Machine learning based intelligent posture design of driver

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Abstract. The automatic adjustment of the driving posture can effectively help improve the driver’s experience, and thus it is one of the important reference indicators for the design of the vehicles. This paper focuses on the intelligent adaptive driving posture using the machine learning (ML). Firstly, laser scanning was used to obtain the point cloud data of the most sold vehicles in the market. Then, the driving posture's key parameters were screened and extracted through the big data processing method. Finally, the deep learning neural network (DNN) was applied to establish a supervised learning model to figure out the intelligent adjustment of driving posture for different vehicles. Numerical results can demonstrate the accuracy and effectiveness of the proposed method by comparing it with the actual driving experiments. The results show that the accuracy of the research is good and can provide a reference for the design of intelligent driving.

Keywords: Prediction model, Laser scanning, Forward design, Machine learning.

1. Introduction

The match between humans, machines, and the environment should be considered in product development. The local vehicle companies of China lack the capability of driving posture’s forward design, while other foreign vehicle companies would not like to make a differentiated driving posture design for Chinese, but just copy the existing design proposal. In the actual driving process, a lot of drivers from China are always in the uncomfortable posture for the difference of driving experience, habits, and other special factors, which would aggravate the uncomfortable, and increases the risk of fatigued driving \cite{1}.

The driving posture model can be constructed through machine learning (ML) methods \cite{2}, which can carry out the intelligent design of driving posture. The intelligence of vehicles will be gradually promoted as a result. Requirements of the different aiming markets, like China, could be met. We can make sure everyone has a different driving posture, which is just for a specific person. Subjective driving requirements such as comfort, safety, and health could be satisfied, and the risk of fatigue driving would be significantly reduced.
2. Vehicle Point Cloud Big Data

2.1. Vehicle Laser Scanning
We do statistics on the vehicle market of China and collect point cloud big data of parts' most popular vehicles by using the laser scanning method. Then, the key points of the vehicle used to feature reconstruction are extracted by processing the point cloud big data.

Laser scanning is a non-contact active technology to quickly obtain three-dimensional dense point clouds of the surface of an object. Comparing with traditional scanning methods [3], the outstanding characteristics of laser scanning are fast measurement and high accuracy to extract information on the surface of an object.

Through laser scanning, the point cloud can be obtained in terms of the contour of the target vehicle and the driver's seat in different extreme states. Thus, the vehicle dimensions for driving posture prediction, such as length, width, height, and wheelbase, can be obtained from the vehicle point cloud data. In order to further obtain the point cloud data of the vehicle seat related to the driving posture, we matched the dummy model with the vehicle seat and scanned it. The coordinates of the H point, which is a standard driving posture related parameter, can be obtained in the driving state, as shown in FIG. 1.

![Fig. 1 Point cloud of vehicle driving posture](image)

2.2. Processing of Point Cloud
The initial point cloud obtained by laser scanning is disordered, which needs to be preprocessed to obtain the required parameter information faster and more accurately. Normally, the preprocessing of point cloud big data will go through three steps which are noise removal, data filtering and cleaning, and feature reconstruction, so as to extract the valuable data hidden in the initial database [4].

Firstly, the noise of the point cloud needs to be removed. A great deal of information will be revealed in the initial point and cloud, which is obviously non-characteristic. Otherwise, the data processing will be greatly interfered with by the mixed noise [5]. It is necessary to remove the redundant and non-characteristic information as soon as possible.

Secondly, the data of the point cloud should be filtered and cleaned. The amount of data is very large, which requires a high amount of calculation. If it is used directly, the calculation efficiency will be affected seriously. Therefore, it is necessary to lighten the point cloud data as much as possible on the premise of satisfying the feature extraction to reduce the subsequent calculation [6].

