Research on Intelligent Damage Assessment System for Time-sharing Rental Vehicles Based on Image Recognition

Qianqian Zhu\textsuperscript{1,}\textsuperscript{,}\textsuperscript{a}, Yingnan Liu\textsuperscript{1,b}, Ying Shen\textsuperscript{2,c} and Zihao Zhao\textsuperscript{1,d}

\textsuperscript{1} Automotive Data of China Co., Ltd., China Automotive Technology & Research Center Co., Ltd., Tianjin, China
\textsuperscript{2} China Banking and Insurance Information Technology Management Co., Ltd., Beijing, China

\textsuperscript{a}zhuqianqian@catarc.ac.cn; \textsuperscript{b}liuyingnan@catarc.ac.cn; \textsuperscript{c}sy_tsinghua@126.com; \textsuperscript{d}zhaozihao@catarc.ac.cn

Abstract. With the popularity of the concept of sharing, car sharing has become a new hot spot. Currently, there are more than 100 brands operating car sharing in the market. The group composition of car rental is relatively complex, and most of them are novices in driving technology. Some minor scratches and other injuries are easy to occur during the driving of rental vehicles, which poses new challenges to the car-sharing operation platform. Therefore, in the operation of car-sharing business, it is very important to realize the automatic determination of vehicle damage in the process of each use. This paper presents a method and system for automatic damage determination of vehicles based on the shared vehicle four-corner images. By comparing the damage information before and after renting each vehicle, this scheme can effectively save labor cost, realize rapid damage recognition, clear responsibility definition, and improve user experience and damage treatment efficiency.

1. Introduction
At present, most car-sharing companies are limited by manpower, material resources and technical capabilities, and they are unable to check the car damage together with the users when they return the car, which leads to the discovery of the damage only after the users have finished using the shared car. Users in the process of using the vehicle collision, scraping and other vehicle damage, whether truthfully reported or not, are faced with many problems.

If the user does not report the damage truthfully, the scraping, deformation and other damage may be left to the next user when they use it. If the next user reports the vehicle damage, it is impossible to know who caused the damage, and the user is likely to give up the car in order to avoid responsibility. At this time, car-sharing companies not only have to bear the damage caused by vehicle damage, but also affect users' rental experience and bear the risk of customer loss. If the user reports truthfully, the car-sharing operating company will assign front-end surveyor to the site for investigation and damage determination, and cooperate with back-end loss determination to complete the accident damage determination. This method has the following disadvantages. Every scraping of the leased car requires manpower to deal with it on site, which will greatly increase the human cost of the operating company, and the human factor will also have the problems of inaccurate damage determination and low efficiency. In addition, for users, parking and waiting for the operator to assign surveyors to inspect and fix the damage on site will affect the user experience.
Therefore, the industry is in urgent need of a set of solutions that can realize real-time and efficient automatic damage determination of shared cars. This paper presents a method and system for automatic damage determination of vehicles based on the shared vehicle four-corner images. As long as the user takes the images from the left front, right front, left rear and right rear of the vehicle respectively when picking up and returning the vehicle, and uploads them to the damage assessment module of the remote server, the damage assessment (if damage occurs) in the process of using the vehicle can be obtained after 30 seconds. This method not only protects the interests of leasing companies, but also improves the customer's car experience.

2. System Structure
The self-service damage assessment process of time-sharing rental vehicles can be divided into two parts, as shown in Figure 1. As shown in Figure 1, the first step is the user shooting part, which requires uploading to the remote server the four-corner images taken by the user when picking up the car and returning the car. The second step is the damage assessment. This module will determine the damage of the four corner images of the vehicle and output the damage location and damage type. Next, give examples for each part of the process to better understand.

2.1. User Shooting Section
The user shooting section includes image shooting and image uploading.

Module 1, image shooting module. In this part, users are required to take images at the front left, front right, rear left and rear right angles of the vehicle under the operation guidance when picking up and returning the vehicle. In order to ensure accurate recognition of components and damage, this part of the image is required to be about one meter away from the vehicle and cover 360 degrees of the vehicle as far as possible after splicing the four-corner images. As shown in Figure 2.

![Figure 2. Four corner images of vehicles](image)

Module 2, image uploading module. This part requires the user to upload a four-corner images when picking up the car, and upload a four-corner images when returning the car, and adds the image judgment function to this part. It is not allowed to upload the non current car process or non current car image, otherwise it will not pass.
2.2. **Damage Assessment Section**

Damage assessment includes damage segmentation, component segmentation and result output.

Module 1, damage segmentation module. Based on the deep learning model, this part is used to identify the appearance damage of the vehicle in the picture. Different colors represent the damage of the vehicle, such as scraping and deformation. Visualization by color is shown in Figure 3. At present, the damage recognition mainly falls into three categories, namely scraping, deformation and rupture.

