Research on Sheepskin Contour Extraction Method Based on Computer Vision Measurement Technology

by

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Abstract

Manual trimming of sheepskin is intensive labor, and the working environment is full of rotten smells. The tannery is facing increasingly severe recruitment difficulties. This paper uses computer vision technology to study automatic recognition of sheepskin contours, which is the basis for the subsequent automatic trimming of sheepskin. After observing and analyzing the raw sheepskin images collected by an industrial array camera, a method of sheepskin contour extraction based on computer vision measurement technology is proposed in this paper. This method uses the fast Otsu threshold algorithm based on the pixel set to perform binary image segmentation. Combined with morphological processing for edge defect filling and topology analysis of boundary contour tracking algorithm to extract maximum contour information, it has a pixel-level three-dimensional de-noising preprocessing function and can accurately extract the sheepskin contour in the raw sheepskin image. The experimental results show that using the fast Otsu threshold algorithm proposed in this paper for binary segmentation to extract sheepskin contours, the detection rate is nearly 160% faster than the traditional Otsu algorithm, the edge protection is better, the error segmentation is reduced by nearly 3% and it has good anti-noise performance. It can meet the industrial production requirements of subsequent automatic cutting of sheepskin.

Introduction

China is recognized as a big country in sheepskin production and processing in the world, but it is not a powerful country in production and processing. Compared with developed countries, sheepskin production and processing automation level is relatively low. The tannery in China is still a typical labor-intensive industry. At present, most sheepskin production and processing enterprises mainly use manual cutting for the cleaning of sheep fillet skin. There are problems such as high labor intensity and poor working environment. Companies are facing increasing employment difficulties. In recent years, with the rapid development of computer vision processing technology,[1,2] the use of computer vision processing technology to achieve automatic edge trimming of sheepskin can liberate the production labor force and greatly improve the production and processing efficiency and optimization cost of sheepskin production enterprises. When computer vision processing technology is applied to automatic cutting of sheepskin, the main steps are image acquisition, image segmentation, coordinate extraction and automatic cutting. Image segmentation is an extremely critical step to realize automatic cutting. Therefore, it is the first task to propose an image segmentation algorithm suitable for sheepskin.

The most basic image segmentation method is the edge-based detection method,[3] and its core is to convolute the image with the help of differential operators. Common differential operators include Sobel, Roberts, Canny, Laplace operators, etc.[4,5] This kind of method is easy to understand, fast in operation and simple in algorithm implementation, but the edge of detection is often piecewise discontinuous and has poor anti-noise ability. Gray threshold segmentation has been widely studied and applied for its simple, effective and easy to understand characteristics. The threshold algorithm proposed by Otsu et al.[6] is most widely used because of its simple algorithm, real-time performance and strong robustness.[7–9] However, it has poor segmentation effect for images with a lot of noise. A large number of researchers have improved the Otsu algorithm. Chung et al. proposed an acceleration algorithm based on heap and quantization to improve the algorithm efficiency.[10] Liu, Jianzhuang et al. added neighborhood mean to promote Otsu in two dimensions, which improved its anti-noise performance.[11] Jing Xiaojun et al. added neighborhood mean and neighborhood value to promote Otsu in three dimensions and further improved its anti-noise performance.[12] Xu Xiangyang et al. proved that the optimal threshold value found by Otsu method was biased towards the party with greater inter-class variance, and proposed that the method of Otsu was used again for the party with greater variance.[13] For the image with bright target and large difference from the background variance, the segmentation effect was better. Wu Fenghe et al. used an iterative method to find the segmentation threshold and used mathematical morphology for edge connection and defect repair. Realize single-pixel edge segmentation, but for multi-pixel edges, a larger area of mis-segmentation will occur.[14] Since sheepskin pictures have large areas of blood spots and creases, and contain a small amount of salt, the use of the above algorithms to process sheepskin pictures has certain limitations.

