A Design of Traffic Accident Analysis Algorithm based on Scene Recognition

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Abstract

In this paper, a scene recognition-based traffic accident analysis algorithm was proposed to automate the vehicle insurance claim process, and the performance was confirmed by establishing a vehicle damage dataset. As a result, it was confirmed that the average detection accuracy of the damaged vehicle of the proposed algorithm is 95%. The proposed system is processed based on the RCNN (mask region of convolutional network) model. Usage models include Convolutional Neural Network (CNN), Region Proposal Network (RPN), and Region of Interest (RoI). The results of this study are expected to be very useful in the field of automated traffic accident type identification and vehicle damage estimation.

I. INTRODUCTION

Recently, among computer vision technologies for extracting image information, research on scene recognition and object detection is being actively conducted. Most of the research uses deep learning algorithms such as Convolutional Neural Network (CNN), Residual Network (ResNet), and Region of Convolutional Network (RCNN) to extract image data. Computer vision covers the core technology of automated image analysis used in many fields such as medicine, machine vision, military and autonomous vehicles.

Applications of computer vision technology today are improving the insurance industry using automobile damage recognition and traffic analysis systems. Using these systems in the field makes it easy to analyze accident types, recognize vehicle damage, predict what types of repairs will be required, and estimate costs. Therefore, it has many advantages, such as reducing the time and effort required for human inspection and providing comfortable service.

Therefore, in this paper, we design a traffic accident type analysis algorithm using the vehicle damage location and vehicle damage volume dataset. In designing the algorithm, the type of traffic accident was analyzed using the vehicle damage location recognition result, and the degree of damage was considered using the vehicle damage recognition result. The dataset is a trained mask RCNN model and analyzes its recognition performance.

II. RELATED STUDIES

A vehicle damage detection segmentation algorithm based on the improved Mask RCNN was proposed by [1]. This algorithm is proposed to quickly solve the traffic accident compensation problem and uses an improved Mask RCNN to train the dataset and improve the detection accuracy. The results show that the improved Mask RCNN has better detection accuracy and AP value.

Vehicle damage detection and classification using deep learning-based algorithms has been proposed using VGG16 and VGG19 [2]. This algorithm detects damage in vehicle advertisements and evaluates their location and severity. In detecting damage, VGG19 is 95.22% accurate and VGG16 is 92.56%. At the location of the damage, VGG19 has an accuracy of 76.48% and VGG16 has an accuracy of 74.39%. Comparing these two results, VGG19 outperforms VGG16 in vehicle damage detection and classification.

III. PROPOSED ALGORITHM

3.1 Design Philosophies

The direction of the algorithm design is to automate the vehicle insurance claim process by analyzing the types of vehicle accidents [3]. Above all, in order to analyze the accident type, the classification process of vehicle damage location and vehicle damage size is important. This paper presents the design philosophies of the dataset construction and recognition process as follows.

- To build datasets of vehicle damage location and vehicle damage volume, each dataset collected 20 images for training and 5 images for validation and 3 images for testing.
- In image annotation process, each image marked using the making tool labeling and save as json format.
- In training process, it was trained by 100 epochs with prep-trained coco dataset and the learning time was about 30 minutes.
- After training the dataset, recognition process is run using trained dataset and Mask RCNN framework [4].

3.2 System Overview

In this paper, we proposed a scene recognition-based traffic accident analysis algorithm to automate the auto insurance claim process. In order to analyze the type of traffic accident, it is necessary to detect the vehicle's path and detect the type of traffic accident. This algorithm can detect and use parts of the damage location to help consider what type of accident has occurred. To figure out what kind of repair is needed and how much it will cost, this algorithm can also detect standard damage volume levels such as A, B, S, N levels based on the ABI category information.

3.3 Algorithm Design

The proposed algorithm is designed based on an object detection system including a dataset and a deep learning model as shown in Fig. 1. The main core of algorithm design is **traffic accident types analysis**. Estimating the location of vehicle damage is very important for analyzing the type of traffic accident.

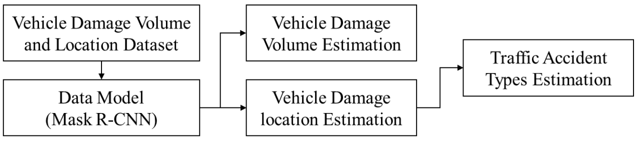

Fig. 1. Algorithm concept.

