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Sheep Image Segmentation and Contour Extraction of Multi-scale Watershed and Fuzzy C-Means Based on Graph Cuts

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Abstract. In order to realize the sheep body size measurement, the sheep image segmentation under real environment is studied. To reach this goal, Lazy Snapping interactive mode and Graph cuts frame are applied to the segmentation models, integrated with multi-scale watershed and fuzzy C-mean clustering algorithms to fulfill the sheep image segmentation. The followings are the procedure. Firstly, R, G, B components of color image were selected respectively and gray image were transformed. Minimal number of regions based on multi-scale watershed pre-segmentation determined the operation for original image. Then, these regions were viewed as the vertex of graph cut, and then the network graph was built through computing the boundary term and data term. Adopting max-flow/min-cut method the minimum energy function of image was got to reach the goal. Finally, by comparing with cloud model, GrabCut algorithm and GrowCut algorithm, the proposed method can segment the sheep images more accurately, and overcome the background noise and reduce the runtime. Its F-measure was around 0.96, slightly higher than that of GrowCut. In addition, the more complete and smooth contour extracted from results of segmentation image is applicable to subsequent extraction of sheep measure points.

Key words. Graph cuts, sheep image, contour extraction, multi-scale watershed, Fuzzy C-Means.

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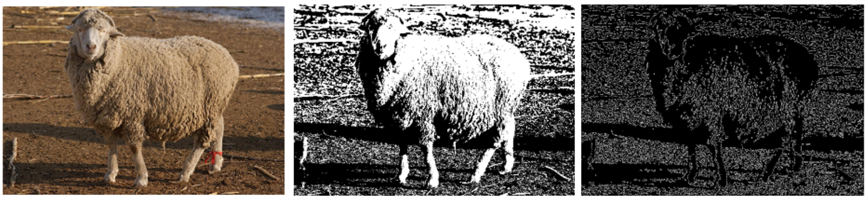
1. Introduction

Inner Mongolia region with natural grassland is the main production base for sheep. Compared with pork and beef, mutton has lower fat and cholesterol levels. The demand for mutton gradually increases each year. So the intensive sheep industry has been continuously [1][2]. However, sheep body measurements can reflect the growth status. Meanwhile, it is an important evaluation index in breeding, production and meat quality process [3]. Combining machine vision and image processing technology, the non-contact and non-stress measurement of sheep can be achieved to improve the health breeding and welfare. In recent years, there are many scholars to study contactless animal body compute. Paolo et al. [4] set up a stereovision system to estimate size and weight of live sheep. But a total number of 4622 distances were manually set in the calibration phase. By extracting the rump region feature positions of dairy goats, A. Vieira et al. [5] developed a visual body condition scoring system. The body measurements of Holstein cows were calculated using digital image analysis, and the live weight was estimated adopting regression analysis [6]. The sheep body parameters were determined using Qt cross-platform C++ graphical user interface application development framework, combined with OpenCV open source computer vision library [7]. Li Z. and Liu T. [8] obtained the body parameters to predict the pig body weight, and did three-dimensional reconstruction of pig body based on binocular stereo vision. J. Jiang [1] realized sheep body size calculation to make the comprehensive evaluation. However, the above studies have low automation or big error, especially wool′s influence. So, in order to achieve high automation and intelligence, the first solved problem is to separate sheep body from background and extract its contour. The outline extraction directly affects the accuracy of measuring points and subsequent body size. Therefore, sheep image segmentation and contour extraction are two key links in the process of non-contact measurement.

Image segmentation is the process of getting meaningful feature area based on gray level, color, texture and shape and so on [9]. At present, there are many segmentation methods, such as based on threshold, edge, region, neural network, cloud model and graph theory [10][11]. Because obtaining image is more complex, in which the color of sheep body, ground and corn stalk are very close, it cannot segment using color information. Light makes the brightness of image uneven, even producing shadows, grayscale processing does not apply. Moreover the influence of texture of sheep and land makes texture segmentation unavailable. So, traditional algorithms are not suit to sheep body image segmentation. By contrast, Graph cut algorithm belonging to the interactive semi-automatic segmentation can be got much information to quickly and accurately segment target, and it has strong practical [12].