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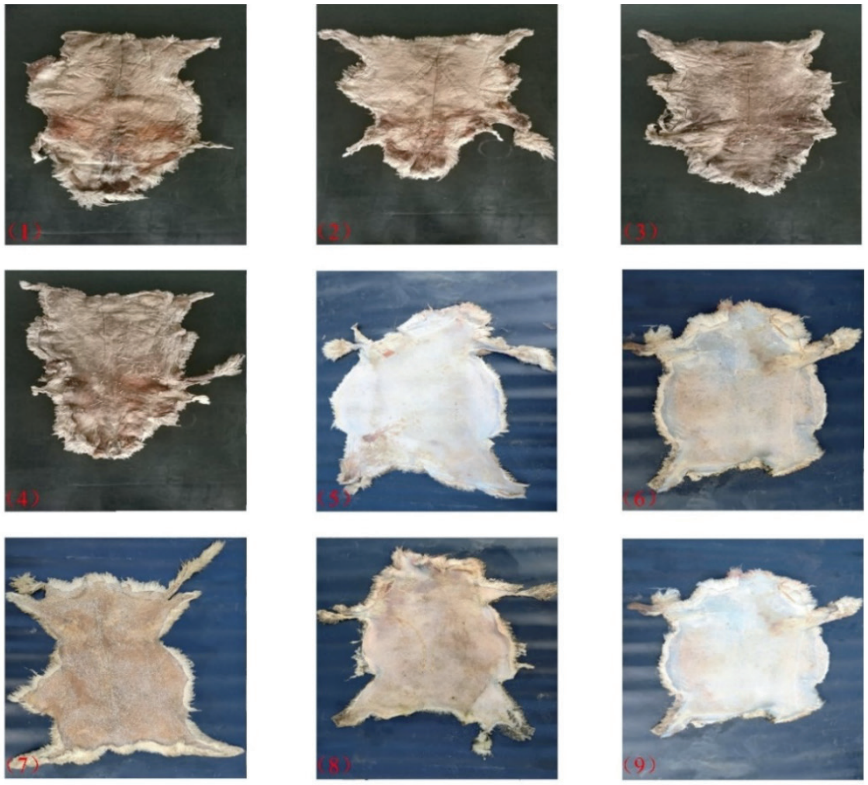


Figure 1. The typical sheepskin pictures collected

According to the characteristics of the collected sheepskin images and computer vision measurement technology, a practical sheepskin contour extraction method based on Otsu and morphology was proposed in this paper, which realized the accurate extraction of the sheepskin contours in raw sheepskin images and provided a theoretical basis for the automation of sheepskin cutting. The method mainly includes four specific steps: (1) The image is preprocessed by pixel-level 3d de-noising system. (2) Binary image segmentation was performed using the fast Otsu threshold algorithm based on image block pixel set. (3) Edge defect filling was performed by morphological treatment. (4) The boundary contour extraction algorithm with topological structure analysis and area threshold algorithm were used to search and extract the contours of the repaired binary images.

Materials and methods

The sampling place of this experiment is a sheepskin manufacturing enterprise in Hebei province. It uses industrial cameras to capture images in indoor natural environments. The sheepskin is placed flat on the conveyor belt. To ensure the reliability of the experiment, a total of 200 different sheepskin pictures were collected in JPG format. The typical sheepskin pictures collected are shown in Figure1.

A preprocessing system based on pixel level 3D de-noising model

Image preprocessing plays an important role in subsequent image processing and can improve image quality. As the first step of image processing, gray transformation is generally used to transform RGB image into gray image.

Sheepskin images collected by camera under natural lighting environment often have some noise due to the vibration of the shooting and cutting platform and the instability of the electrical signal. Secondly, in order to facilitate the storage of raw sheepskin, salt should be sprinkled on the back of the whole piece of sheepskin to prevent the destruction of the sheepskin. The presence of salt also brings interference to the image processing. Common methods to deal with image noise include mean filtering, Gaussian filtering (weighted mean filtering) and median filtering.[15] General de-noising process is on the whole image pixel convolution, then using convolution operator to deal with each pixel, can achieve a certain amount of noise reduction effect, but if to deal with all the pixels that will obscure the details of the image feature and edge points, and the fuzzy degree is proportional to the radius of neighborhood size.[16] In order to achieve the best de-noising effect without destroying details and preserving edge features, a selective de-noising model is proposed.

The selective de-noising model is a three-dimensional grayscale correction model based on the pixel level. The mean value and median value of the field are used to correct the pixel grayscale value, and the size relation among the three is used as the segment judgment mechanism to judge, so as to remove the noise points and bright spots of the pre-processed grayscale image and retain the edges that are easy to be processed into noise.

Assuming an image size is M*N, use $f(x \cdot y)$ to represent the value of the pixel, and $g(x \cdot y)$ to represent the neighborhood mean of the pixel. Use Equation (1) to find the average value of the pixel's neighborhood, Equation (1) is as follows:

$$g(x \cdot y) = \frac{1}{c} \sum_{f \in s} f(x \cdot y) \tag{1}$$

where, c is the number of pixels in the neighborhood, and s is the 3*3 region in the neighborhood. The neighborhood value $h(x \cdot y)$ of the pixel point is:

$$h(x \cdot y) = median\left[\sum_{f \in s} f(x \cdot y)\right] \tag{2}$$

where, median is the operation with a median. According to the pixel gray value, the mean value of neighborhood, and the distance relation between neighborhood values, the relation is:

$$\begin{gathered} |f(x,y) - g(x,y)| > |h(x,y) - g(x,y)| \&\& \\ |f(x,y) - h(x,y)| > |h(x,y) - g(x,y)| \end{gathered} \tag{3}$$

