Research on Mileage Location Method Based on Metro Feature Recognition

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Abstract. Aiming at the problems of low positioning accuracy and poor robustness of traditional odometers, this paper proposes a mileage positioning method based on subway feature recognition. First, use the YOLOv3 target detection method to identify the characteristics of the track fasteners, and obtain the position information of the characteristic points. Then, distance clustering and Lagrangian interpolation are used to complete the feature points that are not detected by deep learning. Finally, the initial mileage value is obtained according to the mileage constraint, and the speed filter method is used to correct the mileage result. In order to verify the reliability of the mileage positioning method, a mobile laser scanning experiment was carried out in Xi'an Metro. Experimental results show that this method has good positioning accuracy and stability. After Kalman speed filter preprocessing, the mileage positioning error is about 7cm, and the standard error is $5.05 \times 10^{-3}$, which provides accurate mileage results for subway inspections.

Keywords: Subway, Mileage Location, Feature Recognition, Deep Learning, YOLO

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With the rapid development of subway construction in major cities across the country, due to complex reasons such as geological conditions, long-term operation, and construction quality, there are a series of problems in the subway such as equipment invasion, filling and falling off, and lining cracks [1]. Therefore, periodic inspections of subway infrastructure are required. The mileage value is an important basis for accurate positioning in the subway, and its accuracy has an important impact on the regular inspection of the subway [2].

The current method of obtaining mileage value is mainly based on the odometer, but the accuracy of the odometer is easily affected by complex environments such as wheel slip, detection speed, rail wear, etc., resulting in accumulated errors in the measurement results. The final mileage result has a large deviation from the true value, which cannot meet the accuracy requirements of long subway line detection [3-5].

This paper proposes a mileage location scheme based on subway feature recognition, using deep learning YOLOv3 target detection algorithm. Extract regular feature points such as fasteners in the orthophoto of the subway, and combine the distance interpolation method with constraints to obtain...
accurate mileage positioning information. According to the Kalman filtering method, the accuracy of mileage positioning is improved, and the effectiveness and feasibility of this method are further verified by manual interpretation.

1. YOLO Detection Algorithm

1.1 Network Structure

YOLOv3 is a target detection algorithm with both accuracy and speed. It inherits and merges the network structure of other target detection algorithms, so that its overall performance has reached a higher level, and its network structure is shown in Figure 1 [6-8].

![YOLOv3 network structure](image)

**Figure 1.** YOLOv3 network structure

Since the identified track fastener is a small object target, the input of the network is changed from 416×416×3 to 533×533×3. The increase in resolution is conducive to retaining more useful information. Through multiple convolution and up-sampling functions between the scale feature maps, the multi-scale fusion operation of the feature pyramid is realized.

In order to improve the accuracy of target detection, strengthen the detection effect of the network on small targets. YOLOv3 not only deepens the network depth through a large number of residual structures, but also uses multiple methods such as feature fusion, multi-scale prediction, and bounding box regression to achieve a greater improvement in detection speed and accuracy.

1.2 Loss Function

The loss function is one of the important indicators to evaluate the performance of the model. In the training process of the model, it is necessary to constantly adjust the parameters in the network to minimize the value of the loss function [9-11]. The loss function is a set of errors, including confidence loss, category loss error, and location loss. The loss function can be expressed by the following formula:

\[ L(O,\hat{O},P,p,l,g) = \lambda_1L_{d}(o,p) + \lambda_2L_{c}(O,P) + \lambda_3L_{l}(l,g) \]  

The target confidence loss is expressed as:

\[ L_{d}(o,p) = -\sum o_{i}\ln(p_{i}) + (1-o_{i})\ln(1-p_{i}) \]  

\[ p_{i} = \text{Sigmoid}(p_{i}) \]  

In the formula, \( p_{i} \) represents the confidence score, and \( o_{i} \) represents the ratio of the predicted frame to the true frame.

The target category loss is expressed as:

\[ L_{c}(O,P) = -\sum_{i\in P_{w}}\sum_{j\in c_{i}} o_{i}\ln(p'_{ij}) + (1-o_{i})\ln(1-p'_{ij}) \]  

\[ p'_{ij} = \text{Sigmoid}(p_{ij}) \]  

In the formula, \( O_{ij} \) represents the binary cross-entropy loss, and \( P_{ij} \) represents the probability of the j-th target in the predicted target bounding box.

