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Vehicle Deflection Angle Detection inAerial Image Based on Deep Learning

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Abstract: Intelligent transportation system and satellite communication technology have made great progress. The satellite navigation system can transmit the image to the land vehicle in real time, so that it can get the traffic information immediately. In addition, deep learning technology has been widely used in intelligent transportation and driverless technology. Therefore, this paper proposes a vehicle deflection angle detection model based on satellite image and deep learning. So, the proposed model needs to output the vehicle deflection angle in real time. To achieve this function, regression convolutional neural network (CNN) is introduced into this paper. First, the regression CNN architecture is constructed for vehicle deflection angle detection. Then the vehicle deflection angle data set is made according to the network requirements. Finally, appropriate activation function, learning rate and optimization method are selected according to the training situation. The experimental results show that the obtained vehicle deflection angle detection model can not only detect the vehicle deflection angle in real time, but also has high accuracy.

Keywords: Intelligent transportation; satellite communication technology; deep learning; regression convolutional neural network; vehicle deflection angel detection.

1. Introduction

The vehicle deflection angle detection is very important for vehicle and traffic accident tracking. Once you know the deflection angle of the vehicle front which corresponds to the horizontal direction of the vehicle, it is easy to judge the possible moving direction of the vehicle. There have been a lot of researches on the object direction and angel detection [1,2,3,4]. In this part, we mainly review the latest research progress in this field and its connection with the content of this study.

Ji *et al*. proposed the improved Faster R-CNN with better feature extraction, multiscale feature fusion, and homograph data augmentation to realize vehicle detection in remote sensing images [5]. Kurniawan *et al*. proposed a method to detect the angle of QR code image for reading the QR code, which involves the image processing and convolutional neural network (CNN). The proposed algorithm increases the reading accuracy of the QR codes and maximizes detection on low-resolution cameras [6]. Zhao *et al*. proposed a bolt loosening angle detection technology based on deep learning and machine vision for structural damage detection [7]. Chen *et al*. proposed the direction RCNN for identifying the buildings angle from aerial images based on the VGG net [8]. Insulators are one of the most important equipment in power line, and their positioning angle detection is an important pretreatment step for accurate positioning of insulators. In order to realize the orientation of multiple insulators in aerial image under complex background, Zhao *et al*. proposed a method to detect the insulator orientation angle [9].

To sum up, there have been many research methods in object angle detection. However, the vehicle deflection angle detection in aerial image based on regression CNN is still rare. And the current object angle detection methods are mostly based on the traditional image processing methods. In order to detect the vehicle deflection angle in real time, it is necessary to introduce regression CNN. Therefore, this paper proposed a vehicle deflection angle detection method based on regression CNN. This method not only can detect the object angle in real time, but also has higher accuracy.

The main contributions of this paper are as follows. A vehicle deflection angle detection framework based on regression convolutional neural network is proposed. The vehicle deflection angle dataset is obtained. A vehicle deflection angel detection model based on aerial image and deep learning is established.

The main structure of the paper is as follows. In section 2, the proposed method introduction is mentioned. In section 3, We mainly introduced the dataset production process. In section 4, the training and testing of vehicle deflection angle detection model is implemented. In section 5，the experiment results and discussion is mentioned.

2. RegressionCNNArchitecture

In autonomous vehicle technology, it is very important for intelligent transportation system to accurately predict the possible driving direction of the vehicle based on the vehicle deflection angle. Regression CNN has been widely applied to such regression problems [10,11]. In order to achieve this goal, this paper proposes a method based on regression CNN to accurately detect vehicle deflection angle. The regression CNN architecture is shown in Figure 1 below. It contains 3 convolutional layers, 3 pooling layers and 2 full connection layers. Sigmoid is used as the activation function, and Euclidean Loss function is used to calculate the error between the detected angle value and the label angle value, and it is used to return the error, back propagation, and iterate the training weights.