Equation (4) is used to correct the pixel gray value, as shown in Equation (4):

$$f(x,y) = (g(x,y) + h(x,y))/2 \tag{4}$$

When pixel gray value, neighborhood mean, neighborhood value and global average gray value are related as follows:

$$\begin{gathered} |h(x,y) - g(x,y) > |f(x,y) - g(x,y)| \&\& \\ |f(x,y) - h(x,y)| > |f(x,y) - g(x,y)| \&\& \\ avr(src) > f(x,y) \end{gathered} \tag{5}$$

where, $avr(src)$ is the average value of grayscale images. The pixel gray value is corrected to:

$$f(x,y) = h(x,y) \tag{6}$$

In other cases, gray levels are not corrected.

Fast Otsu's threshold segmentation algorithm based on the idea of pixel set

Sheepskin images mainly include foreground and background pixels, and the segmentation needs to meet real-time performance. Therefore, the single threshold segmentation method based on Otsu's idea is used to perform binary segmentation on the image. The basic idea is to traverse all gray levels and search for the maximum variance between classes to find the optimal threshold, the function of variance between classes is:

$$G(t) = \omega_0(t)\,[\mu_T - \mu_0(t)]^2 + \omega_1(t)\,[\mu_T - \mu_1(t)]^2 \tag{7}$$

where, $\omega_0(t)$ is the sum of the background probability, μ_T is the average intensity of the whole image, $\mu_0(t)$ is the background variance, $\omega_1(t)$ is the sum of the foreground probability, and $\mu_1(t)$is the foreground variance. When $G(t)$ takes the maximum value, the optimal threshold (t^*) is obtained,

$$t^* = \arg\left\{\max_{0 \le t \le L-1} G(t)\right\} \tag{8}$$

where, t is the gray level, L is the maximum gray level. The final binary image is calculated according to the following Equation:

$$f(x,y) = \begin{cases} 1, & f(x,y) > t^* \\ 0, & f(x,y) \le t^* \end{cases} \tag{9}$$

According to xu Xiangyang's proof in the literature, the optimal threshold selected by Otsu algorithm will be biased to the side with greater variance.[13] For the collected sheepskin pictures, the variance of the foreground is far greater than the variance of the background. The threshold value obtained directly by Otsu algorithm will be biased towards the bright foreground, and a small amount of dark sheepskin with blood will be processed into the background, resulting in false segmentation. At the same time, for sheepskin images with a large degree of distinction between the background and the foreground, traversing all gray levels will cause a waste of computing power. Therefore, an image segmentation optimization threshold method and an accelerated search threshold strategy are proposed.

