

With the rapid development of communication technologies, an increasing number of base stations are built around the world. Antennas work as an interface between radio waves propagating through space and electric currents moving in metal conductors. For providing subscribers with high-quality communication services, it is critical to guarantee the speed and stability of network signals. According to radiation direction, antennas in base stations can be roughly divided into three categories: 1) omnidirectional antennas which have uniform radiation power in the horizontal direction; 2) directional antennas that have uneven radiation power in both horizontal and vertical directions; 3) special antennas which have variable radiation direction depending on their usages. Among these categories, the directional antennas' radiation direction and power are most susceptible to the attitude.

To ensure that each base station antenna works properly, the antenna attitude parameters which determine the electromagnetic coverage of the directional antenna need to be set appropriately. Sector-shaped antennas are one of the most common directional antennas, and their attitude parameters mainly include the pitch angle, the azimuth angle, and the height position. Among them, the antennas' suspension height is fixed. However, the pitch angle and the azimuth angle of the antennas can be easily changed by external factors such as wind and sunlight, which further changes the electromagnetic coverage and weakens the stability of signals. Thus, it is urgent to regularly and efficiently measure the pitch angle and the azimuth angle of sector-shaped antennas on the base station.

Existing antenna attitude parameter measurement methods can be roughly divided into the following two categories.

1) Contact measurement methods. In these methods, engineering surveyors apply physical tools such as inclinometers and goniometers to measure the antennas' relevant posture parameters and then read the measurements manually. However, these methods suffer from the following limitations. First, since antennas are usually installed on high places such as roofs, hillsides, and the top of telephone poles, these methods put the engineering surveyors' life at risk; Second, since the engineering surveyors' wages are high and the measuring tools are expensive, the cost is high; Last but not the least, the time to perform these methods is usually relatively long. Actu-

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ally, nowadays, most countries do not apply these contact methods anymore.

2) Non-contact measurement using drones. Most base station antennas are built on high places which usually cannot be reached easily. With drones being more and more frequently applied in complete high-altitude tasks such as shooting, transportation, and reconnaissance, they are also applied to assist the measurement process of the elevation angle and the azimuth angle of sector-shaped antennas on the base station. Usually, drones are controlled by smartphones to take pictures of the antennas, which can be previewed by the operators in real-time[1]. Then, for obtaining the required antennas' attitude parameters, techniques such as image analysis and three-dimensional reconstruction are applied to analyze collected antenna pictures. Compared with traditional methods, the non-contact measurement methods have advantages of high efficiency, safety, and convenience. Thus, they are becoming more and more popular in both research and industrial communities. However, they also suffer from shortcomings of relatively low efficiency and the requirement of manual intervention.

2 Related Work

To address the above disadvantages of existing non-contact measurement methods, we propose a novel antenna attitude parameter measurement algorithm, which can be divided into an antenna localizing phase and an attitude parameter calculation phase. In the first phase, a deep learning algorithm called the single shot multibox detector (SSD) is applied to automatically identify and localize the antenna from pictures taken by drones. For locating the antennas in real-time, a lightweight MobileNet is applied in the SSD for feature extraction and the ratio of antennas' length to width is used as prior information, which greatly improves the efficiency. In the attitude parameter calculation phase, a straight line detection process is performed on the localized image by applying the line segment detector (LSD), and the longest straight line is selected as a feature line. The attitude parameters are then calculated according to extracted feature lines mathematically.

The remaining of this paper is organized as follows. In Section 2, we demonstrate how the proposed antenna attitude parameter measurement algorithm works. In Section 3, we report the experimental results. The paper is concluded in Section 4.

3 Proposed SSD Algorithm

In this part, we will introduce the related work and technical details of the two phases of the proposed algorithm.

3.1 First Phase

The first phase of the algorithm is to locate the antenna automatically. We propose a deep learning algorithm based on an SSD network, which can locate the position of the antenna accurately.

3.1.1 SSD Network

The regression-based object detection algorithm is called the one-stage detection algorithm. The input image uses a convolutional neural network (CNN) to directly return to the target category and position. It does not need to go through the tedious process of extracting candidate regions like region-based convolution neural networks (R-CNN). It is a kind of an end-to-end efficient object detection algorithm model that mainly includes You Only Look Once (YOLO)[2] and SSD[3].