The image contour extraction is to get target outline from the original image. Traditional methods mainly include edge detection operator and mathematical morphological method [13]. Image edge detection operator is done by the convolution of original image and template, which is simpler and has fast compute speed. But the extracted contour is discontinuous, which is unfavorable to the next processing, as shown in Fig. 1. Mathematical morphology method not only has the characteristics of single pixel and anti-interference, but also exits the discontinuous outline.



(a) Original image (b) Binary Image (c)Canny edge detection

Fig. 1. Image contour extraction based on simple methods

Boykov et al. [14][15] was proposed interactive foreground extraction framework based on Graph Cuts algorithm that mixed the image region and boundary information to improve the effect and speed. This way is widely used in natural images, medical images, etc. [16][17]. Now many improved algorithm about Graph Cuts is proposed. Fan S. et al regarded multi-scale Normalized cuts as objective function, and combined the fine scales and coarse scale without user interaction. It had rapid and accurate segment, but the robustness was low [18]. Aiming at the background and foreground color overlap, a novel method based on visual significance and Graph Cuts was put forward [12]. This method can easily lose some detail information. Wang J. et al.[19] used watershed pre-segmentation, each a small area as a vertex, adopting GrabCut algorithm based on Graph Cuts to segment. The efficiency was improved. But because this method was not based on pixel level, the boundary of segmentation was coarser. It was hard to get good result [20][21].

The traditional K-means implements clustering by minimizing mean of variance function. It is seriously sensitive to the initial clustering center. While Fuzzy C-means (FCM) is a kind of mature clustering way to achieve the fuzziness and uncertainty in image, and is widely used in image segmentation. Mao H. et al. [22] proposed an adaptive segmentation method of crop disease leaf images based on FCM clustering algorithm, which is satisfactory to separate disease part from normal part of leaves. FCM with adaptive weighted spatial information was also applied to the medical image segmentation [23].

In conclusion, the proposed algorithms present good segmentation effect in their own research field. But they are not suitable to the sheep image with complex backgrounds, not being able to separate the color closely part or the shadow region. Moreover, the traditional Graph Cuts algorithm based on pixels has large amount of calculation. Therefore, under the real breeding condition, sheep body is viewed as the object. According Lazy Snapping and Graph Cuts frame, a novel segmentation algorithm is proposed, fusing multi-scale watershed and FCM to raise the real-time interaction [13]. Firstly, image pre-segmentation is implemented by using multi-scale watershed to form super-pixel region blocks. Second, obtaining these blocks adopting FCM algorithm is clustered, then, setting up network of Graph Cuts to use max-flow/min-cut to separate. Finally, morphology, boundary processing and boundary tracking is introduced to extract the sheep target outline for making the basis of subsequent accurate feature recognition and sheep body parameter compute.

2. Graph Cuts Algorithm

Graph Cuts, combining Markov random field theory and max-flow/min-cut, will be map an image to a network diagram in which an energy function is set up. The image is treated as a graph, in which each pixel is a graph node. For the case of two labels the globally optimal pixel labeling (with respect to defined cost function) can be efficiently computed by max-flow/min-cut algorithms. We consider graph structure G=(V,E) with set of nodes V and set of edges E, firstly, as illustrated in Fig. 2. There are two specially designated terminal nodes S (source) and T (sink) that represent "object" and "background" labels. Typically, neighboring pixels are interconnected by edges in a regular grid-like fashion. Edges between pixels are called n-link. Other edges called t-link are used to connect pixels to terminals. All edges are assigned some nonnegative weight. An s-t cut divides the nodes between the terminals.

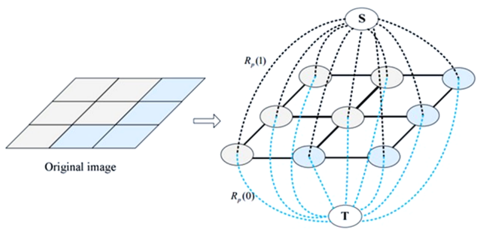


Fig. 2. The s-t graph

Supposing the image as S and the pixel $p \in P$. Image segmentation can be regarded as a label question. Every pixel distributes the label $\alpha = \{\alpha_1, \alpha_2, \cdots, \alpha_N\}$, if $\alpha_i = 0$, it shows this pixel is background; if $\alpha_i = 1$, it shows this pixel is foreground. N is the number of pixels. The Gibbs energy function of image is defined as follow:

$$E(\alpha) = R(\alpha) + (\lambda)B(\alpha)\,, \tag{1}$$

Where,

$$R(\alpha) = \sum_{p \in S} D_p(\alpha_p)\,, \tag{2}$$

$$B(\alpha) = \sum_{(p,q) \in C} B_{\{p,q\}} \bullet \delta(\alpha_p, \alpha_q)\,, \tag{3}$$

$$\delta(\alpha_p, \alpha_q) = \begin{cases} 1 & \text{if } \alpha_p \neq \alpha_q \\ 0 & \text{otherwise} \end{cases}$$

Where $R(\alpha)$ is the region item, and $D_p(p)$ represents the punishment of p distribution α_p. $B_{\{p,q\}}$ is the boundary item. $B_{p,q}$ represents the discontinued punishment of the adjacent pixels p and q. λ, nonnegative real number controls weight balance coefficient of region item and boundary item. The larger this parameter is, the better the regional integration of segmentation is. The smaller the parameter is, the stronger the separability of local details is. According the distribution weight of edges, the max-flow/min-cut of network is calculated. That is to say the minimum of energy function $E(\alpha)$ to achieve the optimal segmentation of the network.

3. Provided Graph Cuts algorithm

In order to improve the efficiency and accuracy of segmentation, using multi-scale watershed implements image preprocessing. Fuzzy C-means is applied to cluster. Graph cuts framework based on Lazy Snapping intuitive interaction is regarded as segmentation model.

3.1. Multi-scale Watershed Segmentation

Watershed is classic segmentation method using mathematical morphology and region. Some small regions of watershed segmentation are regarded as the node of graph cut to improve the efficiency of segmentation. Small regions are super-pixel area. It can be able to retain the boundary information of image, and every region has less differences. However, in practical application, because of the influence of image quantization and image gradient, it can cause the over-segmentation. For avoiding over-segmentation and fuzzy edge information, per-segmentation uses multi-scale morphological gradient operator instead of single scale morphological gradient operator [24][25]. Single scale morphological gradient operator is defined by:

$$G(f) = [f \oplus B] - [f \odot B]\,, \tag{4}$$

In this equation, $\oplus$ and $\odot$ are dilation and erosion operation. B called as structural element shows the performance of the single scale morphological gradient. Multi-scale morphological gradient operator computes the mean, as shown in expression (5).

$$MG(f) = \frac{1}{n}\sum_{i=1}^{n}[f \oplus B_i] - [f \odot B_i] \odot B_{i-1}\,, \tag{5}$$

In this equation, structural element $B_i(0 \le \alpha \le n)$ is square structure, and the size of B_i is $i \times i$ pixels. Multi-scale morphological gradient operator combing dilation and erosion detects the local grayscale level change of image. The open and close operation can make the smoothing effect. Image is calculated by multi-scale morphological gradient. The minimum value in the compute results is regarded as the starting point for watershed flood process.

In the experiment, color sheep body image was captured by the Sony DSLR$-\alpha$350 camera and its size was narrowed down to 1148*764 pixels. The captured image was processed by gray method, rgb2gray function and single channel component. In Matlab R2011b test platform, after color image implemented gray processing, the number of segmentation regions with single-scale and multi-scale watershed was computed, as shown in Table 1. Fig. 3 shows the pre-segmentation results based on G channel component.

Table 1. Statistics of multi-scale watershed segmentation regions

Images	First segmentation				Second segmentation			
	rgb2gray	R component	G component	B component	rgb2gay	R component	G component	B component
Sheep1	33367	33516	33596	34159	5861	5860	5846	5953
Sheep3	46706	46752	46862	46883	5712	5780	5686	5754

(a) Original images (b) The first segmentation (c) the second segmentation

Fig. 3. Results of multi-scale watershed segmentation of single channel G

Table 1 shows that the segmentation region number of single channel G component is the least in the four gray methods, which can reduce the subsequent computation. Therefore, the single channel G is selected as the input of multi-scale watershed. Meanwhile, Compared with the results of the first watershed segmentation, the segmentation area obtained by reusing that algorithm is reduced by 5 times. From the Fig. 3, the single channel G can describe the image edges. The intensity of regions of the second is lower than that of the first. It can be fast to compute, memory efficient, and simple to use.