Finally, the acquired point cloud data is integrated and aligned based on typical feature alignment and other methods. After the point cloud data is acquired, there will be problems such as not being in the same coordinate system, or incomplete features, abnormal visual posture, etc. Therefore, it is necessary to aggregate multiple point cloud data into a required complete point cloud data and adjust it to appropriate coordinates [7-8]. So as to tie down and make it conform to the normal observation angle.

Important demand information can be accessed quickly by feature reconstruction and stored in a more lightweight and visualized form. For example, the shape and hard points of the demand
characteristics can be shown, real-time measurement can be supported. If the point, line, and surface are applied. It is helpful to get hardpoints and parameters demanded.

By scanning the point cloud data of the driver's seat at four different extreme positions (front and top, front and bottom, last top, and last bottom), the four extreme positions of the H point in the driver's seat can be processed as a seat travel box which used to ensure a comfortable driving posture. H point range can be obtained in this way, which is the stroke of the seat travel box, as shown in FIG. 2.

![Fig. 2 Key point of vehicle driving posture](image)

According to the obtained point cloud and driving attitude, cleaning and optimization are carried out by certain methods, and the required key parameters are extracted on this basis, as shown in FIG. 3.

![Fig. 3 Flow chart of point cloud data processing](image)
3. Prediction Model of driver posture

3.1. Parameters of Model

The setting of the driving posture of a vehicle is related to many factors, which can be divided into three aspects from the general aspects.

The first part is the user’s position. Different users have different requirements for driving posture. For example, it is common for a person with tall stature to adjust the seat in the back position, while a person with short stature usually sits in the front for a better driving posture. In addition, the human of different races and regions are also quite different. For example, the leg’s length of Europe and American is larger than that of China. However, the Chinese’s length of waist is longer than that of European and American. It is more comfortable for the Chinese to sit forward actually, who requires more headspace. Many European and American vehicles have complained about insufficient headroom when they drive the vehicle sold in China, such as Mercedes-Benz GLA, which has a poor headroom performance. The reason for that is generally an unreasonable driving posture.

The second part is the type of vehicles. Vehicles of different sizes and types have a huge impact on driving posture. The seating height of a truck is higher, as its ride height (H30) is generally larger, so that the drivers can get a better view and operating experience. Also, the efficiency of the cockpit in the x-direction is also maximized for the large-size vehicle. The seat of a racing car is low and back, which can reduce the height of the vehicle, the drag coefficient, and the windward area effectively. So that there are many differences between large-size and small-size vehicles in the process of postural design. Besides, space utilization requirements are also different. Therefore, two dimensions of parameters are selected for vehicle positioning, the one is the size of the vehicle, such as wheelbase (L101) and width (W103), they are selected as parameter inputs. The other one is the type of the vehicle, such as the height, it is always seen as the distinguish of vehicle. Thus, the height (H100) of the vehicle is selected as the parameter input as well.

The third part is the layout parameters of the vehicle. It is the most important considered factor in the forward design of the driving posture. According to different attributes of design, the layout parameters can be classified into two categories, the first one is structural layout parameters, and the other one is ergonomic design parameters. The driving posture is affected by the package of the steering wheel, the pedal, the armrest, and the shift. For example, the relative operating position of the driver is determined directly by the height and the front and rear positions of the steering wheel. If the steering wheel is set higher, the driver needs to sit higher accordingly to operate more comfortably. The convenience of the driver's entry and exit will be affected greatly by the position of the rocker. The driving posture will be affected accordingly by the height of the driver's seat as well. In this experiment, we select the relative package parameters, like the distance between the steering wheel and the foot (L11/H17), the height of the rocker(H130-1). Besides, the driver's vision will prompt the driver to adjust the seat height. For example, many female drivers like to sit more highly to obtain a better vision of the forward lower field. So, we select the front under vision(A124-1-L) as input.