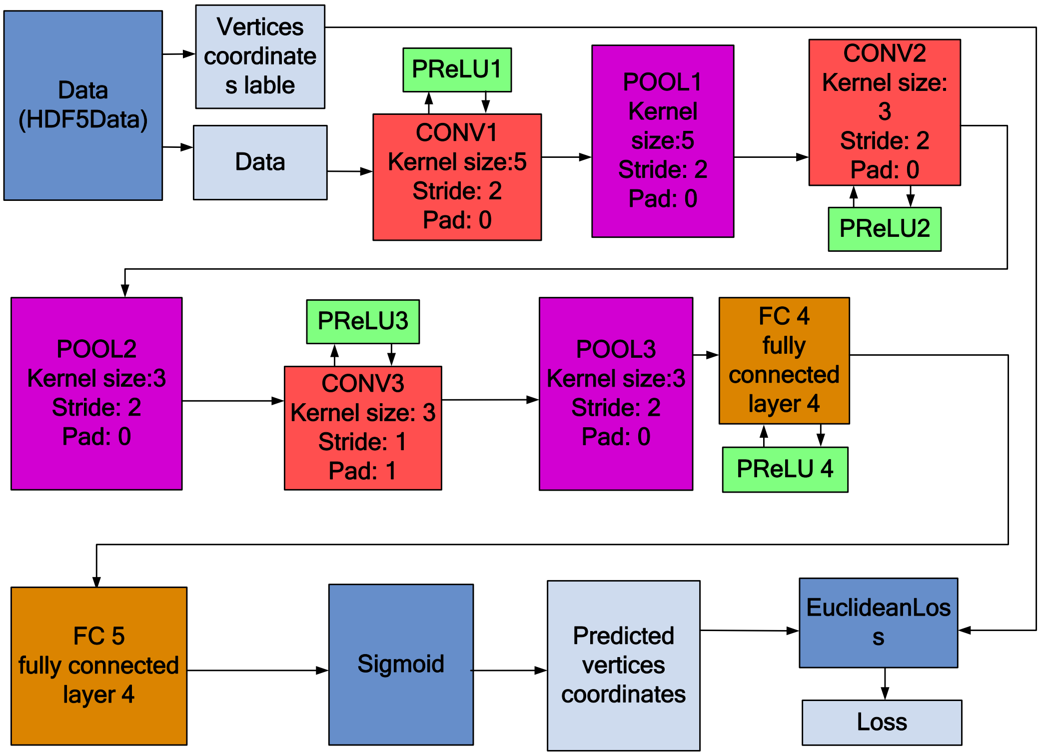

Fig. 1 Regression CNN architecture

By training the network, the vehicle deflection angel detection model can be obtained. This model can detect the input image, which contains the vehicle to be detected, and then output the deflection angle of the vehicle in the image. The detection process of vehicle deflection angle is shown in Figure 2.

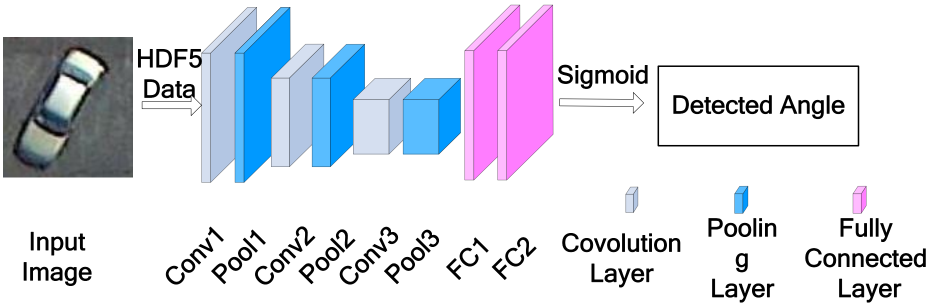

Fig. 2 Vehicle deflection angle detection process

3. Datasetproduction

The data set in this paper is derived from the UCAS-High Resolution Aerial Object Detection Dataset (UCAS-AOD). UCAS is derived from images captured by Google Earth software in parts of the globe [12]. UCAS included 7,114 samples for cars and 7,482 samples for aircraft. The fields and descriptions for each label are shown in the following table.

Tab. 1. Sample label parameters of UCAS dataset

Field	Introduction
x1-y4	(x1, y1) is the upper-left corner coordinate of the target. The four angles are (x2, y2), (x3, y3), (x4, y4) in clockwise order.
theta	Target rotation angle
x, y	After correction, target upper-left coordinates
width	Target width
height	Target height

We cut out the vehicle samples in batches according to these labels. Then 1186 images were selected as training data set and test data set. In order to detect the vehicle deflection angle, we first set the coordinate system for the vehicle deflection angle detection. In Figure 3, α is the vehicle deflection angle to be detected.

