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Optimization of Canny Algorithm for Recognition of Female Clothing Styles from the Perspective of Features

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ABSTRACT

The accurate and fast recognition of women's clothing styles is conducive to the classification and recommendation of merchants, and it is also convenient for customers to choose from. This paper optimized the Canny algorithm used to extract the contour edge of the female clothing image and used a convolutional neural network (CNN) classifier to identify clothing styles based on the edges extracted by the Canny algorithm. Finally, the Canny algorithm and the CNN classifier were tested in the simulation experiment. The performance of the CNN classifier was compared with that of the template matching and SVM classifiers, the Resnet34-based recognition method, as well as the target detection network and genetic algorithm-back-propagation neural network combined recognition method. The results demonstrated that the optimized Canny algorithm extracted more distinct contour edges. The CNN classifier exhibited the best performance and the fastest recognition for female clothing styles.

KEYWORDS

canny algorithm, female clothing, style recognition, convolutional neural network

INTRODUCTION

With the improvement in living standards and the decrease in clothing prices over the past 20 years, people's purchasing quantity of clothing has been continuously increasing. There is also an escalating pursuit of fashionable clothing among individuals [1], including women's pursuit of fashionable styles [2]. The increasing demand for trendy apparel from women has significantly propelled the growth of the fashion industry. The diversity and colours of clothing styles have greatly improved the selection range of female customers, but it also increases the difficulty of selecting clothing' fashion colours [3]. The accurate identification of clothing styles not only helps fashion designers to understand fashion trends but also helps businesses to better classify and recommend clothing, thus reducing the difficulty for customers when selecting clothing styles [4]. Recommendations for clothing can also be made from a psychological perspective [5]. Especially for businesses, the increasing variety of clothing and styles they encounter necessitates a method that can swiftly and accurately identify clothing styles. Machine vision and image processing technology provide a convenient solution for style identification in this

context. The Canny algorithm is an image processing technique that detects contour edges in images, thereby extracting relevant features. These features can then be used for recognition and classification using a classifier, as demonstrated in this article for clothing style identification. Li et al. proposed a multi-depth feature fusion algorithm for clothing image style recognition [6]. The experimental results showed that the algorithm eliminated the influence of interference factors, enabling a more focused recognition process on the clothing itself and significantly improving accuracy compared to the traditional method based on a deep residual network. Yue et al. used clothing attributes to construct design issue graphs (DIGs) to form the global semantic representation of fashion styles [7]. They proposed a fashion style joint recognition model composed of two CNNs based on clothing images and DIGs. Experiments verified that the model can effectively identify clothing fashion styles with different appearances. Zhou et al. proposed a clothing classification approach based on a parallel convolutional neural network (PCNN) and optimized random vector functional link (RVFL) [8]. The experimental results effectively showed the classification performance of the algorithm. In the aforementioned studies, clothing design classification has been explored using image recognition algorithms, which typically identify different types of clothing based on complex images. Although more details can enhance the accuracy of recognition, they also increase the difficulty of identification. Although this article also uses the CNN algorithm for style recognition of clothing images [9], it first utilizes the Canny algorithm to extract the outline of the clothing and then applies the CNN algorithm to recognize styles based on the outlines, reducing the amount of details that need to be processed by the algorithm. In this paper, the Canny algorithm for extracting the contour edge of the female clothing image was improved, and then the CNN classifier was used to identify the clothing style. Finally, both the Canny algorithm and the CNN classifier were tested in the simulation experiment. The CNN classifier was then compared with the template matching and support vector machine (SVM) classifiers, the Resnet34-based recognition method, as well as the target detection network and genetic algorithm-back-propagation neural network (GA-BPNN) combined recognition method. The novelty of the text lies in initially employing the Canny algorithm for extracting clothing image edges, followed by utilizing a CNN classifier for style recognition of these edge images, thereby reducing the level of detail required for image classification by the CNN algorithm. The contribution of this paper is to use both the Canny algorithm and the CNN algorithm for style recognition of clothing, providing an effective reference for recognizing women's fashion styles.