Target positioning loss is expressed as:
In the formula, \( l_{loc} \) represents the value obtained by the activation function processing of the coordinate offset, and \( g_{loc} \) represents the coordinate offset between the real frame and the default frame.

### 1.3 Bounding Box Prediction

The relationship between the YOLOv3 target frame and the prior frame is shown in Figure 2. YOLOv3 does not directly predict the position and size of the target, but obtains the offset of the feature map grid unit through regression, and determines the center position of the target [12-14]. According to the scale factor of the target frame size relative to the prior frame, the target size is determined.

![Figure 2. Prediction box positioning](image)

The regression formula is:

\[
\begin{align*}
    b_x &= \sigma(t_x) + c_x \\
    b_y &= \sigma(t_y) + c_y \\
    b_w &= p_w e^{t_w} \\
    b_h &= p_h e^{t_h}
\end{align*}
\]

In the formula, \((c_x, c_y)\) represents the center coordinates of the preset bounding box on the feature map; \((p_w, p_h)\) represents the width and height of the a priori box on the feature map; \((t_x, t_y)\) represents the offset of the prediction center relative to the grid point; \((t_w, t_h)\) represents the width and height scaling ratio of the predicted bounding box; \((b_{wx}, b_{hy}, b_{hx}, b_{hy})\) represents the final predicted target bounding box; \(\sigma\) represents the use of an activation function to scale the prediction offset to the interval of 0 to 1.

### 2. Mileage Positioning Method

#### 2.1 Mileage Positioning Process

The mileage positioning process is shown in Figure 3. First, the original point cloud is converted into an orthophoto, and input into the YOLOv3 detection network, and the existing fastener training model is used for feature recognition, and the network structure is appropriately adjusted according to the accuracy of the model [15]. For unidentified feature points, clustering and interpolation are used to
obtain specific coordinate values. And according to the mapping relationship between the image coordinates and the actual mileage, the mileage constraint of the feature points is performed. Finally, the average filter is used to estimate the carrier's moving speed optimally, and the final mileage positioning result is obtained.

![Figure 3. Mileage positioning process](https://example.com/figure3.png)

### 2.2 Feature Point Completion
Due to the complex tunnel environment, the YOLO target detection algorithm has certain errors, and it is impossible to extract all the feature point coordinate information only by deep learning. Therefore, this article first uses distance clustering to segment the fastener target set identified by deep learning. If the number of targets in the cluster set is less than three, the set is not calculated. This method can effectively eliminate the wrong feature information, and count the number of missing feature points. Secondly, Lagrangian interpolation is used to complete the missing fastener feature points, and the coordinate values can be expressed as:

\[
y(t) = \sum_{j=0}^{n} \left( \prod_{i=0}^{n} \frac{z - z_i}{z_j - z_i} \right) y_j
\]  

(11)

In the formula, \( t \) is the missing feature node; \( z_0, z_1, z_2, ..., z_n \) are the feature points obtained by clustering; \( y_0, y_1, y_2, ..., y_n \) are the abscissa values in the pixel coordinate system corresponding to the cluster feature points.

### 2.3 Mileage Constraints and Positioning
According to the obtained characteristic point abscissa information, the starting and ending mileage information of the measurement interval is added, and the accurate mileage value corresponding to each characteristic point can be obtained. Solved the problem of mismatch between image coordinates and actual mileage in mobile measurement. The main calculation process is as follows:

1) Mileage constraint: According to the starting and ending milestone information in the tunnel, calculate the total length \( D \) of the interval. Combining the change value \( \Delta y \) of the abscissa of the starting and ending pixels of the feature point, the interval value \( d_i \) of each feature point is calculated.

2) Initial positioning: Starting from the initial feature point mileage, iteratively accumulate the interval value of each feature point to obtain the mileage value of each feature point, and obtain the mileage value between the feature points by pixel value interpolation \( s'_1 \).

3) Speed analysis: According to the scanning frequency \( f \) of the laser scanner, the time interval \( T_i \) of the scanning line is calculated, and the corresponding speed \( v'_1 \) is obtained based on the finite element method, and the Kalman filter method is used to further optimize the speed value. The influence of noise in the system on the speed value is reduced, and the speed value \( v_1 \) of the moving carrier in each time period is obtained.
4) Mileage correction: Correct the initial mileage value according to the optimized speed value to get the final mileage value $s_i$.