3.2. Fuzzy C-means Algorithm

Fuzzy clustering algorithm proposed by Bezdek is an improved version of K-means algorithm. Fuzzy C-means algorithm classifies the image by grouping similar data points in the feature space into clusters [26]. The clusters are achieved by iteratively minimizing an objective function that is dependent on the distance of the pixels to the cluster centers in the feature domain. Fuzzy C-means algorithm belongs to unsupervised fuzzy clustering. The idea of the algorithm is to find the optimal clusters center v_i and the membership vector u_{ik}. Now let $X = \{x_1, x_2, \ldots, x_n\}$ be a sample of N. x_k is the k^{th} feature vector, x_{kj} the j^{th} feature of y_k, c is the number of clusters in $X(2 \leq c < n)$, v_k denotes the center of the i^{th} cluster. The objective function is defined by:

$$J_m(U,V) = \sum_{i=1}^{c}\sum_{k=1}^{n}(U_{ik})^m \|x_k - v_i\| \,, \tag{6}$$

Where $m(1 \leq m < \infty)$ is the weighting exponent on each fuzzy membership which controls the fuzziness of the resulting clusters, u_{ik} is the represents the membership of the x_k in cluster i, the value u_{ik} lies between 0 and 1. $\|x_k - v_i\|$ denotes the square of distance from sample x_k to centroid v_i. The optimum is reached by minimizing equitation (6) using the Lagrange multiplier method to find the v_i and u_{ik}. The general procedure is formalized as follow:

Step1: Initialize some variables, including c, m (set $m = 2$), and set maximum iteration number l, terminal condition and initial iteration counter $b = 0$.

Step2: Randomly initially generated a real $c \times n$ membership matrix U, and normalized processing.

Step3: Compute centers v_i with equation (7) and update membership values u_{ik} with equation (8).

$$v_i = \frac{\sum_{k=1}^{n}(u_{ik})^m x_k}{\sum_{k=1}^{m}(u_{ik})^m} \,, \tag{7}$$

$$u_{ik} = \frac{1}{\sum_{j=1}^{n}(\frac{d_{ik}}{d_{jk}})^{2/(m-1)}} \,, \tag{8}$$

Step4: Compare difference of twice adjacent cluster center with terminal condition. If the difference is less than terminal condition, or if the maximum iteration number is got, stop. Then, output the membership matrix U, and cluster center V. Otherwise, return to step 3, and add 1 to b.

Step5: Remove vagueness. The membership maximum criterion is employed to eliminate vagueness. That is also to say the pixels as the largest membership class. When the algorithm is converged, the cluster center and sample of every class can obtain, so as to complete the Fuzzy C-means clustering.

3.3. Steps of Proposed Graph Cuts Algorithm

Specific steps of proposed Graph Cuts are as follows:

Step1: Image pre-processing. Inputting color image I, and extracting the G component.

Step2: Image pre-segmentation. Multi-scale watershed employing G component implements the pre-segmentation the structural elements of dilation operation and erosion operation are the 1,2,3,4 square structures. The open and close operation is used to smooth processing. Color mean $C(i)$ of every segmentation region i is calculated. The region center coordinates are considered the vertexes of Graph Cuts.

Step3: Interaction operation. User labels some seeds on the image via mouse operated brush of red (for object) or blue (for background) color. And these seeds are mapped to the corresponding region. Using Fuzzy C-means clusters the object regions and background regions, clustering 60. The weighting exponent m is set to 2. the maximal iteration number is 100. After clustering, the object seeds and background seeds denote $\{K_n^F\}$ and $\{K_n^B\}$, respectively.

