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A Method for Predicting Rescue-vehicle Shock Absorption Using Samples Points Covering

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Abstract. This paper discusses a method of shock absorption of rescue equipment during climbing. It is designed based on a points-measured slope surface model. Instead of measuring single distance of slope surface as most previous models did, we directly generate the distance-map image through points by points analysis .We argue that the uphill angles are naturally appealing as it allows us to extract the distance-map and features extracted at a particular image position. These points covering operation can capture structural information about the input image and extracted features, which opens a new avenue along with a strategy can benefit from feature analysis for small sample data. Experimental results show that the method is able to identify shock absorption points and has good interpretability and superiority.

Keywords: Dist-map, shock absorption, samples covering, Deep learning

1. Introduction

At present, autonomous driving technology is one of the research hotspots in the field of artificial intelligence[1]. The existing model-based path tracking control methods mainly rely on the kinematic and dynamic models of the vehicle [2,3], and control is achieved through perception and decision-making modules. Common non model-based control methods are neural network-based control methods [4,5], etc. Wang [6] proposed a multi-scale spatial feature enhancement prediction pyramid algorithm (Centernet auto), which has improved end-to-end recognition methods [7,8], local path planning based on sampling [9,10], and the application of autonomous agricultural machinery in agricultural production [10,11]. There have been some studies on the use of neural networks for secondary autonomous driving on traffic roads. There have been some studies on the use of neural networks for secondary autonomous driving on traffic roads[12,13]. However, there are relatively few reports on rescue autonomous driving in harsh outdoor uneven road environments..

In previous studies, the main focus has been on the general issues of autonomous driving and wheeled vehicles. There has been relatively little research on the motion of non tracked vehicles in specific scenarios, especially the impact of uphill angles combined with vehicle characteristics. This article attempts to use the neural network method to predict and judge vehicle bumps from the perspective of distance maps.

The paper is organized as follow. Definitions and operators necessary for description of the points covering method are provides in Section 2. This discussion is followed by the description of the proposed algorithm in Section 3. Results of dist-map with different type slopes are providing in Section 4, with conclusions in Section 5.

2. Dist-Map Points Covering

During the movement of on-site rescue vehicles, the processing method in this article is not to judge a single point, but to use the road surface area for flatness discrimination. The judgment method uses spatial point coverage, and different layers are used to represent the internal relationships of each point coverage method. The specific structure is as follows.

The concept is embodied in the network layer structure as shown in Fig 1

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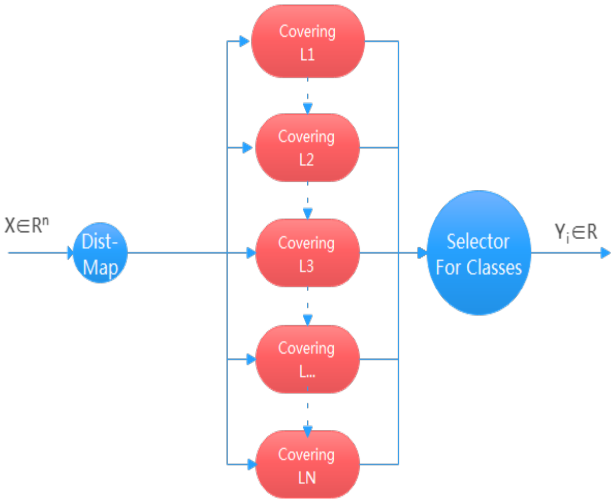


Fig. 1: Data covering Units

The judging unit finally gives the early warning and judgment of the vote through the internal data node and the input of different data, which combined with the existing data analysis model. This process has the characteristics of independent parallel operation.

Basic Principle of the Structure of shock absorption Model

For video picture analysis unit which defined as $\psi_{i,j}^{k}$, stipulate that the individual analysis unit $\psi_{i,j}^{k}$ a node in the large data model, which's stage includes many attribute features. To express these features by means of numbers, the measurement of the similarity is described as follows.

$$F(\rho)=\begin{cases}1,\rho<\theta\\0,else\end{cases}$$

As judging by sample structure, $\psi_{i,j}^{k}$ has the judgment element with the same level is defined as $C(\psi_i^k)$, in which the coverage area of different nodes is not overlapped. $C(\psi_i^{k1})\cap C(\psi_i^{k2})=\phi, k1\neq k2$ Representation of nodes and different computational elements in the same situation.