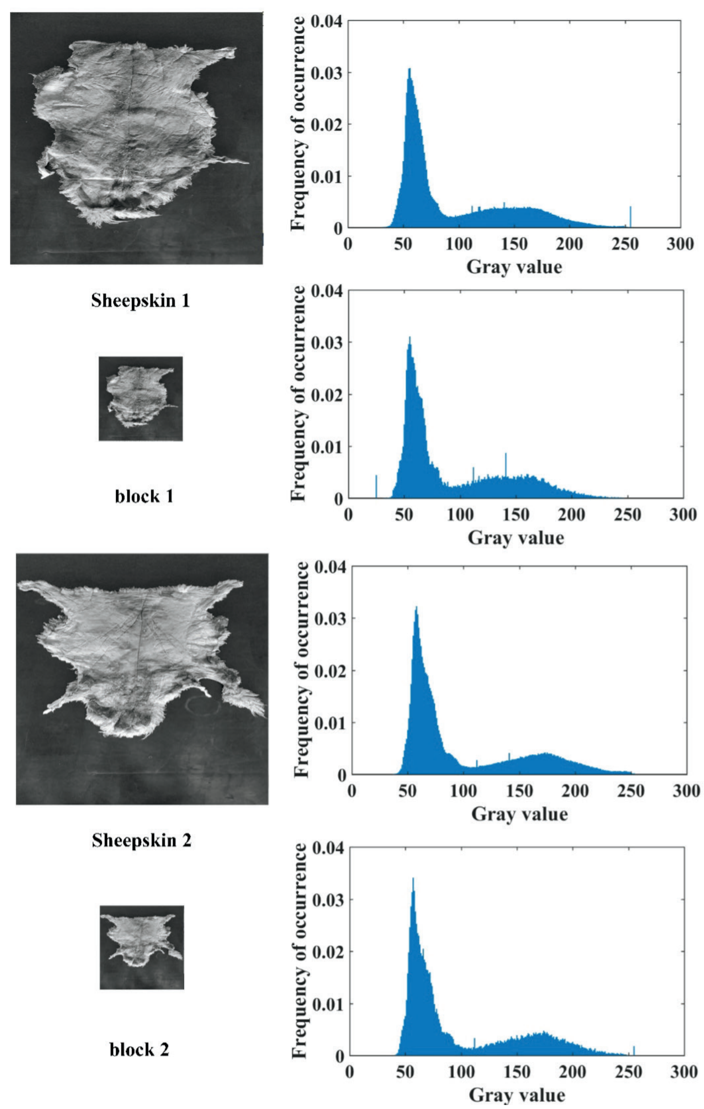


Figure 2. Comparison of gray histogram before and after processing

Image segmentation optimization threshold method

Combining with the threshold bias theory of Otsu's selection demonstrated by Xu Xiangyang, the idea of image segmentation can be used to moderately reduce the variance of the target, and the optimization of the selected threshold can be achieved. The idea of image segmentation is mainly to gather the pixels in the segmentation into a new pixel by averaging or median, forming a new image for threshold selection. This process can effectively reduce the overall variance of the target, help reduce the Otsu selection threshold, and also reduce the image pixels to improve the segmentation speed.

Take k*k pixels in a grayscale image with M×N and grayscale level L as a whole. Calculate the average gray value of the overall pixels of each divided image block and use the average gray value as the new gray value of the pixel block. Use Equation (10) to find the average value of the pixel as the new value of the pixel block. Equation (10) is as follows:

$$F(x\cdot y)=\frac{1}{k*k}\sum_{f\in s}f(x\cdot y) \tag{10}$$

where, $F(x\cdot y)$ is the pixel value of the new image. Then all of the pixel blocks are stored as a whole in a new image whose size is 1/k2 times the original size. (K value is set to 3 for analysis purposes).

The gray histogram comparison of sheepskin before and after partitioning is shown in Figure 2. As can be seen from this figure, the gray histogram before and after partitioning is in a similar bimorphic form as a whole. However, after partitioning, the target area is obviously concentrated and tends to be closer to the background, which can reduce the target variance to a certain extent. This process makes the threshold value obtained by Otsu move towards the background and become lower than before the partition, which is conducive to the expression of the target contour. In order to more visually see the threshold changes before and after image partitioning, the sheepskin in Figure 1 was taken as the experimental object, and the Otsu method was used directly to compare the threshold values obtained after image partitioning, as shown in Figure 3.

Accelerated search threshold strategy

In the Otsu method, for each gray level 0≤t≤L-1, G(t) needs to be calculated once, and finally the G(t) value is compared, and the t value when the value reaches the maximum is selected as the segmentation threshold. The acceleration strategy first calculates the average gray value of the entire image for the obtained gray image and calculates the average value of the gray image with equation 11:

$$arv=t=\frac{K*K}{M*N}\sum_{F\in s}F(x\cdot y) \tag{11}$$

where, *arv* is the average gray average of the image. Using the mean value t of the gray image as the segmentation threshold of the background S0 and the target S1, find their respective mean and variance $\mu_0(t)$, $\mu_1(t)$, $\sigma_0^2(t)$, $\sigma_1^2(t)$. When the maximum inter-variance $G(t)$ was taken, the optimal threshold (t^*) was obtained. Because the background and foreground of sheepskin image were relatively clear, $\mu_0(t)$ and $\mu_1(t)$ had a large difference, which could be used as the upper and lower limits of the threshold search. Value ranges from $\mu_0(t)$ to $\mu_1(t)$, no longer traversing every gray level, greatly improving the search speed. The search equation is as follows:

$$t^*=arg\left\{\max_{\mu_0(t)\le t\le\mu_1(t)}G(t)\right\} \tag{12}$$

Image segmentation algorithm flow

1) Use industrial cameras to collect images on site.

2) Conduct grayscale processing on the collected original images to obtain grayscale images.

3) The grayscale image is denoised robustly by the grayscale correction algorithm in this paper. Equations (1) and (2) are used to calculate the neighborhood value and the mean value. Equations (4), (6) are used to correct grayscale images.