Finally, the comfort of the driver is impacted greatly by the headroom. For example, if space is not enough, the driver will have a sense of local crowding, and feel depressed. Long-term driving is more like to get driving fatigue. In addition, other choices of driving posture will also be affected by other visual field requirements, such as front upper visual field, A-pillar obstacle angle, dazzling, knee room, and driver Y-direction space, etc. Based on calculations, the driver's headroom(H61-1) and the front lower field of view(A124-1-L) are selected as the model input in this paper.

The driving posture is commonly characterized by three dimensions, named H30, W20, and L53. Among them, H30 is the Z-direction distance between the driver's R point and the heel point. L53 is the X-direction distance between the driver's R point and the heel point. W20 is the Y-direction distance between the driver's R point and the longitudinal symmetry plane (Y0 plane) of the vehicle. The driving posture can be determined by these three dimensions, so they are defined as the three output parameters of the model, which are denoted as Rx (distance between the R point and the heel point in the X direction), Rz (distance between R point and heel point in the Z direction), and W20 [9-10].
In summary, the input and output parameters of the test model can be determined as follows:

Input Layer (input layer) contains 9 parameters: body height, L101, W103, H101, H103-1, L11, H17, H61-1, A1234-1-L. The Output Layer contains 3 parameters: Rx, Rz, and W20-1. The relationship between the model’s input and output is shown in FIG. 4.

![Fig. 4 Optimization route of the model](image)

After the model training is completed, it is easy to get the corresponding R point with any given initial conditions, and in turn, the H point is confirmed, which is the predicted driving posture.

3.2. Parameter Acquisition

In the Society of Automotive Engineers (SAE) standard, there are provisions for the seat position reference curve. Based on the SAE human body size, the reference position of the driver’s seat corresponding to the human body of different heights is represented by a curve. Each curve represents the seat position of a typical human body. The group curve can represent the seat position of all human bodies [11]. In the engineering practice of automobile design, this curve is often used to determine the H-point area of the seat in the design stage, as shown in FIG. 5.
Fig. 5 Reference line of H point

Since this curve is set based on the SAE human body size parameters. If this curve is used directly to design the seat reference position for the Chinese customer group in actual use, there will be great deviations. The driving posture based on this design will have complained about the poor comfortable experience in actual use.

Based on this curve, the scope of using range is expanded, it is range from 5% ile female of China to 99% ile SAE male. We can select the seat travel box of the hot-selling cars based on the SAE seat position reference curve and take the intersection of the midline of the stroke and the SAE seat reference curve. Each intersection represents a driving position corresponding to human size. The distances of X and Z direction between the intersection and the heel point are the required output parameters. Based on this method, 15 sets of parameters can be obtained in the above pattern example. Similarly, multiple sets of training data can be obtained from the cars’ seat travel box. We would use the ML to predict the driving posture based on posture data, as shown in Table 1.

| Table 1. Training data for the neural network |
|---------------------------------------------|
| Input | Int1  | Int2  | Int3  | Int4  | Int5  | Int6  | Int7  | Int8  | Int9  | Option/No. |
|       | Manikin Height | L101  | W103  | H100  | L11   | H17   | H130-1| H61-1 | A124-1-L | degree |
|       | mm    | mm    | mm    | mm    | mm    | mm    | mm    | mm    | mm     | degree |
| 1     | 1449  | 1999  | 1682  | 1620  | 370   | 677   | 346   | 949   | 7.0     | 580.1 -235.7 332.6 |
| 2     | 1455  | 2300  | 1622  | 1582  | 297   | 670   | 321   | 987   | 7.4     | 611.7 -329.7 318.9 |
| 3     | 1825  | 2340  | 1630  | 1394  | 383   | 617   | 361   | 936   | 8.7     | 795.0 -330 271.0 |
| 4     | 1462  | 2383  | 1728  | 1574  | 321   | 679   | 408   | 999   | 5.0     | 615.5 -330.1 349.0 |
| 5     | 1484  | 2465  | 1690  | 1463  | 385   | 696   | 341   | 959   | 6.0     | 641.5 -335.0 321.2 |
| 6     | 1898  | 2500  | 1694  | 1488  | 441   | 642   | 373   | 1012  | 6.2     | 846.0 -333.5 264.0 |
| 7     | 1550  | 2515  | 1771  | 1645  | 389   | 674   | 427   | 981   | 6.1     | 651.2 -333.5 357.2 |
| 8     | 1568  | 2550  | 1474  | 1677  | 318   | 674   | 355   | 1018  | 9.0     | 656.0 -299.0 337.7 |
| 9     | 1605  | 2550  | 1807  | 1670  | 344   | 665   | 407   | 996   | 6.8     | 663.4 -355.0 348.2 |
| 10    | 1642  | 2632  | 1799  | 1428  | 390   | 646   | 347   | 964   | 5.1     | 728.7 -352.4 267.6 |
| 11    | 1862  | 2595  | 1743  | 1482  | 376   | 638   | 375   | 991   | 5.4     | 802.0 -360.0 280.0 |
| ...   | ...   | ...   | ...   | ...   | ...   | ...   | ...   | ...   | ...     | ...            |
4. Posture Prediction Based on Machine Learning

