Research Article

Design of an Image Integrated Processing System for Improving Efficiency of Electric Vehicle Supporting Products

Jianyun Xu [1] **, Hui Wang,**[2] **Shuang Lin,**[3] **and Li He**[4]

[1]*School of Art and Design, Taizhou University, Taizhou 318000, China*
[2]*Hangzhou Dianzi University, Hangzhou 310018, China*
[3]*School of Art and Design, Taizhou University, Taizhou 318000, China*
[4]*Creative Design Manufacturing Collaborative Innovation Center, China Academy of Art, Hangzhou 310024, Zhejiang, China*

Correspondence should be addressed to Jianyun Xu; xu-jianyun@tzc.edu.cn

This study analyzes a solution that requires efficient and comprehensive processing of images of a large number of vehicles and their related parts, such as batteries, plastic fastening components, and brake discs, during the design investigation of electric vehicle accessories. The problem involves the extraction of the outer contours of different components, which is important to build a comprehensive image processing system that can handle different vehicle accessories. In this study, a comprehensive image processing system is proposed, which introduces an improved GrabCut and computer vision methods. It can complete the positioning of vehicle batteries, the fastening of automobile components, and the identification of brake discs, which improves the efficiency of inspection and design work. The improved GrabCut uses adaptive median filtering on the electric car accessory to reduce noise from the surface in variable degrees. The image is then sharpened using the Laplacian operator, followed by a contrast-limited histogram equalization (CLAHE) algorithm to boost the image brightness. We have compared our proposed work against existing techniques, i.e., the GrabCut algorithm, region growing algorithm, and K-means algorithm. The comparison clearly shows that our proposed work achieves a much better peak signal-to-noise ratio value as compared to the existing techniques.

1. Introduction

Fuel vehicles have a history of more than 100 years in this world. Due to the shrinking of oil resources, the pressure of environmental pollution is increasing. Electric vehicles, which are environmentally friendly and can solve transportation problems, are becoming more and more popular. It is liked by many automobile consumers. Major automobile manufacturers and newly established enterprises participate in the design and manufacture of electric vehicles. According to the latest data released by JATO, in 2021, the global electric vehicle sales will be 4.2 million units, and the share will double from 3.1% to 6.2% from 2020 to 2021. This will increase sales of electric vehicles, increase the market share of electric vehicles, and increase the demand for products supporting electric vehicles. Electric vehicles and traditional fuel vehicles are very similar in shape. Due to

the difference in energy utilization and transmission methods, there is a huge gap between them in terms of internal structure [1–3]. Some equipment can use the supporting products of fuel vehicles, and there are many products and equipment that require targeted development, which is carried out according to the characteristics of electric vehicles, such as electric vehicle charging devices, electric vehicle fire safety devices, and electric vehicle parking devices. The design of supporting device products requires data related to electric vehicle products, such as the body size of the electric vehicle and the structure and layout of the power battery.

Repeated collection, effective analysis, and orderly storage of various types of information require designers to consume a lot of time. The time required for this product research process accounts for more than 35% of the entire conceptual design process. Among many engineering

support information, engineers spend 40% of their time searching and reorganizing data. In the development of new products, it is necessary to clarify the nature of the product and eliminate the uncertainty. Design research is a crucial element in the process. Based on the fierce market competition and the renewal iteration of design, the manufacturer's internal technology development is also looking for a breakthrough direction in the future. Professional and effective research can comprehensively understand the situation of target products and formulate development strategies. Only when designers have sufficient research information, they can use the mastered design methods to carry out creative activities [4, 5]. From a pure product point of view, it is permissible for some supporting products to have a long development cycle, but some supporting products are aimed at safety issues. For social responsibility, the development cycle of products must be fast. For example, research and development of products are related to spontaneous combustion protection of electric vehicles. The power batteries that can be applied on a large scale in electric vehicles on the market are mainly lithium batteries. As an energy storage device, the battery has a high energy density and is easily stimulated by the external environment (overheating, overcharge, discharge, impact, extrusion, short circuit, etc.) with the influence of its own manufacturing defects, and a significant amount of heat and gas is generated, causing the thermal runaway of the battery, and finally triggering a fire or explosion accident. The increase in the sales of electric vehicles has also led to an increasing trend of safety accidents such as spontaneous combustion and the fire of electric vehicles. At the stage when the power battery is not safe and controllable, it is necessary to quickly introduce corresponding automatic safety protection devices designed according to the technical characteristics of electric vehicles, which reduces the loss of surrounding properties and eases people's anxiety about the potential safety hazards of electric vehicles [6, 7].