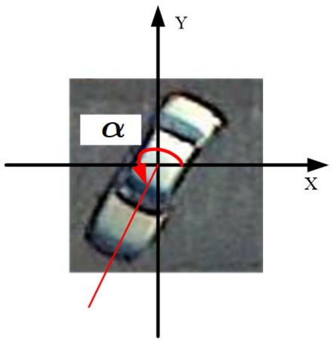

Fig. 3 Vehicle angle detection coordinates

The angle label range of the data set is [0°, 360°] (Model 1). After normalization, the label range is [0,0.36]. Experimental results show that the model is not easy to converge when the data set is trained with the label range between [0,0.36]. This is due to the heterogeneity of the data. In order to solve this problem, we changed the label range of the dataset to [0.36,0.72] (Model 2). The data uniformity of the label of the dataset has been greatly improved. The angle label format of data set is "Image sequence _ normalized angle value.jpg".

4. Trainingandtesting

The optimization method for regression CNN training is AdaDelta. The activation function ReLU and Sigmoid is employed in training process. The regression CNN training parameters are shown in Table 2.

Tab. 2 Regression CNN training parameters

Model / Training parameters	Model 1	Model 2
Training dataset	800 images	
Validation dataset	356 images	
Testing dataset	200 images	
Training loss	0.00165	3.18294e-05
Validation loss	0.00236	9.36489e-06
Iteration	50k	20k
Global learning rate	0.001	
Activation function	ReLU& Sigmoid	
Optimization method	AdaDelta	

The basic idea of AdaDelta is to approximate the second-order Newtonian method with the first-order method. Most gradient descent algorithms need to select the hyperparameter of learning rate. Setting learning rate is usually adjusted constantly, while a better learning rate is generally set manually. Setting the learning rate too high will make the system diverge, but choosing too small will make the learning process slow. For many problems, choosing a good learning rate is more like art than science. As you can see from the Figure 4, the best way to find the optimal speed and accuracy of the solution is AdaDelta. AdaDelta have the following advantages [13].

a. No manual setup of learning rate.

b. Insensitive to hyperparameters.

c. There is a separate dynamic learning rate for per dimension.

d. It can reduce the calculation amount of gradient descent algorithm.

e. Good robustness to large gradient, noise, and different structures.

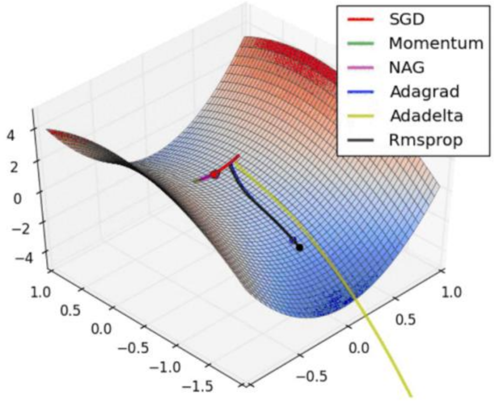

Fig.4. Comparison of optimization methods

The total number of data sets is 1,186 images. There are 800 for the training set and 386 for the validation set. Figure 5 shows the loss curve of model 1, which is trained by data set with label range [0, 0.36]. The learning rate is set to 0.001. It can be seen from the figure5 that the convergence of the model 1 is extremely poor. The loss curve is always oscillating. This indicates that the learning efficiency of the model is very low. In order to improve this situation, we changed the label range of the data set to [0.36, 0.72] (Model2). In this way, the real data will not be affected, and the problem of data heterogeneity will be well solved. We set the learning rate to 0.001 and the number of iterations to 20,000. The loss curve in Figure 6 is obtained. As can be seen from Figure 6, the model 2 has a good convergence performance after only 20,000 iterations. In the loss curve, the red line represents train loss and the blue line represents test loss.