Step4: Adopting Lazy Snapping algorithm to set up the energy function region item and boundary item and build s-t graph. Where λ is fixed to 60 in the equitation (1). Region item is defined as follow:

$$\begin{cases} E_1(l_p=1)=0 & E_1(l_p=0)=\infty & \forall p\in F \\ E_1(l_p=1)=\infty & E_1(l_p=0)=0 & \forall p\in B \\ E_1(l_p=1)=\frac{d_p^F}{d_p^F+d_p^B} & E_1(l_p=0)=\frac{d_p^B}{d_p^F+d_p^B} & \forall p\in U \end{cases} \tag{9}$$

$$d_p^F=\min_n\|C(p)-K_n^F\|,\quad d_p^B=\min_n\|C(p)-K_n^B\|\,.$$

Boundary item is defined as follow:

$$E_2(\alpha_p,\alpha_q)=|\alpha_p-\alpha_q|\cdot g(C_{pq})\,, \tag{10}$$

$$g(C_{pq})=\frac{1}{\|C(p)-C(q)\|^2\cdot|\alpha_p-\alpha_q|+1}\,.$$

Step5: the max-flow/min-cut is employed to solve the minimum value of energy function to get the segmentation result.

Step6: If the result is satisfied, our operation stops, otherwise, go to step 3.

4. Experiment and Result Analysis

The study was carried out in Inner Mongolia Agricultural University experiment base in the Hohhot city in January 2016. Under the natural condition, the photographs of fine-wool sheep were taken using Sony DSLR$-\alpha$350 camera. The configuration of computer equipped with 32 bit Windows XP operation system is an Intel (R) Core (TM) 2 Duo CPU the E7500 @ 2.93 GHz processor with 3GB memory. In Matlab R2011b, sheep images using the improved algorithm were segmented, and Results were analyzed from the aspects of segmentation effect and accuracy.

4.1. Segmentation Results

The proposed algorithm based on multi-scale watershed segmentation and the Fuzzy C-means segmented the sheep images. The results of the algorithm were compared with cloud model, GrabCut algorithm, GrowCut algorithm, as shown in Fig. 4. Cloud model can express the uncertainty, so the model was used for threshold segmentation of sheep image. But it brought error segmentation that the sheep back area with strong light divided into background to lost sheep body parts. GrabCut algorithm continuously iterated to refine the color Gaussian Mixture

Model (GMM) parameters so that minimum the energy function should correspond to a good segmentation. Due to the close color of object and background, the segmentation time was rather slow in the experiment, and the results, even appearing the independent small regions, were not good enough. GrowCut algorithm used cellular automaton for solving pixel labeling task. The method was iterative, giving feedback to the user while the segmentation was computed [27]. This method can roughly extract the sheep body, rightly and smoothly segmenting the back region with great difference, but the sheep limbs regions were the error that was to mistake the background parts for the object. However, the proposed method based on super-pixels can segment a entire sheep body. The wool made the boundary unsmooth, and lost partial details, possessing less error regions. At the aspect of runtime, the relation of four method: cloud model<the proposed method<GrowCut<GrabCut. Because cloud model belongs to the threshold segmentation, the time is the shortest. The other methods iteratively implement. The proposed approach is regarded each region as graph mode. So it is better than the other two algorithms.