In recent years, the rapid rise of China's automobile industry has driven the upgrading and transformation of the brake disc industry [8, 9]. As a typical casting in the industrial field, the production of brake discs is mostly done manually, and the demand for automation is high. The introduction of machine vision technology can greatly drastically labor intensity and improve production efficiency. Taking the brake disc as the region of interest for image segmentation can further improve the matching speed and accuracy, which is of great significance to the realization of industrialization and upgrading of enterprises. Furthermore, it is also of great significance to identify the fastening clips on the automotive plastic assembly [10]. At present, there are three main types of target segmentation methods based on machine vision, namely, the neural network (NN) segmentation method, the traditional automatic segmentation method, and the interactive segmentation method [11].

Images captured by industrial cameras are often noisy when aiming at the complex production site environment of electric car accessories, which includes changing light conditions. The edge information of rough-processed electric vehicle accessories is relatively blurred, making it easy to merge with similar backgrounds. GrabCut and computer vision approaches are used in the entire comprehensive processing system for dealing with various automobile methods. This can improve the efficiency of inspection and design by completing the positioning of automotive batteries, the fastening of automobile parts, and the identification of brake discs.

The rest of this study is organized as follows: in Section 2, related work is presented. In Section 3, the proposed work is discussed followed by the experimental results in Section 4. Finally, this study is concluded and future research directions are provided in Section 5.

2. Related Work

The first category is NN-based segmentation methods. Some scholars have proposed an image segmentation algorithm based on Mask R-CNN (conventional neural network) and watershed algorithm [12]. It achieves accurate segmentation of complex backgrounds and better real-time performance. Other scholars try to solve the image segmentation problem using several state-of-the-art semantic segmentation methods. They are based on deep CNNs. Other scholars have proposed a general training strategy that integrates prior knowledge into the neural network for end-to-end training of the regularized model. This method can adapt to different segmentation tasks and has high model accuracy [13, 14]. A Res-UNet network-based segmentation method for microstructure images was subsequently proposed. It significantly improved the segmentation accuracy of material microstructure images. The neural network models of the above methods require a large quantity of data for training [15, 16]. However, there are many kinds of brake disc materials, the manual detection steps of the fastening clips on the plastic assembly of the automobile are cumbersome, and the colors are different. It leads to the phenomenon of gradient disappearance during the training process, which makes the algorithm fall into the local minimum value and cannot be seen [17–19]. Therefore, at this stage, deep learning is difficult to solve the problem of complex background removal of auto parts such as brake discs and batteries [20]. The second category is traditional automatic object segmentation methods. Some scholars have proposed a workpiece surface image segmentation algorithm that combines multiscale top-hat and morphological opening and closing reconstruction, which uses the maximum succession method for segmentation and can more accurately segment the defects on the workpiece surface. Some scholars have proposed an improved K-means algorithm to remove the background of the workpiece, which has good anti-interference ability to uneven illumination. An adaptive threshold image segmentation method based on sharpness evaluation is also proposed, which can adaptively and accurately find a reasonable threshold and has excellent segmentation performance. Some scholars have proposed a K-means algorithm that combines semantic information and image depth information, which can correctly segment the object of interest with high extraction accuracy. Some scholars have proposed a segmentation method of elliptical spot adhesion image

[21, 22]. This method uses the equiangular hexagonal rotation operator to fill the black spot area on the black and white image, which avoids the oversegmentation of the image and can meet the needs of the high-end production process and precision requirements [23]. The above algorithms can achieve ideal image segmentation in simple scenes, but when dealing with image segmentation in unstructured environments with complex backgrounds, the results are often unsatisfactory due to the lack of targeted improvements to the scene [24, 25]. The third category is interactive object segmentation methods. In 2001, some scholars applied graph cuts combined with the min-cut-max-flow method to image segmentation for the first time. Rother et al. proposed the GrabCut algorithm, which is an iterative graph cut algorithm that divides the image into foreground and background, thereby achieving image segmentation with less interaction. Then, some scholars proposed a segmentation algorithm that combines graph cut with image histogram, which can solve the shortcoming of the graph cut algorithm being insensitive to small objects. The interactive target segmentation algorithm initially divides the foreground and background information through interaction, and the segmentation results are more accurate, but it is sensitive to noise and not robust to illumination changes [26].