CLOTHING STYLE RECOGNITION BASED ON CANNY

The rapid and accurate recognition of deep design in clothing styles is conducive to the development of clothing design and the fashion industry [10]. The basic principle behind clothing style recognition based on computer image processing technology can be divided into three steps: mitigating

interference from clothing images, extracting distinctive features from clothing images, and classifying the extracted features.

In this paper, the Canny algorithm is used for clothing style recognition, which has the advantages of multi-scale edge detection and noise reduction. This algorithm is widely employed in various image-processing tasks [8]. As a classical edge detection algorithm, it can effectively extract the line information of edges in clothing, including outlines and details, and use them as characteristics to classify clothing styles.

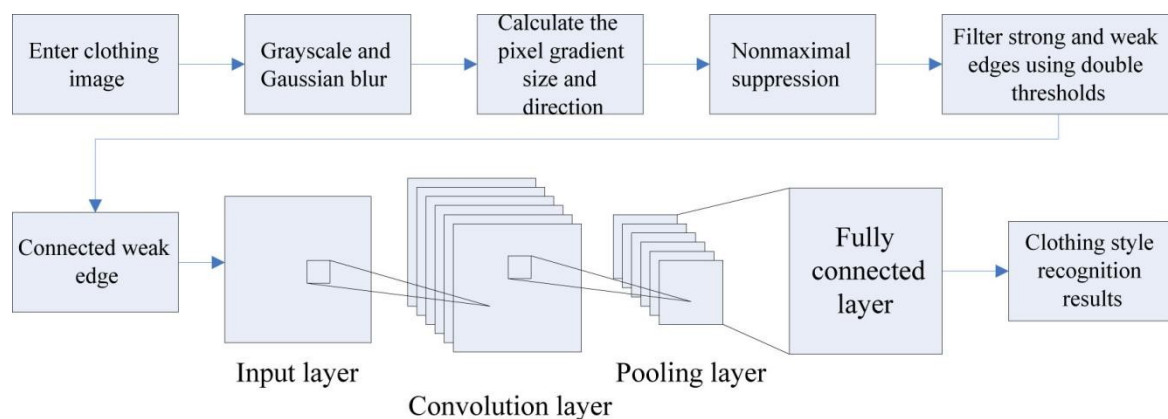


Figure 1. The process of clothing style recognition based on Canny

The Canny algorithm is used to extract the detailed features of clothing contours, and then a classifier is used to classify them according to the input features. The specific steps of the process are shown in Figure 1 [11].

- ① The clothing image to be recognized is input.
- ② The clothing image is grayscaled after dimension adjusting, and then Gaussian blur processing is used for image noise reduction. The fuzzy noise reduction effect of the Gaussian filter on the image depends on variance σ^2 in the Gaussian filter. If the parameter is too large, it will produce false edges, and if it is too small, the noise reduction effect will be poor. Therefore, an improvement is made to σ^2 be able to adjust adaptively. The improved Gaussian filter equation is:

$$\left\{ \begin{array}{l} G(x, y) = \frac{\exp(-\frac{x^2 + y^2}{2N^2})}{2\pi N^2} \\ N = \frac{|f_0(x, y) - f_a(x, y)|}{f_a(x, y)} \\ f_a(x, y) = \frac{\sum_j^8 f_j(x, y)}{8} \end{array} \right., \quad (1)$$

where $G(x, y)$ is the result of applying Gaussian filtering to pixel point (x, y) , N is the contrast ratio between the current pixel and its neighborhood used to replace σ , $f_0(x, y)$ is the gray degree of pixel (x, y) , $f_j(x, y)$ is the gray degree of the j -th point among eight neighborhood points of (x, y) , and $f_a(x, y)$ is the average gray degree of the neighborhood.

