Automatically Segmentation the Car Parts and Generate a Large Car Texture Images

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Abstract: This study is segmentation the car parts in a car model data collection and then use the segment car parts to generate large car texture images to provide automatic detection and classification of future 3D car models. The segmentation of car parts proposed in this study is divided into simple and fine car parts segmentation. Since there are few texture images of car parts, this study produces various parts to generate many automobile texture images. First, segment the parts after texture images in an automated method, change the RGB arrangement, change the color, and rotate the parts differently. Also, this study made various changes to the background, and then it randomly combined large texture images with various parts and the background. In the experiment, the car parts were divided into 6 categories: the left door, the right door, the roof, the front body, the rear body, and the wheels. In the performance of automated car parts segmentation technology, the simple and fine car parts segmentation has good results in texture images. Next, the segment car parts and use multiple groups to generate large car texture images automatically. It is hoped that we can practically apply these results to simulation systems.

1 INTRODUCTION

Autonomous vehicle (autonomous vehicle) and virtual reality (VR), augmented reality (AR), and mixed reality (MR). In the latest technological development, three-dimensional simulation system has become the main research trend in computer vision. A simulation system is a system that presents real-world situations and physical feedback. It is applied to autonomous driving, medical technology, military training, aerospace technology, disaster response, etc. To make the simulation system more widely used and make the user's senses on the simulation system more realistic, when entering different situations, they can more experience the reproduction of the actual scene, allowing the user to experience multiple visual feelings, and the simulation in the real scene contingency and operation in a different environment. According to the material properties assigned to the objects in the simulation system, the system can present the effects corresponding to the real world through the material properties and reflect various environments' physical characteristics in the real world.

In the real world, the color and texture of an object can be visually distinguished from its parts and types by the appearance attributes such as the refraction angle of illumination, color, and transparency of the light source, and determine the material properties of various parts. However, if the parts of an object are manually identified and the types of the parts are marked one by one. Then the type of information of these objects is input into the simulation system. It will cost a lot of workforce and time.

Texture images can compare objects' appearance better than shading and make the 3D model present a more realistic simulation system. However, in the absence of material information, the simulation system's choice of situations will be limited. Therefore, if the texture map can be classified into the material first and map the label of this classification to the 3D model and save the workforce and time of sailing, it can also adapt to the simulation system of different environmental changes. Even so, the number of texture images corresponding to the 3D model is not much. Take the texture image of a car as an example, as shown in Figure 1. Therefore, in addition to the material classification of texture images, this study also proposes a method to generate

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large texture images to detect and classify future 3D car models automatically.

Figure 1: Texture image of the car.

To extract an object from an image, the commonly used method is object segmentation. To accurately distinguish the background and object area of the image from the image, it depends on the precise image segmentation technology (Gonzalez and Woods, 2002; Pandey et al., 2019). In the past, image segmentation methods can be divided into three categories according to image pixels' characteristics. The first type of method is called discontinuity, which refers to the area where the pixel intensity value changes drastically. The algorithms of this type include the Gradient method (Gonzalez and Woods, 2002), Sobel edge detection (Gonzalez and Woods, 2002; Kubicek et al., 2019), Canny edge detection [3,4,5](Canny, 1986; Xu et al., 2019), Laplacian edge detection(Gonzalez and Woods, 2002), and Laplacian Gaussian edge detection. The second type of method is called similarity, which is based on pre-defined criteria and segmentation of similar regions of the image, including Threshold Method (Gonzalez and Woods, 2002), Area Growing (Zhao et al., 2015), Region Splitting and Merging (Gonzalez and Woods, 2002), and Clustering (Zhao et al., 2015). The third type of method is hybrid techniques, which integrate edge detection and region-based methods to obtain more accurate image cutting results (Wang et al., 2016).

This study uses traditional image processing technology to automatically segment parts from the existing two-dimensional car texture images and generate many car texture images from the segment parts. When building a car texture image, in addition to the placement and number of layouts based on the fineness of the car surface, the car parts also be separated. Therefore, this study first performs segmentation of the two-dimensional texture image and then generates large car texture images for the segment parts.

This study has two contributions. First, to reduce the cost of marking object categories, this study uses traditional image processing technology to auto-segment parts with two-dimensional texture images. Second, this study produces the background changes of different texture images of the object model and changes the shape, color, and rotation of the parts and the background color system, and randomly generates many texture images.