Image recognition is primarily based on image processing, which is carried out under various links that take the image as the object in the recognition process. Its specific content includes functions such as encoding, compression, restoration, and segmentation. In image processing, the input image is typically used as the starting point, and the output image is typically also an image. The image that has been processed is fed into this process. Normal operating conditions result in the processing of the output type and image structure analysis. To put it another way, image recognition is the process of determining the type of object after it has been processed in the original image. Several steps are taken after the original image is processed [27]. They include the extraction and comparison of its own features. The sample library resources are used as a reference during the analysis and comparison. It is used to determine the type of image that has been created. The process of image recognition can also be thought of as the process of researching the classification and description of images, which is a subset of research. After extracting the objects from the image itself, it is distinguished by their shape, texture, and other characteristics to be extracted. In most cases, the image processing process is included in the link between the image feature extraction and the image feature extraction process. As soon as the object type has been identified and recognized, it can be further evaluated at the structural level. It should be noted that the number of objects in an image has no effect on the recognition process at this stage of the recognition process in the process of image recognition. There are three main stages in the process of recognition, and each stage has its own set of characteristics that must be considered.

In terms of image recognition technology in the detection of actual mechanical parts, this technology is relatively common in the implementation process. The image serves as the primary research object in this work. When using a comprehensive statistical analysis, it is feasible to grasp the internal structure law and define the image with greater precision than previously possible. After extracting the internal object features, the essential features provide a significant amount of support for the development of image recognition systems. The statistical method is implemented using the scientific concept of mathematics and decision analysis. However, before it can be applied practically, it is necessary to develop a statistical recognition model that can meet the technical requirements of various image recognition applications. Statistical image recognition is flexible in practical applications; it also has certain characteristics that distinguish it from other methods. This picture can be used to provide solid technical support for nondestructive testing of mechanical components because image data error is kept to a bare minimum. The Bayesian model, which is the most commonly used, can help in solving the challenges of finding the optimal decomposer, but it has its own set of limitations.

In the entire process of image recognition technology, the syntax is primarily used to describe the classification features of symbols, which is the most important part of the process. In general, it is regarded as an adjunct to statistical research, and it can play a role in certain types of research and analysis. Image recognition technology is commonly used in the nondestructive damage reduction of mechanical parts. The reference syntax for this technology must first clarify the syntactic layered structure, and then the image should be used as the object for layering. After the subobject is formed, a targeted recognition method is implemented. Symbols are used to describe visual representations. As a result of the use of syntax in image recognition technology in practical work, the ability to recognize patterns can be effectively increased, allowing for the analysis of objects and the recognition of object structures; as a result, image recognition technology's practical application criteria are met. However, there are some flaws in the syntax recognition technology as well, which can be recognized in another context. As a result, if there is too much external interference during the recognition process, the subimages of the image will not be accurately extracted, resulting in an increase in image recognition error. As a result, the accuracy and reliability of image recognition cannot be effectively ensured. Image recognition technology should pay particular attention to the effective function of the image acquisition system throughout the process of nondestructive testing of mechanical parts to truly ensure the accuracy and reliability of image recognition. During the continuous development of current science and technology, the method of image acquisition is being continuously optimized to achieve the best possible results. From the early solid-state image sensor to the current advanced solid-state image sensor, it is primarily based on the charge-coupled device (CCD). This technology has achieved significant innovation and has produced positive results in real-world applications. It is possible to effectively avoid the scanning distortion by using electronic scanning, which is more convenient in computer network connections and has a higher resolution in image processing

when using electronic scanning wider. Meanwhile, due to image processing noise and other issues, the detected object has uncertainty in terms of its shape and structure, and effective results cannot be achieved successfully in the process of template matching, resulting in a lack of absolute accuracy. Under normal circumstances, it is necessary to evaluate each point on the image to determine the matching metric between the template and the image, which has a certain influence. In the observation, as long as it is discovered that when the matching metric exceeds a certain threshold, it can be determined that there is an object to be detected on the image, and it can be concluded that the object has been detected. In the classical image matching method, the matching measure is determined through mutual calculation, and the mismatch measure is determined by using the absolute squared difference as the mismatch measure. In real-world situations, the applications of these two methods frequently encounter the problem of degree mismatching. The matching method of geometric change is, therefore, more beneficial in that. It contributes to improving the actual stability of its effect, allowing it to produce the desired effect more consistently.