The SSD algorithm is an important representative network model based on regression algorithms. It improves the YOLO algorithm and also combines related ideas of anchor boxes in the candidate region algorithm Faster R-CNN. The SSD algorithm is a great breakthrough in the application of deep learning to solve object detection problems. While the SSD algorithm has greatly improved the detection efficiency, it can better detect small objects and has a certain degree of accuracy.

In essence, the SSD network is a CNN that can directly get the position, category, and confidence of the detected object using forward propagation. The basic feature extraction network that the conventional SSD network uses is c-16[4]. It mainly extracts feature maps of different scales and uses a series of fixed-size candidate bounding boxes to predict the location of the object and the classification confidence of each bounding box which probably contains the object, and finally performs a non-maximum suppression (NMS) method to get the final result.

3.1.2 Mobile-SSD Object Detection Network Model

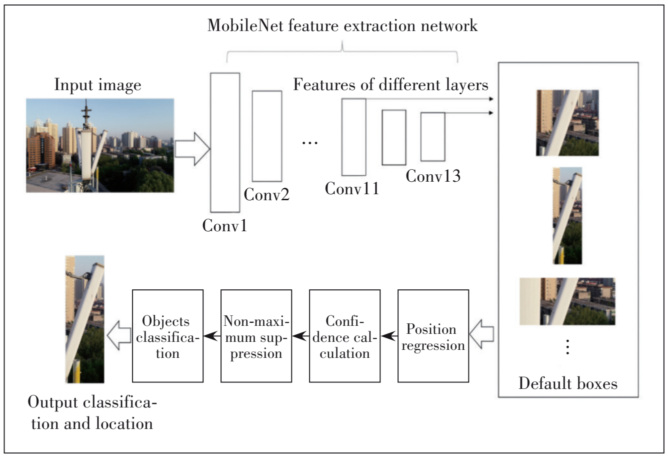
To fulfill the requirement of automatic intelligent detection, we optimize the SSD network based on the characteristics of the antenna object aiming at improving training efficiency and computing speed of the network. The optimized network can be better adapted to real-time work. We call the improved network model in this paper the Mobile-SSD model.

While retaining the overall detection process and end-to-end characteristics of the SSD network, we improve the network by using the following strategy: 1) Modify the feature extraction network; 2) Reduce the network structure's redundancy; 3) Add prior information.

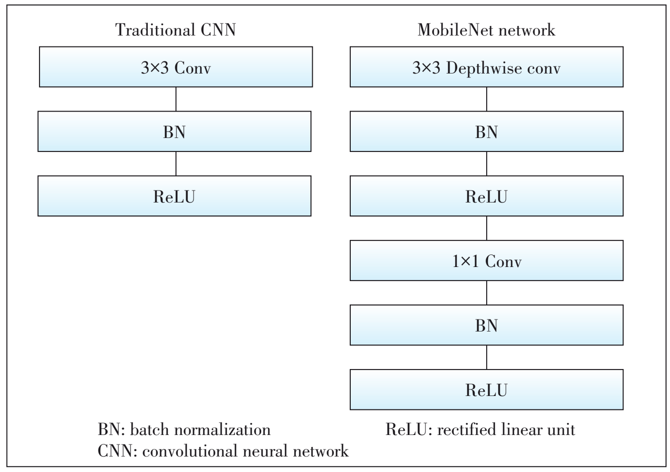
The overall processing flow of the improved model is shown in Fig. 1. The final predicted output of the network is basically composed of two parts: one is the confidence level of the target's category, and the other is the position coordinates of the detected target's bounding box. According to the former, we can obtain the category of each antenna object detected in the image. According to the latter, we can obtain the antenna's position.

The following improvements and optimizations have been made to the SSD network structure.

1) Modify the output categories of the network. Objects



▲Figure 1. Mobile-single shot multibox detector (SSD) object detection network model



▲Figure 2. Difference between MobileNet and traditional network

used for antenna attitude measurement are organized into two categories: antenna side and antenna top. Thus, we only need to obtain the category and location of these two types of antenna objects from the network's output. However, the number of the categories of the original SSD network's output layer is 21, which is unnecessary for our work. Thus, we modify the number of the categories to 3 (background, antenna side, and antenna top). In this way, we can reduce redundancy and improve detection efficiency.