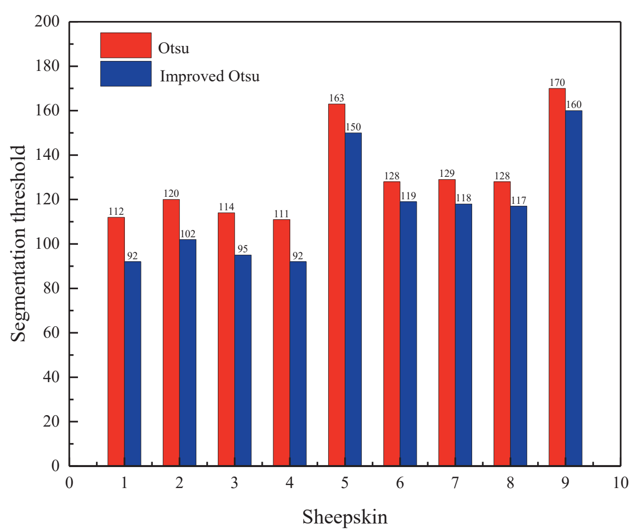


Figure 3. The threshold value obtained by using Otsu method and the improved Otsu method

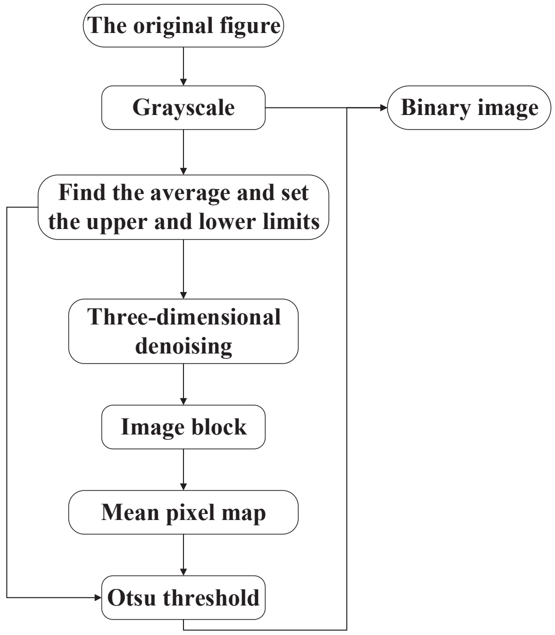


Figure 4. The process of de-noising and threshold segmentation

4) Based on the idea of pixel set, the region mean of the corrected image is calculated by Equation (10), and the pixel value obtained is stored in the new image. The grayscale mean of the whole image obtained by Equation (11) is used as the initial segmentation threshold to divide the image into two categories. The calculated mean value of each category of pixels serves as the upper and lower limit of the threshold value search. Equation (7) was used to calculate the inter-class variance of the gray level between upper and lower limits, and the optimal threshold was searched by comparison.

5) Use the optimal threshold obtained by Otsu algorithm to perform binary segmentation of the corrected grayscale image by Equation (9) to obtain the binary image.

The process of de-noising and threshold segmentation is shown in Figure 3.

Morphological defect repair

Due to the image characteristics and the influence of image noise, the binary image after threshold segmentation is likely to have defects such as rough edges, internal and external holes, broken lines, etc., which will bring difficulties to further contour extraction and further affect the subsequent cutting work. Therefore, effective measures should be taken to eliminate the defects.

Morphological operations are a series of image processing operations based on shapes, which mainly have the functions of dividing independent image elements and connecting adjacent elements. Based on this feature, morphological operations are also selected to deal with these defects.[17,18] Basic operations include: corrosion and expansion of binary or gray values, open and close operations of binary or gray values, morphological gradient, top-hat transformation, etc.

Expansion of A by B means that the structural element B moves from the origin in the Z^2 plane, and "or" operation is performed with the binary image covered by it. The set of expansion images of Point z obtained is as follows:

$$A \oplus B = \{ z \,|\, (B)_z \cap A \neq \phi \} \tag{13}$$

where, A is the calculated binary image, B is structural element, and $\oplus$ is the expansion operation. A corroded by B represents the set of all z points after "and" operation of structural elements and the covered image, namely:

$$A \,\Theta\, B = \{ z \,|\, (B)_z \in A \} \tag{14}$$

where, Θ is the corrosion operation. B performs the closed operation on A, denoted as $A \bullet B$, namely:

$$A \bullet B = (A \oplus B) \,\Theta\, B \tag{15}$$

where, $\bullet$ is a closed operation.

The closed operation eliminates small holes, connects short intervals, and connects adjacent objects.[14] Based on the characteristics of sheepskin images, the selected morphological closure operation can make the detected sheepskin edges smooth, bridge the narrow discontinuity points, and also remove the isolated elements inside.