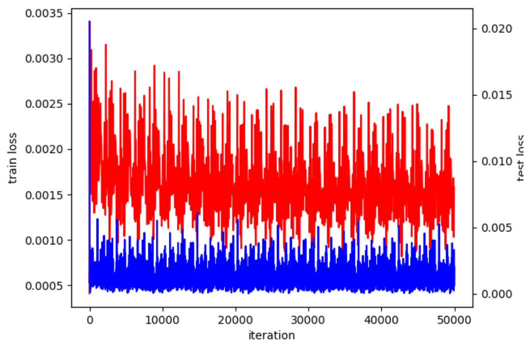

Fig. 5. Loss curve of model 1

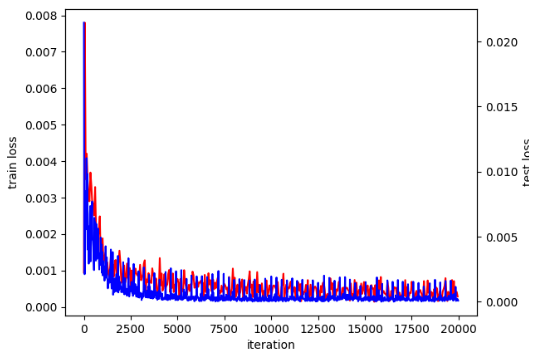

Fig. 6. Loss curve of model 2

From the loss curves above mentioned, the regression CNN has higher requirements on the uniformity of label data, and the flatter the data distribution, the better the convergence of the model trained. The loss function adopted by the regression CNN is Euclidean Loss function. It is used to calculate the minimum distance between the label value and detected value. Euclidean Loss Layer built into Caffe is a solution to this kind of real value regression problem [14]. Euclidean Loss Layer calculates the following errors

$$E_{\text{EuclideanLoss}} = \frac{1}{2N}\sum_{i=1}^{N} \| x_i^1 - x_i^2 \|_2^2 \qquad (1)$$

where x_i^1 is the label angle value, N is the total number of samples, and x_i^2 is the detected angle value. It is worth noting that the Euclidean Loss Layer is only used in the training stage, and the Loss value calculated by it has an important reference role for weight updating in the training process. In the testing phase, Euclidean Loss Layer is no longer required.

5. Experimentresults and discussion

To compare the performance of the trained models. We tested 200 images separately. Then we compare the fitting effect between the test value and the label value. The fitting effect of the model 1 trained by the data set with a label range of [0, 0.36] is shown in Figure 7. From the figure, the fitting effect between label angle value and detected angle value is poor. The detected angel value for this model should be in the range of [0°, 360°]. However, detected angle value is maximum around 680° due to poor uniformity of the data.

The fitting effect of the model trained by the data set with a label range of [0, 0.72] is shown in Figure 8. From the Figure 8, you can see that the fitting effect between label angle value and detected angle value is good. The detected angel value for this model should be in the range of [360°, 720°]. The maximum error between detected angle value and label angle value is only about 25° because the data is uniform. The standard deviation between label angle value and detected angle value of the model shown in Figure 7 and Figure 8 is 10.67982627 and 6.641344797 respectively.

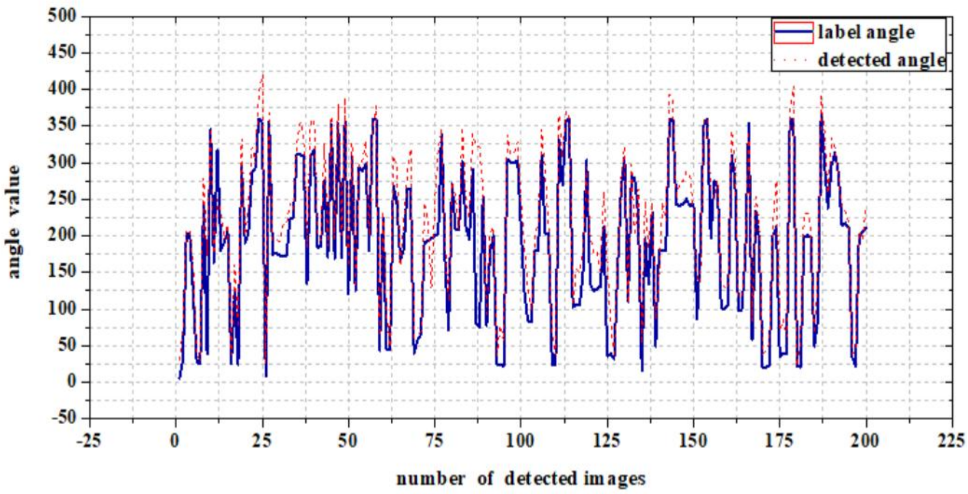

Fig. 7. Fitting curve between labelangle value and detected angle value of model 1.