The three methods listed above are primarily used to remove background from nonbrake discs and automotive plastic fastening workpieces. They are not optimized for the actual production environment of these electric vehicle accessories and are difficult to directly apply to industrial production. Under normal circumstances, the production site environment of electric vehicle supporting products is complex with changing lighting conditions. By observing a large number of images on-site, the characteristics are summarized as follows:

(i) Due to poor light conditions, the images captured by industrial cameras are often noisy.

(ii) The overall imaging brightness of the industrial camera is low.

(iii) The edge information of rough-processed electric vehicle supporting products is relatively vague, and it is easy to merge with similar backgrounds.

As a result, this study focuses on a comprehensive image processing system that can handle different vehicle accessories and introduce GrabCut. The computer vision methods can complete the positioning of automobile batteries, the fastening of automobile parts, and the identification of brake discs, which improves the detection and design efficiency.

3. Design of Image Integrated Processing System

In this section, first, we introduce GrabCut Algorithm in Section 3.1. The operation of the GrabCut algorithm is discussed, which motivates us to present the shortcomings of this algorithm in the form of the improved GrabCut algorithm in Section 3.2.

3.1. GrabCut. Compared with the traditional interactive segmentation method graph cut (i.e. iterative graph cut),
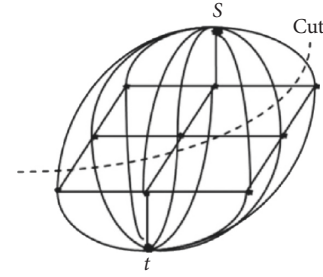

Figure 1: *s-t* net.

grabcut improves the interactive segmentation method. In its simplest form, it consists in mapping the image to be segmented into an *s-t* network, as illustrated in Figure 1. The network graph contains the origin s representing the foreground end point, the sink point *t* representing the background end point, and the edge set *E* representing the connections between the origin, the sink point, and other nodes in the network graph. With simple user interaction, the GrabCut algorithm selects the object of interest and defines the selected area as the foreground, while other areas are considered the background. It then creates a Gaussian mixture model (GMM) for the foreground and background and uses the *K*-means algorithm to differentiate between the foreground and background. It is first clustered into *K* classes, which corresponds to *K* Gaussian models in GMM; then, the segmentation energy weights between each edge set are calculated separately; finally, the *s-t* network graph for the unknown area is constructed, the minimum cut-maximum flow method is used to achieve preliminary segmentation, and iteratively, the process is repeated until the unknown area is completely segmented. The group parameters k and θ are continually optimized. Finally, the segmentation energy is brought down to its minimum value to achieve image segmentation. k, θ, and α are the group parameters.

As a result of the complex workshop environment and the inability to ensure uniform lighting conditions, the brake disc images collected by the vision system are frequently plagued by issues such as low brightness, blurred edges, unclear outlines, and obvious noise. As a result, the robustness of the traditional GrabCut segmentation algorithm deteriorates, resulting in inaccuracies in the brake disc images collected by the vision system.