![Figure 3. Damage segmentation module](image)

Module 2, component segmentation module. This part is used to identify vehicle appearance components in the picture. Different colors represent different appearance components, such as headlamp, left front door, left front fender, etc. The visual image is shown in Figure 4. At present, there are 18 types of vulnerable parts.

![Figure 4. Component segmentation module](image)

Module 3, result output module. This part is used to realize the maintenance scheme recommendation combining component materials and damage under the current damage condition. In addition, the maintenance price is recommended by combining parts price database and man-hour price database. As shown in Table1.

| Component          | Damage   | Area | Price |
|--------------------|----------|------|-------|
| Front Fender - Left| Scraping | 10%  | ¥1250 |
| Front Fender - Left| Deformation | 35% |       |
| Front Bumper       | Scraping | 9%   | ¥400  |

3. **Module Implementation**

3.1. **Data Set Construction**

The training data set is partly from the photos of damaged vehicles recorded by insurance companies over the years of business, and partly from the photos of damaged vehicles accumulated by time-sharing rental companies in the operation process. The training and validation of the model on this
data set can not only satisfy a large data set, but also well represent the expected results on the practical application target.

3.1.1. **Data Annotations.** The whole data is divided into two parts, one is the damage data set applied by the damage segmentation model, each image corresponds to a label file, which gives the image of various types of damage and the corresponding pixel area, through different coordinate values to represent different types of damage. The other is the component data set applied by the component segmentation model, which also corresponds to one annotation file for each image, in which different components of vehicle appearance are represented by different coordinate values [1], as shown in Figure 5.

![Component data set annotation](image)

**Figure 5.** Component data set annotation

3.1.2. **Data Augmentation.** In the field of deep learning, the increase of data tends to improve the accuracy and generalization ability of the model, while image segmentation requires pixel-level annotation. There is currently no publicly available data set in this field, so all data is manually re-annotated, which is costly. Therefore, data augmentation is the only choice [2].

Considering the characteristics of the current task and damage recognition, rotation, clipping, scaling and other transformations are used to enlarge the data. For components segmentation, since the data after rotation and distortion cannot be obtained in normal shooting, that is to say, the generalization ability of the model trained by it is not good in real situation, so for parts recognition, only scaling and flipping are used to obtain new data.

3.2. **Model Constructing**
In this paper, an intelligent damage determination system for time-sharing rental vehicles based on image recognition is described. By using the Mask RCNN image recognition algorithm, the damage of vehicles in the pictures can be accurately determined and the loss evaluation of vehicles can be realized.

3.2.1. **Introduction of Image Recognition Algorithm.** Image classification only needs to predict the category of objects in the image [3]. Object detection not only needs to provide the category of the object in the image, but also needs to provide the bounding box of the object [4]. Semantic segmentation needs to predict which label each pixel of the input image belongs to [5]. On the basis of semantic segmentation, instance segmentation needs to distinguish different individuals of the same class [6]. As shown in Figure 6 [7].

![Image recognition](image)

(a) Image (b) Semantic Segmentation (c) Instance Segmentation

**Figure 6.** Image recognition
In this paper, the recognition of damage and components is required to achieve instance segmentation. One of the more successful methods is Mask RCNN. Mask RCNN is an improvement on Faster RCNN by adding a simple Mask predictor. Mask RCNN training is easier, has better generalization, and only requires a little more computation on Faster RCNN [8]. The influence of the backbone network on the accuracy is a very important factor. This paper chooses the RESNEXT network as the backbone network [9].

3.2.2. Construction of Instance Segmentation Model. The damage recognition model realizes the recognition of scraping, deformation and rupture, which can output the damage type and the location of the damage. In addition, the output of two or more damage types in the case of superimposed damage in the same area can be realized. As shown in Figure 7.

![Figure 7. Damage segmentation results](image)

The system uploads images from four angles: left front, right front, left back and right back. Therefore, the orientation information is labeled as a field in data annotation, and is used as an information input model in training. Therefore, the component recognition model can realize the accurate recognition of the left and right symmetrical components while realizing the component type and position recognition. As shown in Figure 8.

![Figure 8. Component segmentation results](image)

4. Conclusion

In the intelligent damage determination system of time-sharing rental vehicles proposed in this paper, users take photos through mobile phones and other terminal devices before using the vehicles to be rented to obtain the damage situation of the vehicles before renting. When returning the vehicle, use the terminal to shoot again to obtain the damage of the vehicle when returning. In this way, through the comparison of damage information before and after renting, users can automatically identify whether the car has brought damage.

In this scheme, on the one hand, the user can clearly define the damage situation of the vehicle with the leasing company before renting it. On the other hand, the scheme does not require the operator to assign personnel to the site to determine vehicle damage, effectively saving labor costs, achieving rapid damage recognition, clear responsibility definition, and improving user experience and damage treatment efficiency.
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