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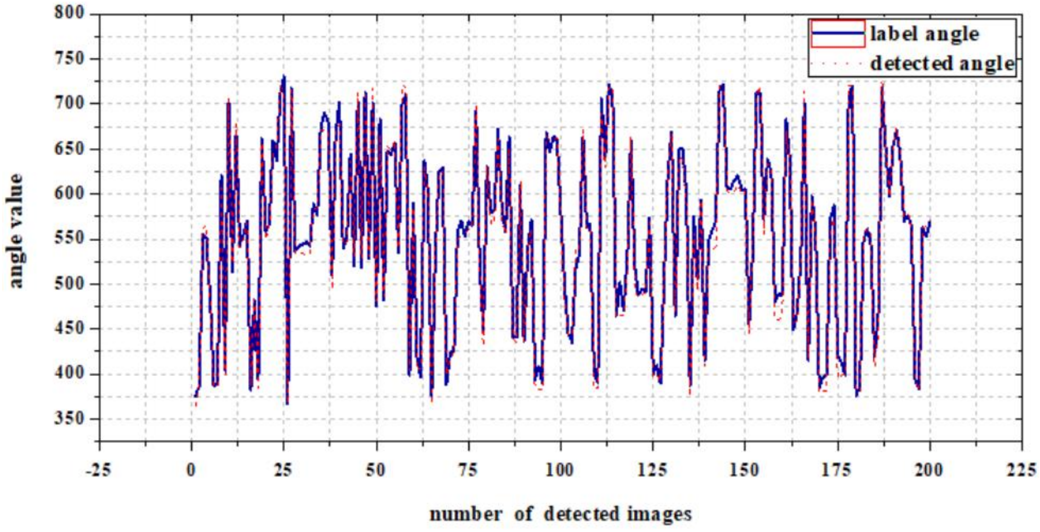

Fig. 8. Fitting curve betweenlabel angle value and detected angle value of model 2.

We calculated the error distribution histogram of 200 samples, as shown in Figure 9. The samples with errors in [0°, 5°), [5°, 10°), [10°, 15°), [15°, 20°), [20°, 25°) accounted for 41%, 27.5%, 16%, 9.5%, and 6% of the total samples respectively.

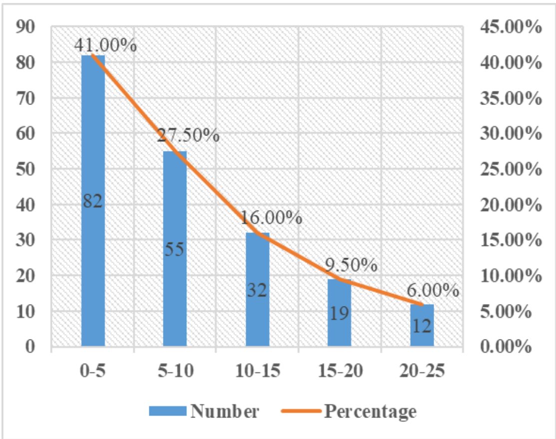

Fig. 9 The distribution histogram of the error between detected angle value and label angle value

Table 3 shows the test results of some test samples. The difference between the detected angle value and the label angel value is shown.

Tab. 3. Detection results of 5 samples

Items / Image	Label angel (°)	Detected angel (°)
	162.86	165.94
	346.50	346.23
	27.96	30.45
	23.03	28.65
	229.40	228.01

6. Conclusion

Vehicle deflection angle detection is of great significance for intelligent traffic and vehicle path planning. With the extensive application of deep learning in the field of autonomous vehicle technology, the real-time and accuracy of object detection have been greatly improved. Therefore, this paper proposed a vehicle deflection angle detection model based on regression CNN. It is the combination of satellite image technology and deep learning technology. The proposed method can not only detect the deflection angle of the vehicle in real time, but also achieve high accuracy. The method proposed in this paper can be applied in autonomous vehicle technology and parking system. By detecting the vehicle deflection angle, we can accurately detect whether the vehicle is parked at the designated parking position. In order to further improve the performance of the model, a deeper network architecture can be considered to train the more robust model in the future, such as Faster RCNN *et al.*

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