3.2. Improved GrabCut. It is proposed that an improved GrabCut algorithm is used to overcome the issues mentioned above. First, adaptive median filtering is used on electric vehicle accessory products to remove the noise of varying degrees on the surface. Then, contrast-limited adaptive histogram equalization (CLAHE) is applied to improve the image brightness, and finally, the Laplacian operator is used to sharpen the image. Finally, the GrabCut algorithm is used to precisely segment the brake disc, allowing the complex background of the brake disc to be completely removed. The improved GrabCut algorithm process is depicted in Figure 2.
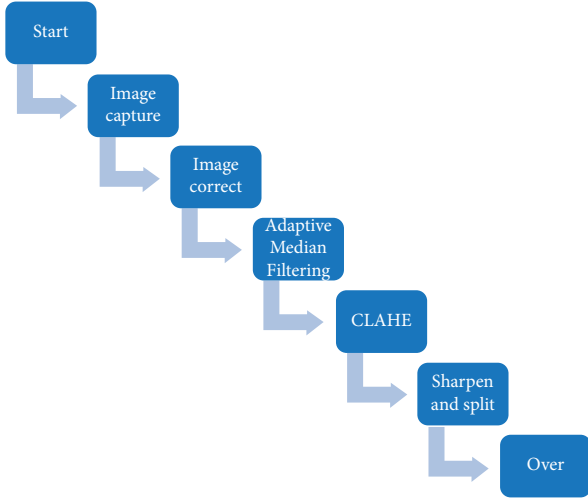
FIGURE 2: The proposed flowchart of our proposed approach.

Adaptive median filtering can change the window size of the filter dynamically in response to predetermined conditions. The adaptive median filter differs from the conventional median filter, in that it defines a rectangular window $S(x, y)$, its size changes gradually as the filtering progresses, and finally outputs a pixel to replace the pixel at the center point (x, y) of the filter window. As a result, the adaptive median filter can better preserve image details, while ensuring that the salt and pepper noise is filtered out.

During the actual brake disc image segmentation process, it has been discovered that either strong or weak light will have a greater impact on the segmentation results; as a result, maintaining a healthy image brightness balance is essential. When used in conjunction with adaptive histogram equalization (AHE), the contrast-limited CLAHE algorithm can effectively enhance or improve the local contrast of the image in order to obtain more image edge and detail information, as well as optimize the problem of amplifying noise in AHE.

The main implementation steps of CLAHE are as follows:

(i) Divide the filtered and denoised electric vehicle accessory product map (M pixels × N pixels) into several subregions of the same size.

(ii) Calculate the histogram of each subregion separately, denote the number of possible histogram grey levels as K, where the number of clusters in the dataset is K, and the grey level of each subregion as r, and then the histogram function corresponding to the region (m, n) is $H_{m,n}(r), 0 \leq r \leq K - 1$.

(iii) Confirm the shear limit value β:

$$\beta = \frac{MN}{K\alpha}, \tag{1}$$

where $0 < \alpha \leq 1$ is the truncation coefficient, which is used to represent the maximum percentage of pixels in each grey level.

(iv) Fill the pixels beyond the β to the lower grey level in the image, thereby improving the overall brightness of the image.

(v) Equalize the histograms of all divided subregions.

(vi) Process each pixel with the bilinear interpolation method and calculate the grey value after processing.

Let L be the position of the pixel and e is the pixel value at the position L, that is

$$S_{i,j} = e. \tag{2}$$

The transformation functions are $F_A(e)$, $F_B(e)$, $F_C(e)$, and $F_D(e)$, respectively. The value is recorded as $e\prime$ in the output image, which is obtained by the weighted sum of the transformation functions in four regions. Let a and b be the distances from position L to AC and AB, and both I_{AC} and I_{AB} are 1, then for each (a, b), we have

$$e' = (1 - b) \cdot [(1 - a)F_A(e) + aF_B(e)] \\ + b \cdot [(1 - b)F_C(e) + aF_D(e)]. \tag{3}$$

Each pixel has a transformation function, which can be expressed as follows:

$$\text{RGB}T(i, j, e) = (K - 1) \sum_{i=0}^{e} F_{i,j}(e), \tag{4}$$

where $(0 \leq e \leq K - 1)$ and $F_{i,j}(e)$ is the distribution function of pixel (i, j).

The Laplacian operator is one of the most widely used edge detection methods. In n-dimensional Euclidean space, the Laplacian operator is a rotationally invariant second-order differential operator. This operator can sharpen the edges of an image while maintaining more background information, allowing the image's details to be more prominently presented when employed for image enhancement. To compensate for this sensitivity to noise, the adaptive median filter denoises the brake disc image before it is passed through the Laplacian operator. This is illustrated in Figure 3 by the mask corresponding to the operator, and it can be seen that the Laplacian operator is isotropic.