2 MANUSCRIPT PREPARATION

This study separates the car parts from the existing car model's texture image by automatic segmentation method. It then generates large car texture maps from these parts to provide the future 3D car model to detect and classify car parts. The processing flow is shown in Figure 2. This study is divided into two stages. The first stage uses automated segmentation technology to segment the parts of two-dimensional car texture images. In the second stage, various types of changes and different background types are added to these parts to generate large car texture images.

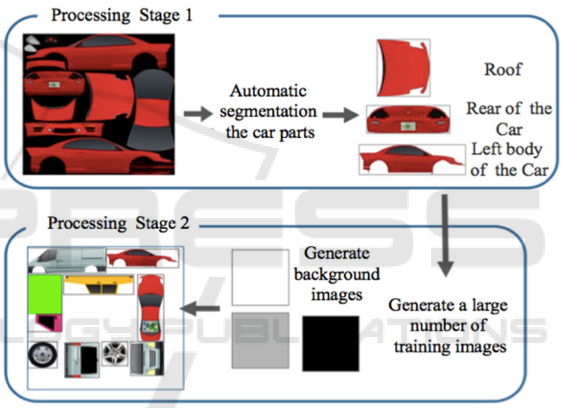

Figure 2: The processing flow of this study.

2.1 Automated Segmentation of Car Parts

The two-dimensional car texture image is composed of multiple parts. Because the parts are closely arranged, and there are no rules, the texture's presentation method varies for the creator. The styles presented on the texture also have obvious differences, as shown in Figure 3. Therefore, this study proposes a segmentation technology for car parts. Two different segmentation technologies are proposed according to the different characteristics of the texture images. The first segmentation technology is for textures with large differences between the parts and the background color and is called the simple segmentation method of car parts. The second segmentation technology is for textures with small differences between the parts and the background color and is called the fine segmentation method of car parts. The two segmentation technologies used above are referred to as automated segmentation of car parts.

Figure 3: Texture image of the car.

Simple Segmentation Method of Car Parts: First convert the color car texture image into a grey image, then do the binary image, and finally perform the part's labelling to detect the part and segment.

Fine segmentation method of car parts: if a simple segmentation method is used to the color difference between parts and the background color in an image is small, and the parts cannot be completely segmented. Therefore, this study first converts the color image into a grayscale image, then adjusts the contrast of the image grayscale by histogram equalization, then performs binarization, and then uses erosion blurring to remove the impurities of the part. Finally, the parts are labelled, and the parts can be detected and segmented. The processing flow is shown in Figure 4. To filter the overlap of some parts, large objects segment to more than two parts are caused. Therefore, after calculating all parts' size in this study, if the cut part's length or width exceeds 4000 pixels, we convert the part image to a grayscale image. Then the grayscale image is binarized to the opening is processed to remove the noise between the parts, and then the parts are cut so that we can cut out those independent parts.

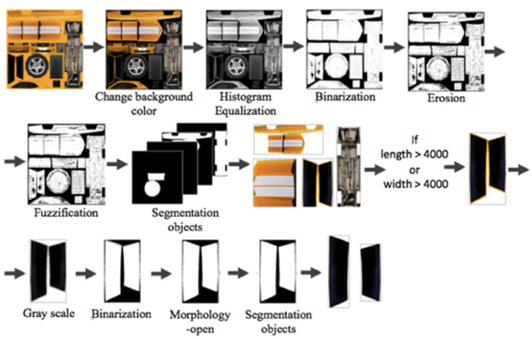

Figure 4: Fine segmentation process flow of car parts.

Histogram Equalization: When the color of the parts in the texture image is similar to the background, the parts are not easily separated from the background, or the parts' outline is less obvious. Therefore, this study equalized the histogram of the grayscale image to make the overall color scale distribution of the image more uniform to enhance the contrast of the image color scale and improve the discrimination between the part and the background.

Gaussian Blur: The parts in the texture image are the areas surrounded by contour lines, and they are enclosed in a closed shape. Because some parts in the texture have light shades and noise points in the background area, this study uses Gaussian blurring to reduce the image's noise.

Binarization: First convert the color texture image into a grayscale image, then use Otsu's(Otsu, 1979) method to obtain the binarization threshold, and finally binarized the grayscale image.

Erosion: It uses a fixed-size filter to perform a convolution operation on a grayscale image.

Dilate: Use filters of different sizes to perform convolution operations on grayscale images.

Contour: This study can obtain the contour of the part by subtracting the original part from the area of the part that has been eroded or expanded.

Segmentation of Parts: After obtaining the contour mask of each part one by one, we can obtain the parts in the original texture corresponding to the mask area.