2) Replace the basic convolutional neural network for feature extraction. The original SSD network uses VGG16 as the basic feature extraction network. Most of its structure is composed of standard convolutional layers, so it takes a long time to extract features through convolution operation, and the overall detection efficiency cannot meet the requirement of mobile object detection which needs high efficiency. Therefore, it is a key problem to reducing the convolution complexity of the network and improve the efficiency of the network.

In order to improve the efficiency of feature extraction, we replace the feature extraction network in the original SSD model with a lightweight CNN MobileNet[5], which can complete image feature extraction through a more efficient convolution operation. The lightweight CNN network model with deep separable convolution is more suitable for mobile or embedded devices. As shown in Fig. 2, the image detection process of the MobileNet network model is different from the traditional deep CNN.

In normal circumstances, the MobileNet model will use a 3×3 convolution kernel for convolution operation. The calculation of the convolution in MobileNet can be reduced by about 8 times compared with the traditional standard convolution. At the same time, the parameter number of the overall network is also reduced, so that the complexity of the network model during the training is reduced. And after completing the convolution, MobileNet will convert the convolution results into normal distribution by regularization, which can better avoid the overfitting phenomenon that always occurs during the training. In this way, the network performance has been greatly improved.

3) Set the aspect ratio of the default box according to the prior information of the antennas. According to the characteristics of the SSD algorithm model, different types of objects should be accurately detected, which is completed by using several default boxes with different aspect ratios on the feature map. The basic size and shape of the default box are all subjectively set based on experience. The default aspect ratios of the original SSD network are 1:2, 1:3, and 1, 2, 3. However, most of the sector antennas are produced with a unified standard, so the aspect ratio of the side and top of antennas has been basically determined. Adding the aspect ratio of antennas as prior information can reduce the detection interference obviously. Therefore, by collecting antenna pictures for calculation and statistics, we obtain that the aspect ratio of the antenna side is 1:4, and the aspect ratio of the antenna top is 3:1. Then by removing the useless default aspect ratio and adding the specified aspect ratio of antenna objects, we can reduce the interference of useless information and make the network more targeted and efficient.

3.2 Second Phase

After completing the automatic detection of the location of the antenna objects by the Mobile-SSD algorithm, the second phase is the measurement of antenna attitude parameters. The main process of the measurement algorithm is as follows. Firstly, use the LSD straight line detection algorithm to detect and extract the image straight line from the selected area. And then according to the length of the straight lines that exist in the feature detection images, sort the sequence of straight lines and take the longest straight line as the antenna feature line. At last, combine the drone's own parameters to calculate the azimuth angle and pitch angle. In the following parts, we will introduce the details of the algorithm for antenna attitude parameters calculation.

3.2.1 LSD Line Detection Algorithm

In the field of image process, in 1962 the Hough transform[6] laid the foundation for the detection of line segments and shapes in images. Subsequently, RAFAEL et al. proposed a linear detection algorithm LSD[7] based on the Hough transform, and the accuracy of detection can achieve sub-pixel precision. The main difference between the LSD algorithm and the Hough transform is that the former uses the concept of the gradient to determine the straight line. The gradient in the selected area is calculated, and the area which has the same gradient is regarded as a straight-line segment. The direction of the line segment is also the same as the gradient average direction. Detecting the straight line in the image is implied by looking for the pixel area in the image with large gradient changes. The efficiency and effect of the LSD algorithm are much better than those of the Hough transform, therefore we use the LSD algorithm to complete extracting the characteristic line of the antenna object in the determined area.