③ The gradient magnitude and direction of the image pixel are calculated. The formula is:

$$\left\{ \begin{array}{l} Sobel(\vec{x}) = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \\ Sobel(\vec{y}) = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \\ G_x = A(x, y) \times Sobel(\vec{x}) \\ G_y = A(x, y) \times Sobel(\vec{y}) \\ G = \sqrt{G_x^2 + G_y^2} \\ \theta = \arctan(G_y / G_x) \end{array} \right., \quad (2)$$

where $Sobel(\vec{x})$ and $Sobel(\vec{y})$ are *Sobel* operators of x and y directions [11], $A(x, y)$ is a 3×3 pixel region centred on pixel (x, y) , G_x is the gradient of pixel x in the direction of x ($Sobel(\vec{x})$ is used to perform convolution summation on $A(x, y)$), G_y is the gradient of pixel (x, y) in the direction of y ($Sobel(\vec{y})$ is used to perform convolution summation on $A(x, y)$), G is the modulus of pixel (x, y) , i.e., the magnitude of gradient, and θ is the angle between gradient and the x axis.

④ Non-maximization suppression of gradient magnitude is performed on the image, i.e., whether each pixel is a local extremum in the gradient direction is determined. If not, the gradient response of the pixel is deleted; otherwise, it is retained.

- ⑤ The pixel with gradient response is classified as strong edge, weak edge or flat point according to high threshold H and low threshold L . If the gradient response of the pixel is higher than H , the pixel has a strong edge. If the gradient response is between H and L , the pixel is a weak edge. If the gradient response is lower than L , the pixel is a flat point.
- ⑥ The eight adjacent pixels of the weak edge pixel are judged. If the adjacent pixels are not strong edges, the pixel point is regarded as a flat point and discarded; otherwise, the pixel point is regarded as a strong edge and retained.
- ⑦ The edge image of the clothing is input into the CNN classifier for forward calculation. The CNN classifier is divided into input, convolution, pooling, and output layers in structure. The clothing edge image is fed into the input layer of the classifier, and then multiple convolution kernels are used in the convolution layer to extract features from the image. The convolutional features are then compressed by using a pooling box in the pooling layer. The compression method involves sliding the pooling box over the convolutional features, and for each slide, taking either the maximum or average value within the box. Convolution and compression can be repeated many times as needed, and finally, the clothing style recognition results are output in the output layer.

SIMULATION EXPERIMENTS

Experimental Environment

The experiment was carried out in the server of a laboratory. The relevant configuration of the server was Windows 10 operating system, i7 processor, and 16 GB memory.

Experimental Data

The image data required for the women's clothing style recognition test were from the clothing styles available in the market. According to statistics, there were 7,000 images of women's clothing, including seven different styles (Figure 2), with each style consisting of 1,000 images. Seventy per cent of them were used as the training set, and the remaining thirty per cent were used as the test set.



Figure 2. Pictures of seven clothing styles

Experimental Setup

The relevant parameters of the Canny-based CNN classification algorithm are as follows. The parameter σ was adaptive, and the adjustment method was as described above. The parameters of the dual threshold were determined by the maximum between-class variance. The basic steps are as follows. The mean grey gradient of the image was calculated. Then, the mean gradient T_1 of the image part greater than the mean gradient and the mean gradient T_2 of the image part less than the mean gradient were obtained. Gradient threshold T was searched between T_1 and T_2 . Between-class variances $g(T-1)$, $g(T)$, and $g(T+1)$ when the threshold was $T-1$, T , and $T+1$ were calculated. When $g(T-1)$ and $g(T+1)$ were both smaller than $g(T)$, T was used to represent the high threshold, and the low threshold was set as $0.5T$. As to the CNN classifier part, in the convolutional layer, there were 32 convolution kernels, the specification was 3×3 , and the activation function used sigmoid; in the pooling layer, the specification of the pooling box was 2×2 , and the mean pooling was used.