For the analysis process, a dataset of vehicle damage and location images is collected and trained by the Mask RCNN data model. We also use the vehicle damage data set and the Mask RCNN framework to perform the vehicle damage amount and damage location estimation process. After obtaining the results, we use the location of the vehicle damage to perform an accident type analysis.

3.3.1 Vehicle Damage Volume Estimation

Building a vehicle damage image dataset is an important part of both **vehicle damage volume estimation** and **vehicle damage location estimation**. Therefore, the proposed algorithm collects enough vehicle damage images and performs image annotation on each image. The image dataset is then trained as a data model. After training the data set, we perform the vehicle damage estimation process using the trained dataset.

In the estimation process as shown in Fig. 2, a vehicle accident image is input and the image is extracted as a feature map. Using this feature map, the damage part is extracted with the bounding box, and the extracted damage part is classified at what level of damage volume.

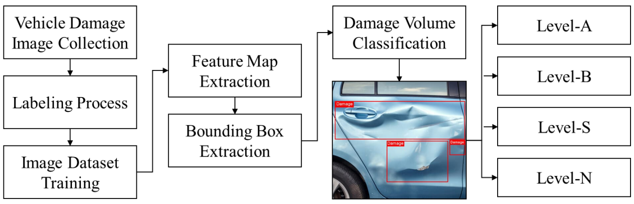

Fig. 2. Architecture of vehicle damage volume estimation.

In this paper, the standard of vehicle damage volume is defined according to Association of British Insurers (ABI) category information such as level A, B, S and N as shown in Table I.

3.3.2 Vehicle Damage Location Estimation

It is also important to build another dataset for estimating the location of vehicle. Building the dataset proceeds in the order of collecting enough vehicle damage images, performing image annotation processing on each image, and training the image dataset with the data model shown in Fig. 3.

TABLE I. ABI CATEGORY INFORMATION OF VEHICLE INSURANCE

ABI category information of vehicle insurance	
Level-A	Scrap only
Level-B	Break and crush body shell or chassis
Level-S	Structurally damaged but repairable
Level-N	Non-structurally damaged but repairable

The vehicle damage location estimation function defines vehicle damage locations as front, left, right, and rear. The vehicle damage location estimation part plays an important role in the **traffic accident types analysis**.

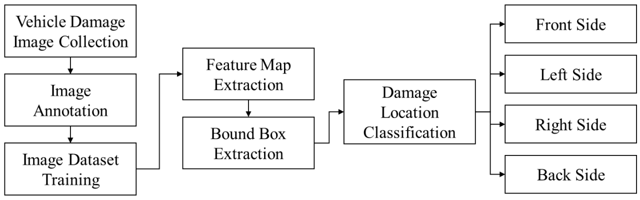

Fig. 3. Architecture of vehicle damage location estimation.

3.3.3 Vehicle Accident Types Analysis

A vehicle accident analysis algorithm was designed for only two vehicle accident situations. First, the crash vehicle is set to VEHICLE -A and VEHICLE -B, both crash vehicles detect the damage location, and then analyze the vehicle accident type through the damage location. According to Fig. 4, the proposed algorithm can recognize the types of traffic accidents from front to right, front to left and right, and front to rear.

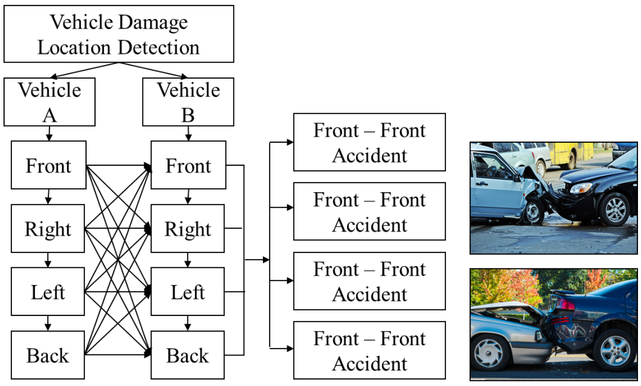

Fig. 4. Architecture of vehicle accident types analysis.