The specific process of the LSD line detection algorithm can be summarized as follows[7]:

Algorithm 1. Algorithm of the specific process of the LSD line detection

Input: the image to be detected $\boldsymbol{I}$

Output: the line detection result set $\boldsymbol{L}$

a) Do Gaussian down-sampling on the input image $\boldsymbol{I}$ at a certain scale, usually scale=0.8.

b) Calculate the gradient of each pixel in the down-sampled image and the corresponding level-line direction.

c) Pseudo-sort all pixels according to the obtained gradient, establish the corresponding state sequence table, initially set all pixels to NOT USED.

d) Traverse all the gradient, change the state in the state sequence table to USED for the points whose value is less than the threshold ρ, and record it in the table for an update.

e) Take the pixel with the largest gradient in the state table as the seed point, and set the state to USED.

do:

1. Starting from the seed point, change the state of NOT USED points that meet the condition of the direction in $[k,-k]$ around the pixel points to USED.

2. Use the circumscribed rectangle R to enclose all the satisfying points.

3. Determine whether the density of the homogeneous same-sex point meets the set threshold. If not, cut the circumscribed rectangle R into a new circumscribed rectangle, until the density reaches the requirement.

4. Calculate the corresponding nondeterministic finite automaton (NFA) of the final circumscribed rectangle R.

5. By changing the NFA of R, when NFA(R)$\leqslant\varepsilon$, the rectangle is considered to be the output line l, and it should be added to the line detection result set $\boldsymbol{L}$. Repeat the algorithm until the state of all pixels is USED.

3.2.2 Antenna Feature Line Extraction

After the detection by the Mobile-SSD network, in an image with an antenna object, we will get the coordinate position of the antenna object, and mark it with a rectangular box. We call this area the region of interest (ROI). By using the LSD algorithm introduced in Section 2.2.1, we can detect all straight lines in the ROI area. In the actual scene of antenna attitude parameter measurement, the one that can generally represent the two parameters of the antenna is the longest line segment on the antenna's side and top, so we need to select the longest straight line in the ROI area. We sort by the support domain line sequence in the region and connect the longest line group in the same gradient direction to the longest line, and then mark it in the image as the feature line.

As shown in Fig. 3, the longest red line is the feature line extracted from the side of the antenna. We use this longest straight line to represent the antenna's feature. The subsequent calculation of antenna attitude parameters is based on the feature line.

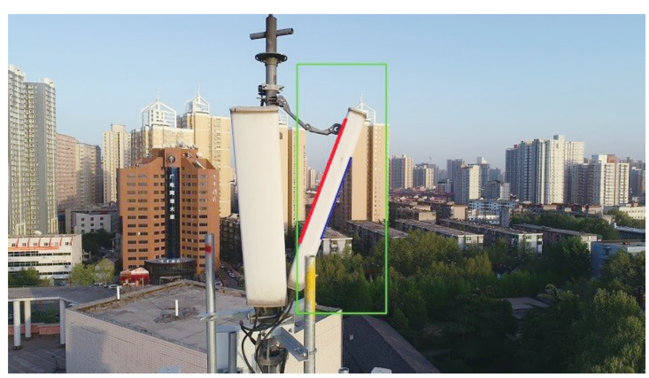
3.2.3 Calculate Antenna Attitude Parameters

For the sector antenna, we find that its hanging height, orientation, and other parameters are basically fixed, and the main parameters that affect the normal operation of the antenna are the pitch angle and the azimuth angle, which are the parameters we need to calculate. The pitch angle is physically the angle between the object and the horizontal plane; the azimuth angle is the angle between the direction parallel to the horizontal ground and the true north of the earth.

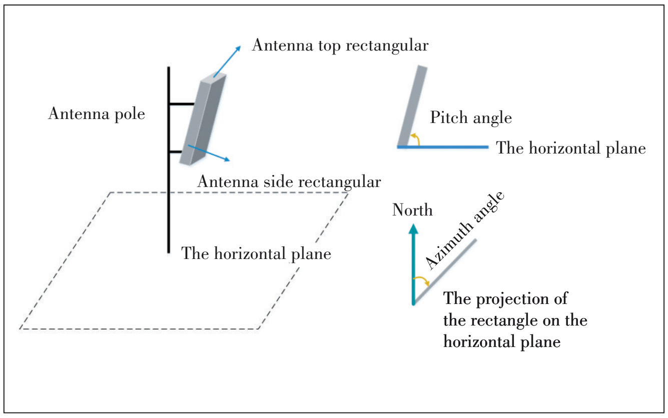
The schematic diagram of the pitch angle and the azimuth angle defined in the main three-dimensional space is shown in Fig. 4.