2.2 Automatically Generate Large Car Parts Texture Images

Due to the small number of existing texture images, there are not many parts. Therefore, to increase the number and variety of training images, this study produces large and diversified texture images for training. First, make different changes to the parts after automatic segmentation, such as the RGB channel arrangement, color, and parts of different angles. We also make different changes to the textured background and then randomly combine various parts with the background to generate large texture images, which can be used as training images for future deep learning models. This study changes the shape, color, and rotation of the parts and the color system of the background and then randomly combines them to generate a large number of texture images.

The Shape of the Part: The part's appearance is changed on an equal basis and meets the part types of conditions. This study adds three new arrivals: (1) Add red rear lights and exhaust pipes on the rear body of the car and the rear windshield, as shown in Figure 5.; (2) The yellow headlights and cyan headlights of the front body of the vehicle are added, as shown in Figure 6.; the tire frame and part of the new car tires. The tire frame and tire skin are shown in Figure 7. Figure 7b. is to remove the black part of the tired skin in Figure 7a., and only the silver tire frame is taken; Figure 7c. is to extract the disc surface pattern in the center of Figure 7b.; Figure 7e. is to take Figure 7d. The black tire skin part. In this study, we added additional small details to the original parts and extracted some features from the original parts, and we added parts and quantities in this way.

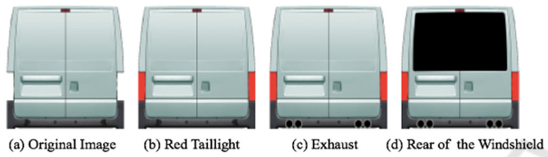

Figure 5: The car rear body.

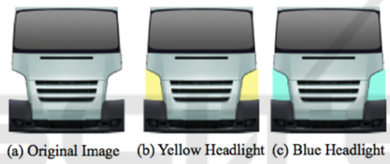

Figure 6: The car front body.

Figure 7: Car tires.

The Color of the Parts: Because the car's metal shell has the possibility of various colors, this study changes the order of the RGB channels to combine the parts with multiple colors. The way to change the channel is to change the RGB channel's arrangement without changing the RGB value. A total of 6 arrangements (RGB, RBG, GRB, GBR, BGR, BRG) can generate 6 different color textures images.

Rotation of Parts: randomly rotate each part, the angle of rotation is in units of 90 degrees, and the range of part rotation is from 0 to 270 degrees.

Background Color: After observing the background color of the original texture image, this study uses white, grey, and black as the background color of the new texture image.

Texture image generation: Because of the irregular arrangement of the parts of the texture image, the angle, and direction of the placement are also not fixed, the number of types of parts is also different, and the background colors of the textures are also quite diverse. Therefore, this study generates large car texture images based on the original texture images' design and placement. The production process is shown in Figure (17)-first, randomly select parts from all categories, with 8 to 10 parts. Next, the rotating parts are arranged in a non-fixed interval, and finally, various parts are randomly arranged and placed to generate large car texture images.

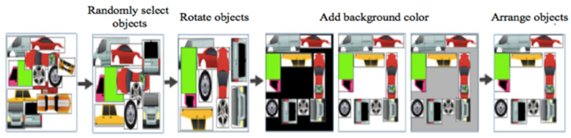

Figure 8: The process of generating texture images.

In this study, the number of parts categories, part type, and RGB channel sorting is used to generate texture images. The texture training set will be generated in 4 different ways, called "Type-1", "Type-2", and "Type-1", "Type-2", and "Type-2". The "Type-3" and "Type-4" texture training sets are generated and combined. The number of parts categories in the table is the number of parts categories in the generated image, divided into "all categories" and "single category only." The part types are combined by "original parts" or "newly created parts," respectively. The RGB channel refers to the "grayscale part image" and "the arrangement and combination of all color channels." Type-1 is a new texture image composed of all parts categories, original parts, and 6 color images. Type-2 is a new texture image composed of all types of parts, newly generated parts, and grayscale images. Type-3 is a new texture image composed of all parts categories, newly generated parts, and 6 color images. Type-4 is a new texture image composed of all single part types, newly generated parts, and 6 color images.

3 EXPECTED RESULTS

This experiment uses a small amount of 2D car model datasets. In addition to verifying the effectiveness of the automatic segmentation of car parts proposed in this study, we also segment the car parts to generate large car texture images. In this experiment, the 2D car texture image is used for the automatic part segment. The car part images are produced according to different settings to produce multiple sets of different types of image data.