In addition to the recognition algorithm, the Canny-based SVM classification algorithm and the Canny-based template matching algorithm were also tested. The relevant parameters of the Canny SVM classification algorithm are as follows. The parameters of the Canny algorithm part remained consistent with those mentioned above. The kernel function of the SVM part was the sigmoid function. The penalty parameter was set to 1. The relevant parameters of the template matching algorithm based on Canny are as follows. The parameters of the Canny algorithm remained consistent with those mentioned earlier. In the template matching part, the curvature of clothing contour curves was

calculated. The points with extreme curvatures were identified as characteristic points of the clothing. These characteristic points were then compared with those from different styles of template clothing. The style of the recognized clothing was the template style with similar characteristic points. In addition, the CNN classifier was compared with the Resnet34-based recognition method, as well as the target detection network and GA-BPNN combined recognition method [12, 13].

Experimental Results

The partial extraction results of the traditional Canny algorithm and the improved Canny algorithm for clothing edges are shown in Figure 3. It can be seen from Figure 3 that the improved Canny algorithm extracted the contour edge of the clothing, while the traditional algorithm also extracted these edges but tended to incorporate shadows resulting from folding. The inclusion of shadow extraction as edges could impede subsequent recognition by classifiers.



Figure 3. Partial clothing edge extraction results of traditional and improved Canny algorithms

In the experiment, the improved Canny algorithm was used to extract the contour of female clothing pictures, and then three classifiers were used to recognize female clothing styles. The Resnet34-based recognition method the target detection network and the GA-BPNN combined method were also used for comparisons. The test results of the recognition performance are shown in Table 1. Different algorithms exhibited varying recognition capabilities for different styles of women's

clothing. In terms of comprehensive performance, the comprehensive recognition rate of the template matching classifier was 74.0%, the comprehensive recognition rate of the SVM classifier was 83.9%, the comprehensive recognition rate of the CNN classifier was 96.9%, the rate of the Resnet34-based method was 85.1%, and the rate of the GA-BPNN method was 85.7%. It can be seen that the CNN classifier had the best recognition performance for female clothing styles.

Table 1. The recognition performance of five algorithms for female clothing styles

	SVM, %	Template matching, %	Resnet34, %	GA-BPNN, %	CNN, %
Short-sleeved blouse	82.1	73.6	83.9	84.7	98.7
Long-sleeved blouse	84.5	74.8	85.8	86.4	96.4
Short-sleeved T-shirt	83.6	73.5	84.7	85.3	97.5
Long-sleeved T-shirt	82.1	74.2	83.6	84.2	96.3
Shorts	84.7	74.9	85.4	86.3	95.8
Trousers	83.5	73.5	84.7	85.6	96.9
One-piece dress	86.8	73.3	87.4	87.2	96.7
Total	83.9	74.0	85.1	85.7	96.9

The average recognition time of the five classifiers for female clothing styles is shown in Figure 4. Specifically, the average recognition time of the template matching classifier for female clothing styles was 241 ms, the average time of the SVM classifier was 135 ms, the average time of the CNN classifier for female clothing styles was 98 ms, the average time of the Resnet34-based method was 103 ms, and the average time of the target detection network and GA-BPNN combined method was 109 ms. It can be seen that the average time of the CNN classifier was the least.