Considering the type of accident, if the damage location of VEHICLE-A is in the front and the location of damage in VEHICLE-B is in the front, it is recognized as a front accident. If the breakage location of VEHICLE-A is at the front and the breakage location of VEHICLE-B is at the rear, the system recognizes this as a front-to-rear accident.

IV. EXPERIMENTS AND RESULTS ANALYSIS

4.1 Experimental Environment

4.1.1 Labeling

The labels are predetermined by the machine learning engineer and are chosen to provide information about the computer vision model shown in the image as shown in Fig. 5.

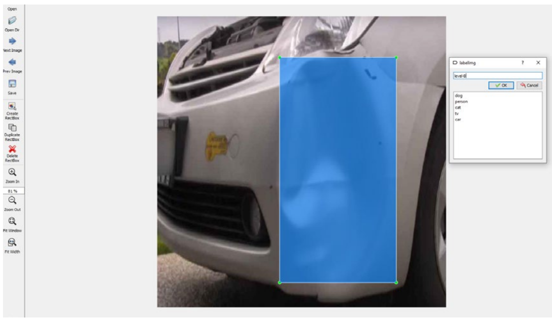

Fig. 5. Labeling in vehicle damage image.

4.1.2 Experimental environment information

As shown in Table 2, the hardware used for the experiment is a GeForce RTX 2080Ti GPU, and the software is Python 3.7, Tensorflow 1.3.0, Keras 2.0.8, Mask RCNN framework, Window10 64bit.

TABLE II. SPECIFICATION OF HARDWARE AND SOFTWARE FOR EXPERIMENTS

	Specification	
HW	GPU	GeForce RTX 2080Ti
SW	Python version	3.7
	TensorFlow version	1.3.0
	Keras version	2.0.8
	Framework	Mask RCNN
	Operation system	Window 10 64bit

4.2 Experiment Results on Vehicle Damage Detection

To validate the accuracy of vehicle damage volume, an experiment was performed using 20 images of damaged vehicles and 20 images of undamaged vehicles. According to Fig. 6, vehicle damage detection results are tested using a confusion matrix table. The experimental results confirmed that in the damaged vehicle image test, the system correctly detected 19 out of 20 images and correctly detected all images of the undamaged vehicle image.

	Damaged	Undamaged
Damaged	19	1
Undamaged	0	20

Fig. 6. Confusion matrices for vehicle damage detection.

According to Fig.7, the average detection accuracy of the damaged vehicle image test is 95%, and the average detection accuracy of the undamaged vehicle image is 100%. Since the performance of detection accuracy can vary depending on the dataset and data model, improvements in the dataset and data model can improve the detection accuracy performance.

V. FURTHER STUDIES AND CONCLUSION

In this paper, we propose the traffic accident analysis algorithm based on scene recognition to automate the vehicle insurance claim process. As a result of the experiment, it was confirmed that the vehicle damage detection accuracy of the proposed algorithm was 95%.

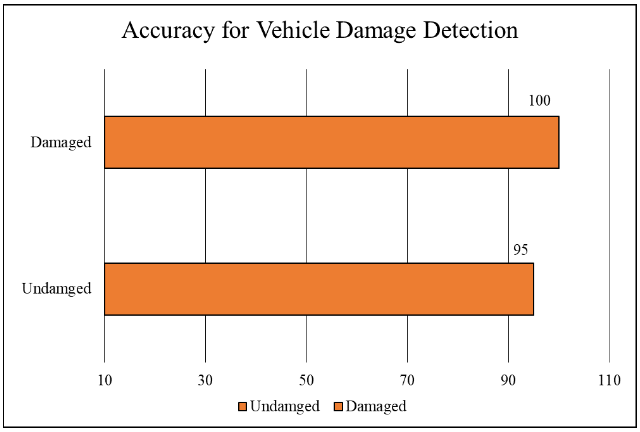

Fig. 7. Vehicle damage detection accuracy.

The purpose of this paper is to detect the location of damage to the vehicle and the amount of damage to the vehicle, ultimately to analyze the accident type, and to estimate the repair type and cost. However, it is very difficult to accurately detect the location and volume of vehicle damage, so better datasets and data models need to be built to improve performance. In practice, we tried to solve the problem using the popular models Mask RCNN, Yolov5, and detectron2, but there was still difficulty in detecting damage.

However, in the future, we plan to use the new data model to improve the algorithm and also detect vehicle routes to better analyze types of traffic accidents.

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