3. Experiment and Analysis

3.1 Experiment Overview
In this paper, a mobile tunnel detection system equipped with a Z+F laser scanner is used to conduct on-site collection according to the sampling parameters with a scanning frequency of 100HZ and 1.016 million points per second. The measurement site is shown in the figure. The system obtains full coverage and high-precision point cloud scanning data in a certain section of Xi'an tunnel, and generates an orthophoto map for feature recognition.

![Figure 4. Metro mobile laser scanning](image)

3.2 Accuracy of Feature Point Recognition
The collected orthophotos are used as the test data set, and the trained model is used for detection and analysis. In deep learning, three indicators, precision, recall, and AP (Average Precision) are used to comprehensively evaluate the accuracy of the algorithm. The precision rate is expressed as the proportion of the positive samples that are correctly predicted in the actual positive samples in the prediction data set, and the recall rate is the proportion of the positive samples that are correctly predicted in the samples considered to be correct by the model. Changing the detection threshold (IOU) will cause the accuracy and recall rate to change. Establish a curve based on the recall rate on the abscissa and the precision rate on the ordinate. Define the area under the curve as the AP value. The better the single-type target detection effect is. As shown in Figure 5. The calculation formula of precision rate and recall rate is as follows:

$$\text{Precision} = \frac{TP}{TP + FP}$$ (12)

$$\text{Recall} = \frac{TP}{TP + FN}$$ (13)

In the formula, TP represents the positive sample that the model correctly identifies as a fastener; FP represents the negative sample that the model incorrectly identifies as a fastener; FN represents the positive sample that the model incorrectly identifies as a fastener.
Figure 5. YOLO accuracy results

The accuracy rate of track fasteners extracted by YOLOV3 is stable above 94.3%, the recall rate is stable above 91.6%, and the AP value is 93.65%. A total of 1,958 track fasteners were identified, and some of the fastener identification results are shown in Figure 6. The feature point completion method is used to perform interpolation completion on the missing fasteners to obtain the center point position information of all fasteners in the interval.

Figure 6. Fastener recognition image

3.3 Analysis of Mileage Positioning Results

According to the mileage constraint and positioning algorithm, the initial mileage positioning result of the interval and the carrier running speed are calculated. Use the mileage result of manual interpretation to verify the accuracy of mileage positioning. In order to avoid the influence of factors such as motion vibration and track irregularity, Kalman filter is used to optimize the speed, as shown in Figure 7. According to the optimized speed value, the final interval mileage positioning result is calculated.

Figure 7. Kalman filtering speed result analysis
The comparison result of manual interpretation and mileage positioning algorithm is shown in Table 1. The mileage positioning error before filtering is within 0.15m, the mileage positioning error after filtering is within 7cm, and the standard error is $5.05 \times 10^{-3}$. The accuracy of the mileage positioning is high, which can meet the accuracy requirements of the infrastructure detection in the subway.

| Manual interpretation | Before filtering | error  | After filtering | error |
|-----------------------|------------------|--------|-----------------|-------|
| ZK194+00.02           | ZK194+00.12      | 0.10   | ZK194+00.08     | 0.06  |
| ZK193+00.19           | ZK193+00.31      | 0.12   | ZK193+00.24     | 0.05  |
| ZK192+00.36           | ZK192+00.44      | 0.08   | ZK192+00.39     | 0.03  |
| ZK191+00.15           | ZK191+00.26      | 0.11   | ZK191+00.20     | 0.05  |
| ZK190+00.21           | ZK190+00.35      | 0.14   | ZK190+00.28     | 0.07  |
| ZK189+00.42           | ZK189+00.49      | 0.07   | ZK189+00.41     | 0.01  |
| ZK188+00.57           | ZK188+00.65      | 0.08   | ZK188+00.54     | 0.03  |
| ZK187+00.49           | ZK187+00.56      | 0.07   | ZK187+00.53     | 0.04  |
| ZK186+00.85           | ZK186+01.00      | 0.15   | ZK186+00.90     | 0.05  |
| ZK185+00.22           | ZK185+00.26      | 0.04   | ZK185+00.20     | 0.02  |
| ZK184+00.17           | ZK184+00.31      | 0.14   | ZK184+00.21     | 0.04  |

4. Conclusion
In this paper, deep learning methods are used to identify track feature points, combined with distance interpolation and filtering methods to achieve mileage positioning. According to the test results of the Xi'an subway, this method can provide accurate mileage information and provide a simple and reliable technical method for subway mileage positioning. In the future, it is planned to further expand the dataset of subway features and use a generative confrontation network to improve the generalization ability of this method.

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