Contour Extraction

The sheepskin contour extracted using the above-mentioned techniques still has defects, such as internal holes and external noise areas. According to the characteristics of sheepskin contour, the boundary contour tracking technology based on topological structure analysis and the area threshold method are used to extract the outer contour of the sheepskin from the binary image, and the boundary form of the vector is stored. The main principle is to traverse the entire picture in an orderly manner, mark all outer boundaries, hole boundaries and their hierarchical relationships in the image; extract all outer boundaries, discard all hole boundaries; calculate the area of all outer contours, set one contour area threshold, exclude the interference area, and finally the outer boundary contour of the sheepskin is extracted; it is stored in the form of the boundary of the vector point.

Boundary contour tracking technology

Boundary tracking is one of the basic techniques in digital binary image processing and has been studied in depth. Satoshi Suzuki et al. proposed a boundary tracking algorithm with certain topological analysis capabilities. The algorithm extracts the topological structure of the image with less workload and extracts the surrounding relationship between two types of boundaries: external boundary and hole boundary. This algorithm is the most widely used and efficient, so it is used to extract the target contour. Based on the traditional boundary tracking algorithm, this algorithm uses the idea of coding to assign different integer values to different boundaries. At the same time, the process of obtaining the parent boundary along the boundary is added to determine the outer boundary, hole boundary, and the hierarchical relationship.

The input binary image is the image of 0 and 1, and the pixel value of the image is represented by f(i, j). The raster scan starts from the upper right corner of the image, and the raster scan is interrupted in the following two situations:

$$f(i,j-1)=0, f(i,j)=1 \tag{16}$$

where, f(i, j-1) is the left pixel.

$$f(i,j)\geq 1, f(i,j+1)=0 \tag{17}$$

Boundary tracking is performed on the starting point of the outer boundary of the pixel (i, j) or the starting point of the hole boundary respectively. Here a unique identifier is assigned to the newly discovered boundary, called NBD. Initially, NBD=1, add 1 each time a new boundary is found. Follow the found border from the starting point and mark pixels on the border. The marking strategy is as follows:(a) If the current next boundary is between the 0 component of the pixel (i, j + 1) and the 1 component of the pixel (i, j), please change the value of the pixel (i, j) to NBD. (b) Otherwise, unless (i, j) is on the already followed boundary, set the value of pixel (i, j) to NBD.

Conditions (a) and (b) respectively prohibit the pixel (p, g) from becoming the boundary after the starting point of the hole boundary and the outer boundary that have been followed. After tracking and marking the entire boundary, the raster scan is resumed. When the scan reaches the lower right corner of the picture, the algorithm stops.

Target contour extraction

After the binary image is converted to the boundary representation, only the outer boundary is retained, and the inner hole boundary is discarded. In this way, all the outer boundaries of the binary image are extracted. Next, the area of each contour is calculated, and an area threshold is set at the same time. The area threshold can be set to be less than half of the pixel area of the sheepskin image, and the contour larger than the threshold is retained as the target contour, which is stored in the image matrix in the form of the boundary of the vector point.

Experimental results and analysis

Experimental hardware environment: Inter Core i5 CPU 2.3 GHz, RAM 8GB, Windows 10 64-bit operating system. The programming environment is Open CV2.4.7 + Visual Studio 2010.

Effect analysis of contour extraction method

In this experiment, the sheepskin pictures collected on site are simulated and verified. In order to more clearly analyze the processing effect of the contour extraction algorithm proposed in this paper and understand the role of each link, three methods are added for comparative analysis with the method in this paper. To facilitate observation and comparison, each method uses the

Figure 5. Segmentation effect comparison of four methods

result after contour tracking processing. The three methods are the Otsu segmentation method without morphological processing, the Otsu segmentation method with morphological processing and the improved Otsu segmentation method without morphological processing. Four methods were used to process the collected sheepskin images, and the results of the three image segmentation methods were compared with the methods presented in this paper, as shown in Figure 5.

By comparing the two groups of sheepskin pictures (b), (d) or (c) and (e) in Figure 5, it can be observed that the higher threshold treated some darker sheepskin with blood into the background, with poor edge retention. Algorithm in this paper the threshold is lower than traditional Otsu algorithm, because the sheepskin compared with background brighter, lower threshold will make