1) The pitch angle of the antenna. In space, the pitch angle α can be converted to the angle formed by the side rectangle of the antenna and the horizontal plane in the image taken by the drone from its front view, which is usually defined as the pitch angle of the sector antenna. From the plane view, it can be regarded as the angle obtained by rotating the side rectangle of the antenna object counterclockwise along the horizontal plane.

As shown in Fig. 5, the image plane taken by the drone is



▲**Figure 3. Feature line extracted**



▲**Figure 4. Pitch angle and azimuth angle**

G. The projection of the feature line l on the image plane G is l'. h is a horizontal line, and the projection on the image plane G is h'. The antenna pitch angle is the angle α between l and h, and it can be converted into the angle α' between l' and h'. Suppose l' and h' intersect at point $A(x_1,y_1)$, take a point $B(x_2,y_2)$ on l' and take a point $C(x_3,y_3)$ on h', and then the antenna pitch angle α can be calculated by the following formula:

$$\alpha = \cos^{-1}\frac{\overrightarrow{AB}\cdot\overrightarrow{AC}}{|AB|\times|AC|}. \quad (1)$$

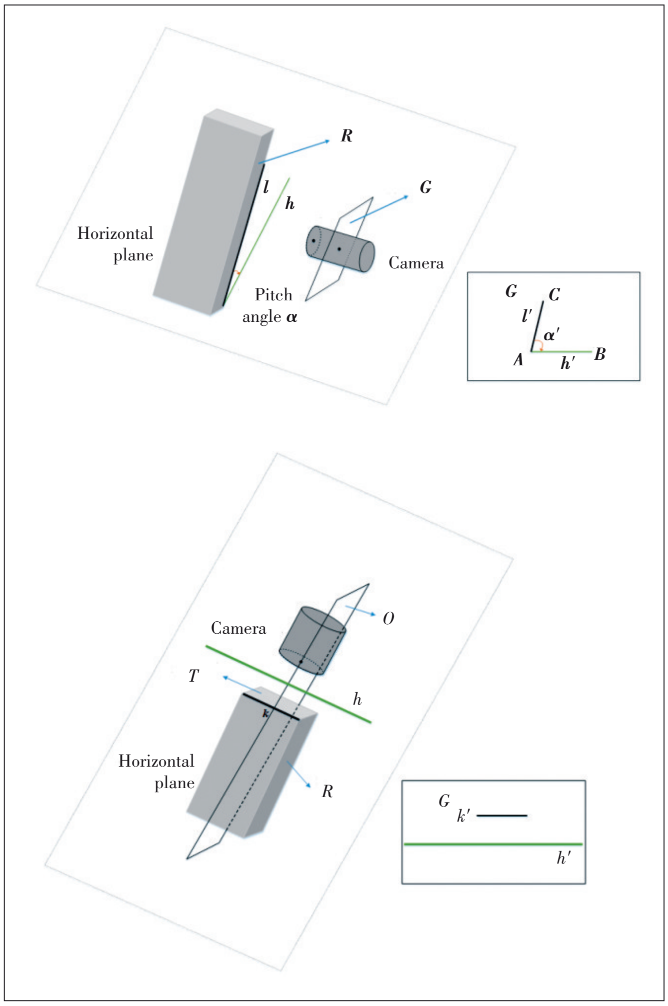
2) The azimuth angle of the antenna. In space, the azimuth angle β can be converted to the angle between the top rectangle and the direction of the north pole of the magnetic field in the image taken by the drone from its top view, which is usually defined as the azimuth angle of the sector antenna. From the plane view, it can be regarded as the angle obtained by rotating the top rectangle of the antenna target clockwise along the vertical direction indicated by true north.

According to the drone's related sensors and GPS position, we can obtain the drone's heading angle as θ, and the antenna azimuth angle β can be calculated by the following formula.

$$\beta = (\theta + 180)\,\%\,360. \quad (2)$$

The value range of θ and β is [0, 360), where 0 means facing true north, 90 means facing true east, 180 means facing true south, and 270 means facing true west.