The calculation method is to multiply and sum the selected pixel point in the image and 8 points in its neighborhood with the mask shown in Figure 3 and replace the pixel value of the original center point in the nine-square grid with the new pixel value obtained. Then, for the point (i, j), we have

$$L(i, j) = \sum_{m=-1}^{1} \sum_{n=-1}^{1} k(m, n)p(i - m, j - n). \tag{5}$$

Each iteration of the GrabCut algorithm optimizes the GMM parameters for modeling the target and background. The algorithm is divided into two steps: initialization and iterative minimization.

3.2.1. Initialization

(i) First, frame the region of interest through user interaction, define the pixels in the frame as target pixels T_U, and define other pixels as background pixels T_B.

Figure 3: Laplacian mask.

(ii) Initialize the background pixel n in T_B, and mark the label of n as $a_n = 0$. Similarly, initialize the pixel n in the T_U target pixel, and mark the label of n as $a'_n = 1$.

(iii) Following the completion of steps (1) and (2), the target and background pixels can be preliminarily classified, and then the GMM for the target and background pixels can be determined. The K-means algorithm divides the target pixels into K classes in order to ensure that the GMM is achieved. GMM is the mean vectors of each component and the matrices of covariances for each component as well as the weights assigned to each component. A specific pixel sample is used for each Gaussian model in this, and the parameter mean and covariance are determined by the RGB value of the pixel. The Gaussian component weight is determined by the ratio of the pixel of the Gaussian component to the total number of pixels.

3.2.2. Iterative Minimization

(i) In the first step, the Gaussian component of GMM is assigned to each pixel, and the RGB value of nth target pixel is replaced by obtaining the component with the highest probability as k_n:

$$k_n := \arg\min_{k_n} D_n(a_n, k_n, \theta, z_n). \tag{6}$$

(ii) According to the given image data z, further learn and optimize the GMM:

$$\theta := \arg\min_{\theta} U(a, k, \theta, z). \tag{7}$$

(iii) Calculate the weights by the Gibbs energy term analyzed in equation (1), and then estimate the segmentation by the min-cut-max-flow algorithm:

$$\min_K E(\alpha, k, \theta, z). \tag{8}$$

where $E(\alpha, k, \theta, z)$ is the Gibbs energy of the GrabCut segmentation algorithm.

(iv) The GMM can continuously optimize by repeating the prior steps. Using equation (3) as a starting point, it is feasible to further confirm the attribution of the target pixel, after which the k and GMM of each pixel are finally confirmed, and the GMM

can be continuously optimized through the continuous iteration of the algorithm. This process is guaranteed to converge to a minimum value because steps 1–3 are the processes of decreasing energy, and this ensures that the segmentation result is obtained.

(v) Because the boundary after segmentation may be discontinuous, border matting is used to smooth the segmentation results as well as other postprocessing operations.

4. Experimental Results and Discussion

First, this study evaluates that the proposed algorithm can effectively recognize and segment graphs. Taking the battery in the electric vehicle accessory product as an example, we tested the performance of the algorithm in this study, as shown in Figure 4.

It is demonstrated in this study that the suggested algorithm outperforms other complex background removal algorithms when it comes to segmentation effects. The experiment was conducted on 300 sets of brake disc images under various light conditions and scenes, including a cluttered background, a pure background, and the front and back of the brake disc with or without shadow influence. The results were compared to the results of the prior experiment. Figure 5 compares the results of the traditional GrabCut algorithm, the region expanding algorithm, and the K-means segmentation approach. The original GrabCut algorithm, as shown in Figure 5, does not perform image filtering or image enhancement; as a result, the algorithm is sensitive to noise and not robust to illumination, resulting in undersegmentation and inconspicuous brake disc edges, as shown in the figure. In a simple scene, as shown in Figure 5(b), the region growing algorithm can effectively remove the background of the brake disc area, but in a complex scene, or in images where the greyscale is not uniform, the algorithm may be unable to accurately segment the brake disc area, as shown in Figure 5(c). Because the K-means clustering segmentation algorithm is sensitive to noise and outliers, and because the algorithm finds the local optimal solution, the algorithm oversegments when removing the complex background of the brake disc, as illustrated in Figure 5(d). Compared to other segmentation algorithms, the outline of the brake disc segmented by the algorithm in this study is distinct, and the details are preserved in Figure 5(e).