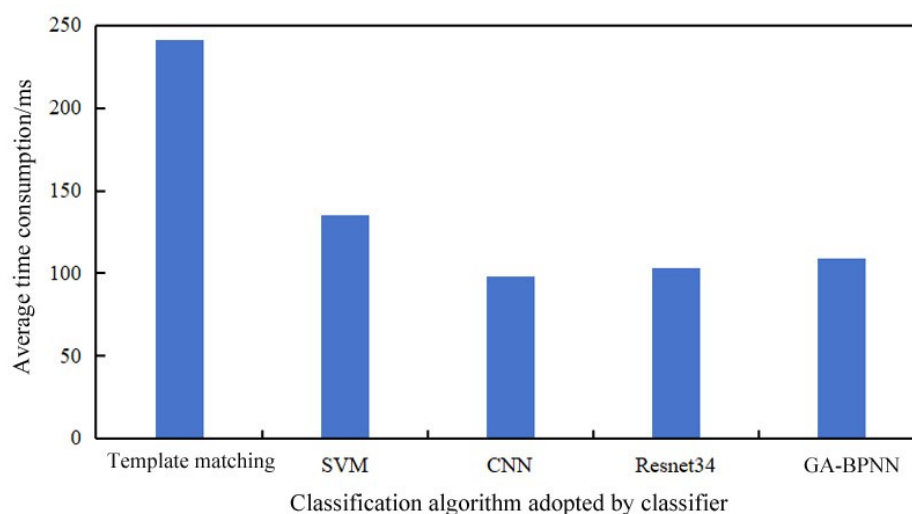


Figure 4. The average recognition time of the five classifiers for female clothing styles

The reasons for the above results were analyzed. σ used to reduce the noise of the image by the Gaussian filter of the traditional Canny algorithm was a fixed value and the dual threshold used to judge the strength of the pixel edge was also a fixed value, which cannot adapt to different images. The inadequate noise reduction effect and improper setting of the dual threshold resulted in errors in the judgment of edge pixels, and some pixels that were not the edge of the contour were also extracted as edges. The improved Canny algorithm changed σ and dual threshold into adaptive parameters, which could better fit different images.

In the classifier test results, the CNN classifier exhibited the best recognition effect and higher recognition efficiency. The template matching classifier compared the feature points of the clothing contour to be identified with the feature points of the template clothing contour and judged the clothing style based on their degree of approximation. On the one hand, the fixed template lacked flexibility and demanded high standards for clothing images. On the other hand, comparing and traversing feature points of both required a significant amount of time. The SVM classifier recognized the clothing style based on the support vector surface obtained through training and fitting without the need to traverse the feature points; therefore, its recognition accuracy and efficiency were relatively higher. The convolutional features extracted by the CNN classifier reflected the local features and the combination of multiple convolutional features reflected the overall features. In other words, this means that the extracted features were more comprehensive and resulted in a higher recognition accuracy.

CONCLUSION

This paper optimized the Canny algorithm used to extract the contour edge of the female clothing image and used the CNN classifier to identify the clothing style based on the edge extracted by the Canny algorithm. The Canny algorithm and CNN classifier were tested in the simulation experiment. The CNN classifier was then compared with the template matching and SVM classifiers, the Resnet34-based recognition method, as well as the target detection network and GA-BPNN combined recognition method. The results obtained are as follows: (1) the outline of female clothing extracted by the improved Canny algorithm was clearer; (2) the recognition performance of the CNN classifier for female clothing style was the best; the average recognition time of the CNN classifier was the least. The reason why the accuracy of using the improved Canny algorithm to extract clothing contours and then applying CNN for fashion style recognition is higher than other algorithms lies in two aspects. On one hand, the enhanced Canny algorithm can extract clearer and more accurate clothing contours while reducing interference from irrelevant details. On the other hand, the CNN algorithm can utilize multiple convolutional kernels to extract local detailed features from clothing contour images and

combine them to obtain overall characteristics. It can be said that it takes into account both global and local details, thus possessing the best recognition performance.

Author Contributions

Conceptualization – Liu Z, Luo M; Methodology – Liu Z, Luo M; Formal analysis – Liu Z, Luo M; Investigation – Liu Z; Resources – Liu Z; writing-original draft preparation – Liu Z, Luo M; writing-review and editing – Liu Z; visualization – Liu Z; supervision – Luo M. All authors have read and agreed to the published version of the manuscript.

Conflicts of interest

The authors declare no conflict of interest.

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