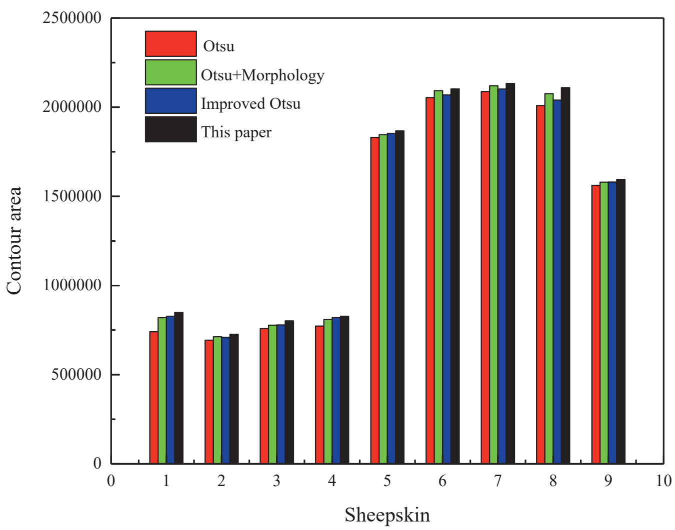


Figure 6. The comparison of contour area obtained by the four methods

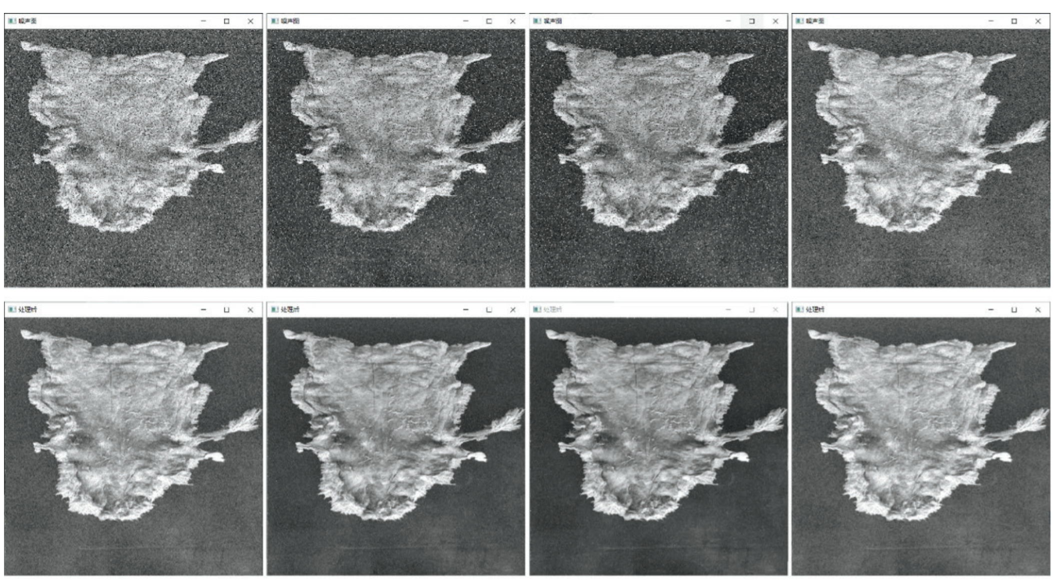
dark speck to effectively express, also on sheepskin outside of the image contour recognition more accurate, effective protection of the edge information, to obtain a relatively complete sheepskin outer contour, is advantageous to the subsequent cutting processing.

By comparing the two groups of sheepskin pictures (b), (c) or (d) and (e) in Figure 5, it can be observed that there are more broken edges in sheepskin edges without morphological treatment, and the extracted contour edges are incomplete and have large errors. After adding morphological treatment, the edges containing defects were connected to obtain a complete sheepskin contour.

In general, the contour method proposed in this paper can extract relatively accurate sheepskin contour. In order to quantitatively analyze the extraction precision of sheepskin contour, the area of contour extracted by the four methods mentioned above was calculated. The comparison of contour area obtained by the four methods is shown in Figure 6. It can be seen from Figure 6 that whether the traditional Otsu is improved or morphological defect processing is added, false segmentation can be effectively reduced. In contrast, the improved Otsu segmentation algorithm has a slightly greater impact on contour extraction than morphological post-processing.

Comparison and analysis of pre-treatment de-noising effect

In order to verify the denoising effect of the model, different levels of Gaussian and salt-and-pepper noise were added to the sheepskin images, and then gray scale correction was carried out under the model. In this experiment, several groups of noise variables are set, and the Gaussian noise levels are σ=0.3, σ=0.5 and σ=1. Salt and pepper noise densities are 10000 and 100000. The final noise diagram and processing results are shown in Figure 7.



σ=1；n=100000 σ=0.5；n=100000 σ=0.3；n=100000 σ=1；n=10000

Figure 7. The algorithm in this paper processes the results of noisy graphs

As shown in Figure 8, the denoising algorithm proposed in this paper has a good filtering effect on general additive noise and random noise, and at the same time, it plays a certain smoothing effect on the image and has excellent edge protection. Especially for the removal of salt and pepper noise has intuitive removal effect.

To objectively evaluate the effectiveness of the algorithm proposed in this paper, 3*3 mean filter, Gaussian filter and median filter were used to process the sheepskin original image of the above experiment, and three evaluation indexes relatively recognized by the industry were used to evaluate and analyze the filtering effect.