4.1. Deep Neutron Network

As shown in FIG. 6, our DNN model is divided into an input layer, two hidden layers, and an output layer. Since the input is distributed in a relatively wide range and has different physical meanings, it is easy to cause some small or physical input with different dimension to be obliterated in the DNN. Thus, the inputs and outputs should be normalized, and the normalization rules are as follows:

\[
\tilde{x}_n = \frac{x_n - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}
\]

(1)

\(x_n\) is the \(n\)-th sample value. \(x_{\text{max}}\) and \(x_{\text{min}}\) are the maximum and minimum values of the input layer, respectively. It worth to point out that the number of neurons in each hidden layer of the DNN is 50. In addition, the ReLU function is used to process the input of the hidden layer neurons and the Sigmoid function is involved to process the input of the output layer neurons.

![Diagram of DNN model](image)

**Fig. 6** The designed DNN of the driving posture prediction model

4.2. Model Training

In the DNN model training process, we use the directional propagation algorithm to modify the weights, and the random gradient method adjusting the weights in batches to improve the training speed. Since the gradient method will make the DNN fall into the local minimum, the momentum method is involved in our training process to modify the weight [12].

FIG. 7 presents the performance of DNN used in our design. Obviously, the prediction results can be obtained quickly, where the epochs are less than 50. Further, the learning accuracy and prediction accuracy are as high as 97% and 88%, respectively, which imply the effectiveness of the proposed prediction scheme.
4.3. Performance Evaluation
Using the uncomfortable analysis module of RAMSIS, 94 comfort analysis models are built. Using the identical input condition, we compared the output results of the model and current design from the market, a total of about 47 groups. We can see from Fig. 8 that the SgRP (seating reference point) designed by the model is basically equivalent compared with the original preferred design results, and the dispersion is better than the comparison data.

Fig. 7 The performance of DNN of driving posture prediction

5. Summary
In this paper, a large number of vehicles’ driving posture parameters were obtained through the point cloud big data using laser scanning. We set up an intelligent prediction model of driving posture based on DNN, which can be seen as a realization of the driving posture’s ability for intelligent prediction. Besides, we can use this intelligent model to make forward driving posture design for the consumer from different areas, and we can make sure everyone has a different posture, which is just for him. This effect can greatly promote the driver’s intelligent interaction feeling and the product’s commerciality.

However, due to the limitations of data acquisition conditions and experiment cost, the amount of data for model training and the selection of parameters for model construction in this paper was not large enough, which would in turn affect the accuracy of the model prediction. In the following research,
we would find some method to improve the data acquisition efficiency. So that a large amount of training sample data can be obtained, which could improve the prediction accuracy of the model, and promote the level of intelligent interactive experience.

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