In terms of measuring the segmentation effect, PSNR and algorithm running time T are used as performance indicators to measure the algorithm, as shown in Figures 6 and 7. This can be clearly demonstrated in Figure 7 that the improved GrabCut has greater running time than K-means but have greater PSNR than K-means, region growing, and GrabCut. This image segmentation algorithm is shown in the study, which is based on an improved GrabCut and achieves a better average PSNR than the other several segmentation algorithms, as shown in Figures 6 and 7. This clearly shows that the algorithm discussed in this study has a greater effect on noise suppression than the other several
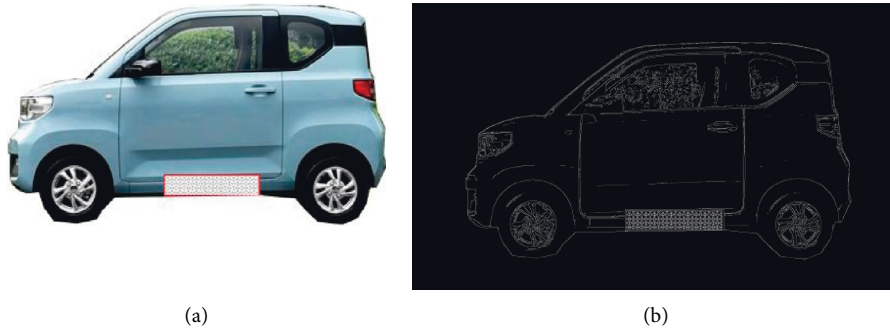
(a)   (b)

FIGURE 4: Electric vehicle battery identification map. (a) The effect obtained byGrabCut. (b) The effect of the improved method.
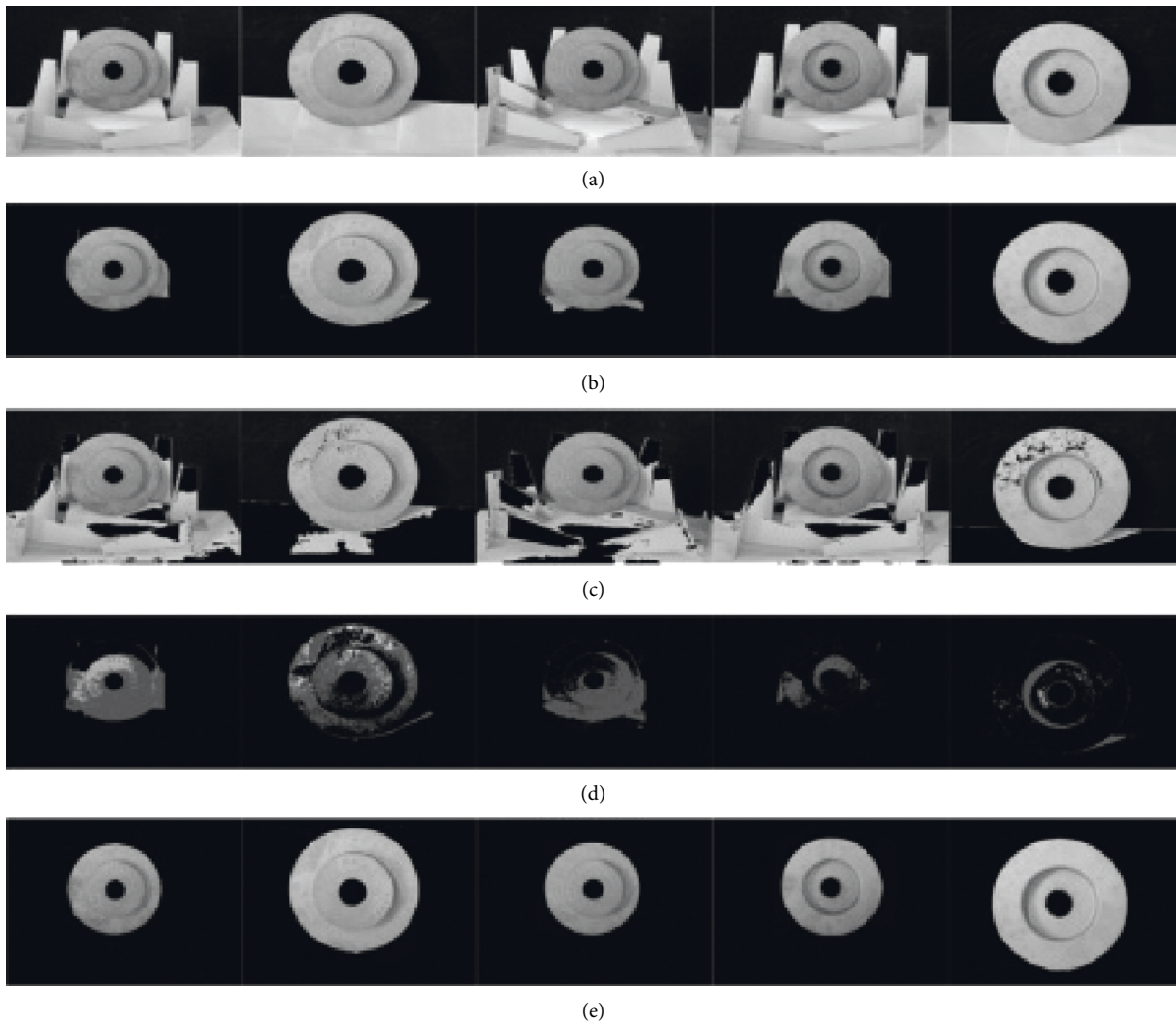