To sum up, when we use the SSD algorithm to complete the antenna object intelligent detection in the image, we will obtain the classification of the antenna image while locating the object. When the object is classified as an antenna side, the corresponding pitch angle parameter is calculated; when the object is classified as an antenna top, the corresponding azimuth angle parameter is calculated. In this way, we can achieve an intelligent and automated calculation method that can reduce the cost of manual measurement.



▲**Figure 5. Calculation of angles**

4 Experiments

In this part, we will present details of the experiment on the two phases of our algorithm.

4.1 Experiments on First Phase

4.1.1 Standard of Evaluation

The output of an object detection task usually includes the classification results, the confidence of each classification, the coordinates of the prediction frame, etc. According to the characteristics of the output results, precision P and recall R are selected as the main standards of evaluation.

The precision rate refers to the ratio of the true positive samples in the correctly identified samples; the recall rate refers to the ratio of the correct identification in all positive samples. It can be calculated mainly through the confusion matrix of the classification results, as shown in Table 1.

In the process of object detection, judging positive samples and negative samples is not as simple as the classification problem, and it needs to be judged according to the classification confidence and threshold of the prediction result. The re-

▼**Table 1. Confusion matrix of the results**

	Predicted Positive Samples	Predicted Negative Samples
Real positive samples	TP	FN
Real negative samples	FP	TN

FN: false negative FP: false positive TN: true negative TP: true positive

sults that indicate that the detection is correct mainly include the following samples. True positive (TP) is a positive sample, and the intersection over union (IoU) is greater than the set threshold; True negative (TN) is a negative sample and the IoU is greater than the set threshold. On the contrary, false positive (FP) and false negative (FN) are the corresponding cases of detection errors. During the experiment in this paper, the IoU threshold is set to 0.5.

Therefore, the calculation formulas for precision and recall are defined as follows:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} ,$$
$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} . \tag{3}$$

In fact, when conducting large-scale experiments, in order to evaluate the performance of the algorithm more comprehensively, the average precision (AP) is usually used for measurement, and the average of all APs of the detection classification is calculated to get the mean average precision mAP, which is most commonly used as the standard of evaluation. The mAP can better prevent some classifications from being too extreme to weaken others. Therefore, we choose the mAP as our object detection model.

4.1.2 Experiment Results and Analysis

In the experiment, we use the Mobile-SSD model proposed in Section 2 and YOLO and SSD models to train and test on the antenna data set under the same hardware conditions. The detection objects include the antenna side and the antenna top.

In the training phase, we collect a total of 1 832 original antenna images including antennas under different backgrounds and lighting conditions. What's more, through data augmentation, the total number of images that can be used for training reaches 3 856. The training epoch of each network model reached 1×10^5 times. The convergence speed of the Mobile-SSD model is fast and stable, which proves the model has strong adaptability to datasets and has great stability.

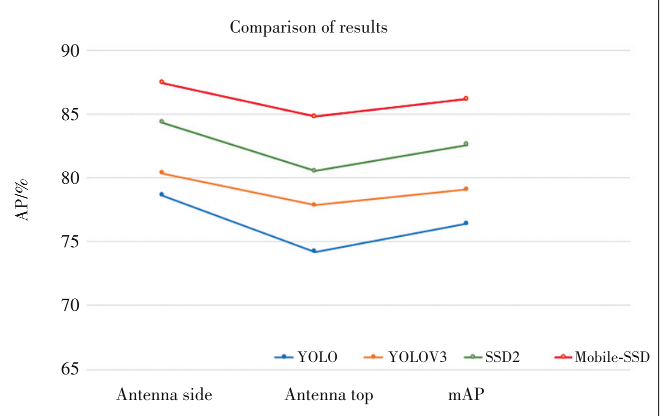
In the testing phase, 500 images were selected as the test dataset. The trained model was applied to detect the antenna side and the antenna top surface respectively. Table 2 mainly shows the accuracy of each model. The AP value and the overall mAP value of several algorithms are shown in Table 2 and Fig. 6.