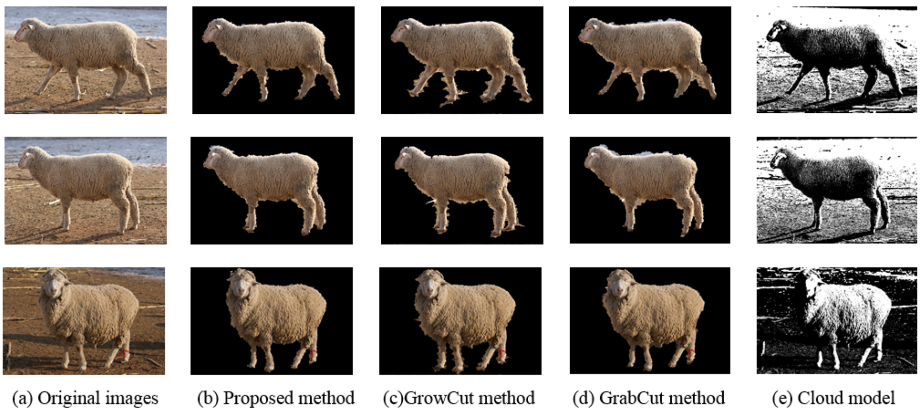


Fig. 4. Comparison segmentations between the proposed method and other methods

4.2. Accuracy of Segmentation

For quantitative comparison of the experimental results, the segmentation results were analyzed by F-measure (denoted as F) [28][29]. Taking the F-measure into account, it can be further analyzed in terms of precision (denoted as P) and recall (denoted as R). Precision P is computed with $P = TP/(TP + FP)$, which is the accurate part of present segmentation in the proportion of ideal results. Recall R is computed with $R = TP/(TP + FN)$, which is the present segmentation in the proportion of ideal results. By definition, if a pixel in the machined-detected object is also in the human-marked object, then the pixel is taken as a true positive (TP). Otherwise, the pixel in the machine-detected is taken as false positive (FP). If a pixel in the machined-detected background is also in the human-marked object, then the pixel is taken as a false negative (FN). F-measure is a linear weight of precision and recall, computing with $F = P * R/\zeta R + (1-\zeta)P$, where ζ is set to 0.5 in the experiments. The bigger the value of F-measure is, the more satisfactory the segmentation results according to the subjective judgment is. The computing value of them is listed in the Table 2. From the Table 2, F measure is slightly better than the GrowCut approach. The proposed approach obtains the superior results.

Table 2. Computation of precision, recall and F-measure

Images	Proposed method			Crowcut method		
	P	R	F	P	R	F
Sheep1	0.9923	0.9141	0.9516	0.9329	0.9566	0.9446
Sheep2	0.9821	0.9533	0.9675	0.9344	0.9748	0.9541
Sheep3	0.9793	0.9512	0.9651	0.9456	0.9694	0.9573

4.3. Contour Extraction

For the further study, feature points of sheep body need to search form the segmentation results. Because of the rough edge, the extracting contour is smoothly processed by implementing row elimination and column elimination. The flowchart of extraction contour is shown as in Fig. 5, and the results are presented in Fig. 6 in details. The completed and smooth sheep body outline are obtained.

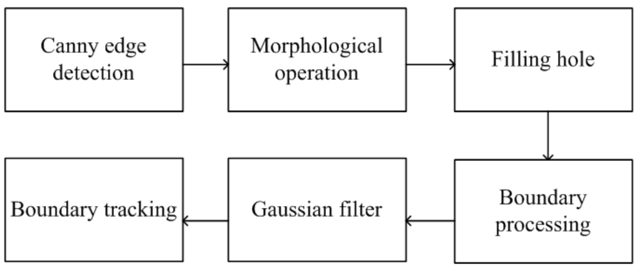


Fig. 5. Process of contour extraction

5. Conclusions

The new algorithm for splitting sheep image with complex background is developed based on multi-scale watershed and Fuzzy C-means on the basis of Graph cuts. It includes advanced splitting of sheep image, clustering the background and foreground, performing the segmentation and analysis of the results. The experiments using some sheep images demonstrate that the propose algorithm achieves the superior performance of segmentation, and accuracy. For the future work, the satisfactory contour of sheep is extracted. The experimental results show that it works a promising way, and is capable of dealing with quite complex sheep image. As a future work, we would like to research the automatic segmentation method for sheep image, which will obtain some foreground and background seeds without

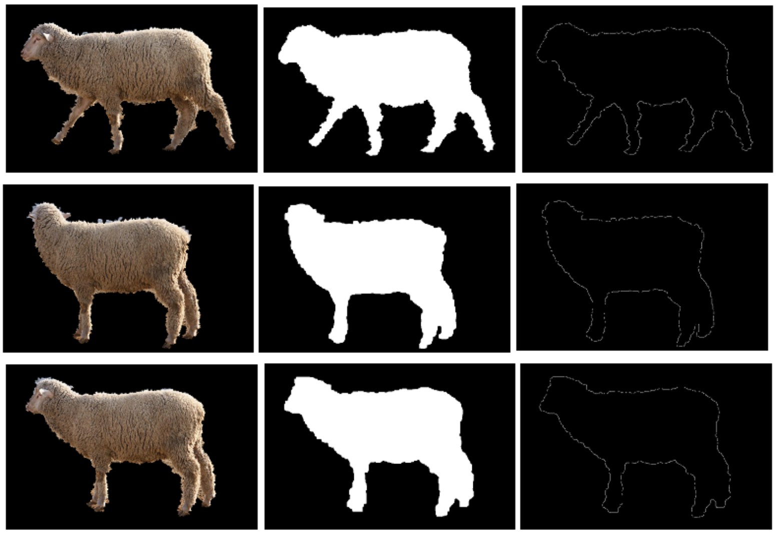


Fig. 6. Results of contour extraction

manual operation. This solves the main problem for improving the health breeding and welfare of sheep industry.