3.1 Experimental Environment

In this study experiment, the CPU processor system is Intel Core i7-4790, the GPU processor is NVIDIA GeForce GTX 1080Ti 11GB, and 16GB memory is used. The host uses Windows 10 as the system environment, the programming language uses Python, and the image pre-processing and other image processing programs use the OpenCV Library.

3.2 Datasets

The parts in the texture image of this experiment are all related parts of the car body. In this study, five texture images with target types of parts are selected for use in the cutting experiment of texture image parts. Among them, there are mainly two styles of 3 images of "cars" and 2 images of "RVs." On average, each image has 6 different types of parts.

3.3 Car Parts Segmentation Results and Analysis

The experimental evaluation of the part segmentation of the car texture image is based on the number of parts after the division and the part appearance's completeness as the judgment standard. There are a total of 88 car parts in the experiment. After simple segmentation, the correct part number is 61, the loss parts are 27, and the over segment parts are 62. There is no gap between the parts, and the color difference between the background and the parts is small, resulting in unsatisfactory segmentation results. After fine segmentation, the correct part number is 59, the loss parts are 29, and the over segment parts are 19. The number of correct cuts for fine segmentation has been reduced by two, but the number of over-segment parts has been reduced from 62 to 19. Finally, the results of the two segmentation are combined to obtain parts for simple and fine segmentation.

3.4 Generate Texture Images of Car Parts

Since the ready-made 3D model provides few texture images, the texture image production method is artificially generated, so there are no rules. The parts are not easy to separate, and there are not many parts after segmentation. Therefore, this study creates training images with diversified parts. First, the texture image parts automatically segmented, change the RGB channels' arrangement, change the color and rotate the parts. Also, various changes are made to the background. Large texture images are randomly combined with various parts and backgrounds to serve as training images for deep learning models.

Table 1. is a statistical table of the number of parts in this study. There are a total of 50 original parts from the texture image. Among them, the number of parts for the front body is the least, with only 3 parts for the front body, and the number of parts for the wheels is the most, with 20. Therefore, this study modifies the color of the original parts, attaches small parts to the original parts, and increases the parts' diversity and applications. Finally, 281 parts, the original parts, and the newly added parts generate large car texture images.

Table 1: Statistics of the number of parts.

Class label	Number of parts after segmentation	Add parts	Parts total
The car left body	6	39	45
The car right body	4	26	30
Roof	12	4	16
The car front body	3	117	120
The car rear body	5	20	25
Wheel	20	25	45
Parts total	50	231	281

Table 2. shows the initial number of images, the number of parts, and additional training sets for the subsequent 4 groups. Type-1 is a new texture image composed of all parts categories, original parts, and 6 color images. Type-2 is a new texture image composed of all parts categories, newly generated parts, and grayscale images. The content of the data set has changed more than the Type-1 data set. Type-3 is a new texture image composed of all parts categories, newly generated parts, and 6 color images. Type-4 is a new texture image composed of all single part categories, newly generated parts, and 6 color images so that the number of parts is more even.

Table 2: Statistics of the number of parts and training images.

	Image	Type-1	Type-2	Type-3	Type-4	Total
Left car door	6	305	450	245	2240	3246
Right car door	4	240	460	275	2095	3074
Roof	12	245	570	355	2090	3272
The car rear body	5	285	450	300	2125	3165
The car front body	3	260	605	385	2155	3408
Wheel	20	305	565	295	2080	3265
Parts total	50	1905	3100	1855	12785	19695
Image total	5	4500	10500	5250	6300	26555

4 CONCLUSIONS

This study proposes a set of processing procedures for the material classification of the part model of the simulation system to reduce the manual increase of the part model's material information and reduce the huge workforce and time. The texture image hand first uses traditional image processing technology to segment various parts in the texture image and generate large texture images. The part classification of 2D texture images is to overcome a small number of texture images. The texture image used in the experiment has a total of 88 parts. After the automatic segmentation experiment, the number of fine segmentation is reduced by two than the correct segmentation of simple segmentation. Still, the number of over-segment parts is reduced from 62 to 19. The reason is that there are no gaps between the parts, and the color difference between the background and the parts is small, resulting in unsatisfactory segmentation results. The two segmentation methods have good results in different texture images. Combine the results of the two segmentation to obtain automatically segmented parts. This study automatically segmentation the texture image parts, changes the arrangement of the RGB channels, changes the color and rotation of the parts, etc., and makes various changes to the background and randomly combines large texture images of various parts and backgrounds deep learning model. Training images to improve the classification accuracy of the parts category.

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