The experiment results show that the model proposed in the

▼**Table 2. Comparison of results of the accurary of each model**

Network Structure	Antenna Side	Antenna Top	MAP
YOLO	78.62%	74.21%	76.42%
YOLOV3	80.34%	77.85%	79.10%
original SSD	84.34%	80.52%	82.58%
Mobile-SSD	87.42%	84.78 %	86.18%

mAP: mean average precision SSD: single shot multibox detector
YOLO: You Only Look Once



AP: average precision SSD: single shot multibox detector
mAP: mean average precision

▲**Figure 6. Comparison of results**

paper is more accurate compared with the two models of the YOLO series. This is mainly due to the improvement of the detection details of the SSD network's anchor mechanism and the high efficiency of the candidate frame mechanism. Compared with the original SSD network, the addition of prior information about antennas makes Mobile-SSD more accurate.

In conclusion, the results prove that the improvement strategy proposed in this paper is feasible and accurate. However, we find in the experiments that the detection accuracy of the network decreases when there exist obstacles. The current antenna object detection network implemented has a good effect only in identifying unobstructed and intact antennas.

4.2 Experiments on Second Phase

4.2.1 Pitch Angle Measurement Experiment

The main goal of the experiment in this section is to verify the feasibility and correctness of the proposed scheme for measuring the pitch angle of the sector antenna. In the experiment, the sector antenna model is used for indoor measurement experiments. First, manually adjust the antenna attitude to obtain different elevation angles and use the inclinometer to manually read and record them as the reference value of each group of experiments, and then use the measurement system to perform measurement calculations through the drone. A total of 5 sets of experiments with different pitch angles are performed. Each group of experiments performed 10 measurements, and the difference between the obtained measurement value and the reference value was used as the error value for analysis.

The experiment results and the error values obtained from each group of experiments are shown in Fig. 7.

4.2.2 Azimuth Angle Measurement Experiment

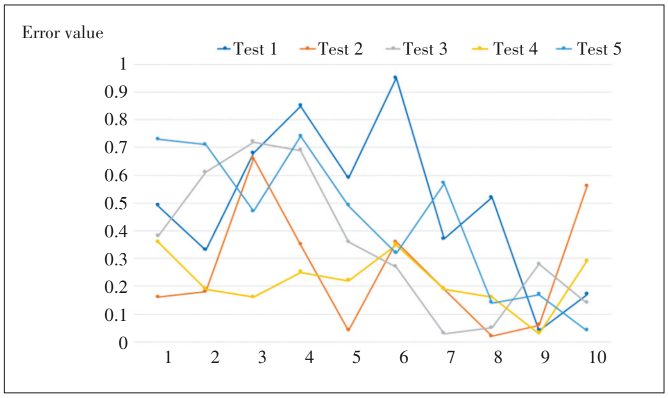
The main goal of the experiment in this section is to verify the feasibility and correctness of the proposed scheme for measuring the azimuth angle of the sector antenna. In the experiment, the sector antenna model is used for indoor measurement experiments. First, manually adjust the antenna attitude to obtain different azimuth angles, read the parameters using the mechanical compass and record them as the reference value of each experiment. And then use the measurement system to perform measurement calculations through the drone. A total of 5 sets of experiments with different azimuth angles are performed. Each group of experiments performed 10 times, and the difference between the obtained measurement value and the reference value is used as the error value for analysis.

The experiment results and the error values obtained from each group of experiments are shown in Fig. 8.