When constructing the big data internal judgment model, thinking fully about the effective attribute range of early warning judgment. In the initial stage of the operation the range of node coverage is limited, but with the continuous data entering, the overlay unit and the overlay layer are increasing, and the collection of the covering nodes is formed. The function range of the effective features in the large data model is reflected by the collection.

The network acceptance data $x\in R^n$ which waits for input. Sequence of neuron output response of each neuron O_k .
Definition discrimination:

$Y_i:=\{i\,|\,i=\{0\,|\,q:=\{\min(k)\,\&\,\{O_k>1\rightarrow p\}\}\}\}$ The feature partition of the early warning is divided by Y_i to the sample $x\in R^n$ which waits for identify. $Y_i=\begin{cases}\text{category } i,\ i>0\\ refuse,\ i=0\end{cases}$

From the type of category recognition network, judgment can effectively avoid "false negatives", and this is suitable for the characteristics of shock absorption point.

3. Modeling and Method

Firstly, the distance image data of the road is obtained through a planar sensor, which is then fed into a neural network as input. The network collects point data to achieve point coverage and extract features for controlling vehicle operation judgment. The specific technical architecture is as follows:

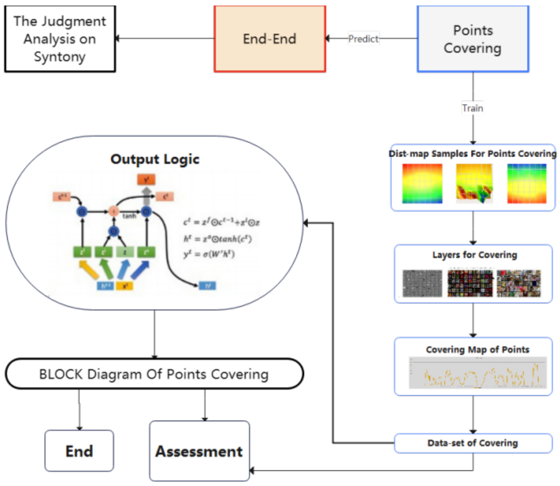


Fig.2: System architecture of distance judgment

By setting the end-to-end inspection structure, it can be found that the convolutional neural network and fully connected neural network for damping points have both similarities and differences. In terms of computation, convolutional neural networks. The network adopts convolutional calculation, and the distance map is processed through a fully connected neural network using matrix multiplication operation. In terms of structure, convolutional neural networks. Only some nodes are connected between adjacent layers, and in a fully connected network, each node is tightly connected to all nodes in the next layer.

The structural diagram is shown in Fig.3. The whole work process is to encode and convert the input image into two-dimensional information, further perform pooling encoding and other operations, gradually compress image information, extract key feature information, and finally use loss function control. It can calculate the convergence of the model and obtain the output results of the damping points.

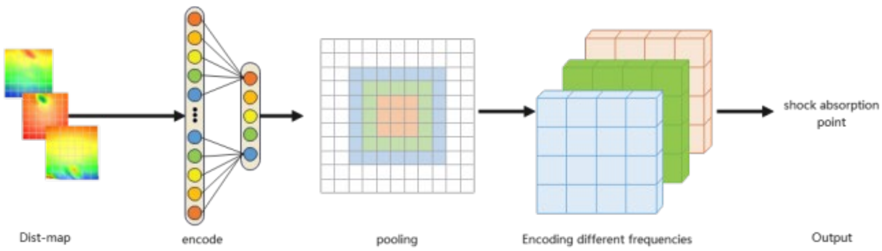


Fig.3: End to End of predicting rescue-vehicle shock absorption point

In the process of data convolution, in order to obtain the value of each cell of the output tensor, the convolution kernel moves through a sliding window on the input feature and repeats the convolution operation. The process of convolution operation is to slide the convolution kernel in a total of 8 directions up, down, left, and right on the input distance image, and calculate its correlation with the current window.The dot product of matrices. This dot product result is output as data for one cell, and this process can make Use the step size parameter to control the distance of each slide. The convolution operation uses padding to ensure that the output size is consistent. Parameters are used to control the size of the output image, taking into account the unevenness of the road surface and filling in a pixel value of 1, which can ensure that it does not affect the characteristics of the image.The output formula after convolution operation is calculated using the following formula.