(a)

(b)

(c)

(d)

(e)

FIGURE 5: Comparison of algorithms.

segmentation algorithms, as shown in Figures 6 and 7. When segmenting images is in complex backgrounds, the image enhancement algorithm is also used, which significantly reduces the time required for the segmentation algorithm to complete its task. The segmented brake disc has smooth edges and distinct details, as seen in the actual segmentation
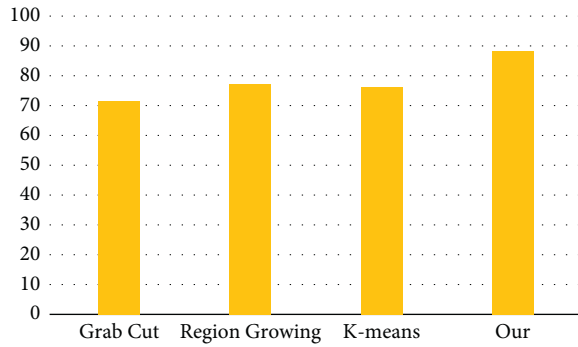
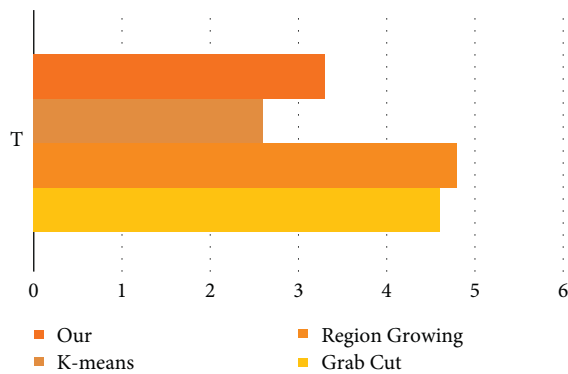FIGURE 6: Comparison of PSNR.

FIGURE 7: Comparison of running time.

results shown in Figure 5, which has been confirmed by the manufacturer. The effectiveness of the algorithm is demonstrated in this study.

5. Conclusion

We looked at the different types of electric vehicles, the technology employed, the benefits over internal combustion engines, charging systems, and future advancements in this article. We also discussed the important research concerns and prospects in depth. In electric vehicles, batteries are crucial since they define the vehicle's autonomy. We looked at a variety of batteries based on these parameters. We also discussed how to approach technology such as graphene, which is expected to provide a solution for storing more electricity and charging it faster. In terms of design investigation solutions for electric vehicle accessories, this study requires the efficient and comprehensive processing of images of a large number of vehicles and related components during the design investigation process (e.g., batteries, plastic fasteners, and brake discs). Because the problem comprises the extraction of the outer contours of various parts, a comprehensive image processing system is required that can manage a wide range of automotive accessories. We propose an integrated image processing system that uses GrabCut and computer vision methods to complete the positioning of automotive batteries, fastening of automotive parts, and identification of brake discs, therefore increasing inspection and design efficiency.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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