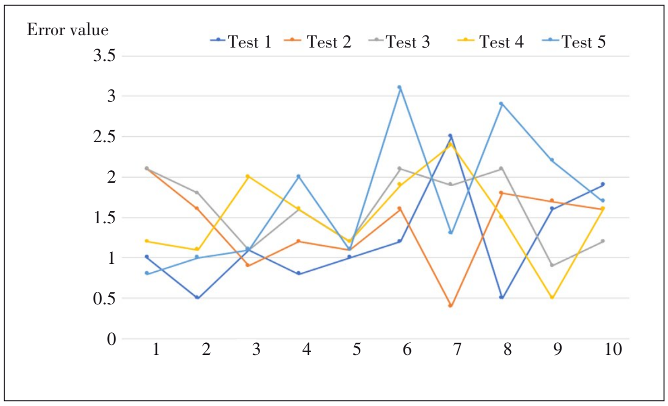
4.2.3 Comparison to Existing Schemes

The experiment in this section is to compare the algorithm proposed in the paper (Algorithm 1) with the existing antenna attitude measurement algorithm, including a non-contact antenna attitude measurement scheme based on the 3D reconstruction and rendezvous measurement proposed by WANG[8] (we refer it as Algorithm 2) and an image antenna attitude measurement scheme based on the drone's aerial photography proposed by ZHOU[9] (we refer it as Algorithm 3). The main experimental method is to manually adjust the attitude angle of the fixed antenna model and measure the pitch angle and the azimuth angle using different schemes. The results are compared and analyzed. The results are drawn as a line graph for a more intuitive comparative analysis, which is shown in Figs. 9 and 10.

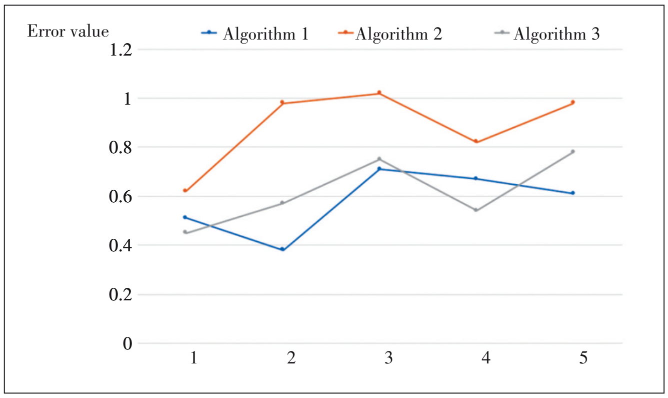
From the experiment results, the pitch angle error in the measurement of the scheme in the paper is basically within the range of 1°, and the azimuth angle error is basically within the range of 5°. Compared with other methods in the pitch angle experiment, the difference of the detection error is not large, and it can meet the standards required by the industry. The performance in the azimuth experiment is much better than Algorithm 2 which proves the effectiveness of our method. Algorithm 3 has relatively good measurement accuracy in two experiments and has a similar error value with Algorithm 1. However, manual intervention is required for antenna location using Algorithm 3 while Algorithm 1 automatically locates the antenna position through the SSD network. When the hardware can be guaranteed, Algorithm 1 may have better performance.



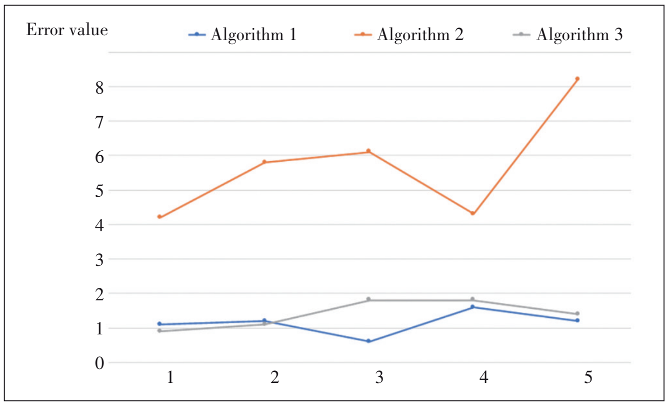
▲**Figure 7. Result of the pitch angle measurement experiment**



▲**Figure 8. Result of the azimuth angle measurement experiment**



▲**Figure 9. Pitch angle measurement comparison**



▲**Figure 10. Azimuth angle measurement comparison**

5 Conclusions

In this paper, we propose a novel antenna attitude parameters measurement algorithm, which can be divided into an antenna location phase and an attitude parameter calculation phase. Compared with traditional methods, we apply deep learning algorithms to the measurement, which achieves the function of automatic positioning of the antenna and reduces manual intervention in the measurement process. Experiment results show that the accuracy and efficiency of the proposed algorithm outperform those of existing methods. In addition, the measurement accuracy reaches the industry standard, which shows that the proposed algorithm can be applied in real applications.

In the future, we will conduct our studies from the following aspects: 1) optimizing the deep learning detection model to make it more efficient and accurate; 2) investigating the automatic cruise of drones based on deep learning; 3) automatically identifying whether antennas are affected by external factors such as obstruction, damage and bad weather.

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