The evaluation indexes are as follows: Mean Square Error (MSE) refers to the expected value of the square of the difference between the image to be evaluated and the original image, and the smaller the value is, the better the image recovery will be. Peak signal-to-noise ratio (PSNR) is the ratio of the energy of the peak signal to the average energy of the noise. The greater the value, the better. Structural similarity (SSIM) is also a full reference image quality evaluation index. It measures the similarity of two images from brightness L(x,y), contrast C(x,y) and structure S(x,y). The larger the value is, the better, and the maximum value is 1. The evaluation values were recorded in Table I.

It can be seen from Table I that the method in this paper has the highest structural similarity, the peak signal-to-noise ratio and the lowest mean square deviation. The low mean square error indicates that the image distortion is the least after the proposed algorithm is used. The larger PSNR indicates that the proposed algorithm has the best denoising ability. The structural similarity between the Gaussian filter and the proposed algorithm is large, which indicates that the mean filter and the median filter sacrifice the detail of the image in order to achieve the ability of image denoising. It also indicates that the detail and edge protection performance of the proposed algorithm are better than other filters. All the numerical results show that the method presented in this paper is the best for sheepskin image processing. These three kinds of evaluation systems can show that the method proposed in this paper has scientific effectiveness and applicability.

Force analysis of image segmentation algorithm

The experimental subjects are mainly sheepskin images with pixel sizes of 1080×1920, 2457×1627 and 2589×1846, etc. The proposed segmentation algorithm was compared with Otsu and 2-D Otsu algorithms. The Otsu and 2-D Otsu algorithms are matched with the algorithms in this paper, such as Table II. The calculation time of Otsu algorithm is at the level of 100ms, while that of 2-D Otsu algorithm is about 4.5 times that of Otsu. The speed of this algorithm in processing sheepskin images is improved by 170% and 1080% compared with the traditional Otsu algorithm. It greatly improves the efficiency of the algorithm and meets the real-time requirement of industrial field cutting.

Conclusion

The use of computer vision measurement technology to realize the automatic cutting of the edging has changed the work mode of the company's manual cleaning of the edging. It solves the problem of labor intensity caused by high labor intensity and poor working environment in enterprise production and processing, and at the same time improves production efficiency and optimizes costs. The sheepskin contour extraction method proposed in this paper has a pixel-level three-dimensional denoising preprocessing system, uses a fast Otsu threshold algorithm based on image block pixel sets to segment binary images, uses morphological processing to fill edge defects, and using the boundary contour tracking algorithm based on topology analysis to extract the contour information, the largest the algorithm for sheepskin image processing effect is better. The 3d selective noise reduction model overcomes the noise interference caused by salt and effectively protects the sheepskin edge. Compared with the traditional one-

Table I
The evaluation values

Evaluation method	Average filtering	Gaussian filter	Median filtering	This paper
MSE	7.98101	4.75446	4.07791	3.30345
PSNR	39.1102	41.3598	42.0264	42.9411
SSIM	0.325682	0.32858	0.32766	0.328812

Table II
Comparison of the efficiency of Otsu 2D-Otsu and this paper (ms)

Sheepskin	Otsu	2D-Otsu	This paper	Faster than Otsu	Faster than 2D-Otsu
1	132.8	591.6	52.4	153%	1029%
2	141.3	611.4	54.3	160%	1026%
3	140.6	594.5	51.0	176%	1066%
4	139.4	580.0	55.1	153%	953%
5	257.1	1226.7	89.5	187%	1271%
6	331.7	1277.4	109.0	204%	1072%
7	269.4	1276.8	118.0	128%	982%
8	312.5	1273.4	108.5	188%	1074%
9	257.1	1218.1	90.5	184%	1246%
Average				170%	1080%

dimensional Otsu algorithm, the fast Otsu threshold segmentation technology of image block pixel set improves the processing rate by nearly 160%, meeting the real-time demand of industrial cutting. At the same time, the edge positioning is more accurate, and the outer contour with more complete and larger area is obtained with lower threshold, which reduces the mis-segmentation by nearly 3%. Morphological processing is used to fill in edge defects, and the boundary contour tracking algorithm of topological structure analysis obtains complete and accurate outer edge information. The sheepskin contour extraction method can obtain the accurate sheepskin contour information which can be operated by the cutting platform, which provides the theoretical basis for the sheepskin image cutting and a solid step for the realization of automatic sheepskin cutting. The algorithm presented in this paper is also suitable for the segmentation of other simple images with clear target and background and bright target, so it has a certain application prospect.

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