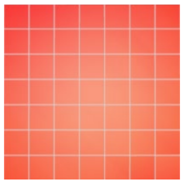
$$n_{\text{out}} \text{ x } n_{\text{out}} = [\frac{N+3(p-1)}{s}+1]*[\frac{N+(p-1)}{s}+1]$$

Among them, n_{out} is the size of the output image, N is the size of the input image, parameter p can be filled with 1, and n is the ruler of the convolution kernel, s is the step size for convolution calculation. For dist-map, we use bilateral grids at the edges to ensure that the details of the original concrete image are not compromised.

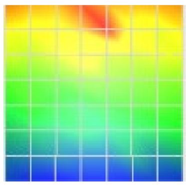
This paper studies the identification of vehicle shaking points using distance maps from sensors for discrimination, which are defined as the visualization of ground state acquisition of external data. The distance map comes from the capture of external sensors, but from the surface data of multiple sample points. This method has generalization ability and can be converted into other types of 2D graph data. The distance map used in this article is a 7x7 imaging with a visible angle range of [-45 °,+45 °]. The specific distance map will vary with the ground distance, as shown in Figure 3. The color depth of the image metadata determines the size of its distance.

The spatial coverage algorithm is used to approximate the circle coverage of each layer, and the conic is used to fit each circular point, and then the average circle size is used to find the sliding. The covering process is shown in the figure below. By calculating the coverage relationship of different layers, we can finally get the corresponding 3D spatial structure.

a) Climbing rescue vehicle



b) Dist-map of flat areas



c) Dist-map of non flat areas

Fig.4: Dist-Map

Tracked rescue vehicles have the characteristic of overall movement during their movement, with front and rear wheels connected by tracks, corresponding to different uphill angles and bumpy conditions. The following figure shows the different effects and distance maps of the vehicle when going uphill.

Train and analyze the distance map through the network, obtain its characteristic data, and obtain the deceleration point for uphill shaking. By judging the situation of the distance map, intelligently find the vehicle deceleration point, and achieve vehicle speed control to obtain shock absorption effect.

4. Experiment

During the experiment, distance image images were analyzed under different tilt angles. In this paper, 15 degree, 30 degree, 45 degree, and 60 degree slope motion jitters were used for forward point detection. The analysis results of the inspection are shown below.

Table 1: Shock-absorbing result of different angle

Uphill angles	Correct rate (%)	Error rate (%)	Rejection rate (%)
15	95.75	4.25	0
30	96.15	3.85	0
45	97.10	2.90	0
60	93.32	6.68	0

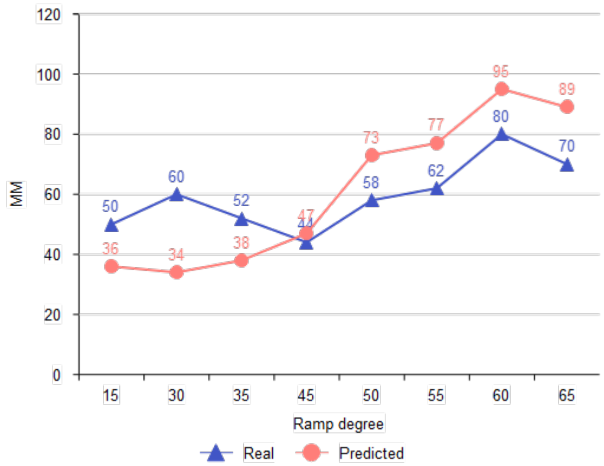


Fig.5: Comparison between predicted and actual shock absorption points

From the table 1, it can be seen that the distance image recognition rate is basically correct, but as the slope increases, the recognition rate will decrease due to the angle between the distance image and the ground, resulting in insufficient area. The improvement of this situation can be achieved by using a large area angle for image analysis. Of course, it does not affect the calculation method in this article.

5. Conclusions

This paper proposes a method for track climbing vibration reduction by combining motion damping with distance image point analysis. The main contributions of this article are as follows.

- Propose the use of spatial point coverage method to judge and analyze distance points, which can provide shock absorption effect for non wheeled tracked vehicles climbing slopes;
- This method uses small samples for analysis, which is different from other deep learning framework methods. This method can be used in low-power computing scenarios such as vehicle autonomous driving.

From the perspective of rescue applications, the next

step is to further study the small sample method, targeting more continuous climbing scenarios and achieving the practical goal of using small data to achieve intelligent control.

6. Acknowledgment

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