References

[1] J. Jiang, L. N. Zhou, G. Li: *Sheep body size measurement based on computer vison.* J of Computer Applications *34* (2014), No. 3, 846–850.

[2] L. N. Zhang, P. Wu, C. Z. Xuan, Y. Q. Liu, J. Wu: *Advances in body size measurement and conformation appraisal for sheep.* Transactions of the Chinese Society of Agricultural Engineering *32* (2016),No. z1, 190-197.

[3] J. Y. Bai, S. L. Zhang, Y. Z. Pang: *Principal components analysis on body sizes of Fat-tailed sheep.* Hubei Agricultural Sciences *50* (2011), No. 14, 2912–2914.

[4] P. Menesatti, C. Costa, F. Antonucci: *A low-cost stereovision system to estimate size and weight of live sheep.* Tamkang Journal of Science and Engineering *103* (2014), No. 2, 33–38.

[5] A. Vieira, S. Brandao, A. Monteiro: *Development and validation of a visual body condition scoring system for dairy goats with picture-based training.* Journal of Dairy Science *98* (2015), No. 9, 6597–6608.

[6] S. Tasdemir, A. Urkmez, S. Inal: *Determination of body measurements on the Holstein cows using digital image analysis and estimation of live weight with regression analysis.* Computers and Electronics in Agriculture *76* (2011), No. 76, 189–197.

[7] T. Feng: *Construction and implementing for non-touch measurement system of cattle body.* Yangling:Northwest A and F University (2014).

[8] T. Liu, G. Teng, S. Zhang: *Reconstruction and application of 3D pig body model based on point cloud data.* Nongye Jixie Xuebao *45* (2014), No. 6, 291–295.

[9] J. L. Ren, W. H. Xian: *The Granular Theorem of Quotient Space in Image Segmentation.* Chinese Journal of Computers *28*, (2005), No. 10, 1680–1685.

[10] Y. Zou, R. J. Shuai: *Improved segmentation algorithm of medical images based on SOM neural network.* Computer Engineering and Design *9* (2016), No. 1, 2533–2537.

[11] F. F. He, G. Y. Wang, X. Liu: *Multi-granularity Color Image Segmentation Based on Cloud Model and Spatial Information.* Journal of Chinese Computer Systems *37* (2016), No. 8, 1832–1836.

[12] Y. Liu, B. Huang, H. J. Sun: *Image Segmentation Based on Visual Saliency and Graph Cuts.* Journal of Computer-Aided Design and Computer Graphics *25* (2013), No. 3, 402–409.

[13] B. X. Zou, J. R. Lin: *Contour extraction research of image.* CEA *44* (2008), No. 25, 161–165.

[14] Y. Y. Boykov, M. P. Jolly: *Interactive graph cuts for optimal boundary & region segmentation of objects in N-D images.* Computer vision proceedings eighth IEEE international Conference *8* (2001), No. 3, 105–112.

[15] Y. Boykov, G. Funka-Lea: *Graph Cuts and Efficient N-D Image Segmentation.* International Journal of Computer Vision *70* (2006), No. 2, 109–131.

[16] Z. G. Guo: *Interactive image segmentation based on graph cuts.* Changsha: Central South University (2013).

[17] T. Chen: *Study on interactive medical X-ray image segmentation based on Graph Cuts algorithm.* Beijing: Beijing Jiaotong University (2014).

[18] S. Y. Fan, S. F. Ding: *An improved multi-scale Graph cut algorithm.* Journal of Shandong University (engineering science) *46* (2016), No. 1, 28–33.

[19] J. M. Wang, L. X. Gao, L. Zhao: *Grab cut algorithm based on watershed persegmentation.* Technical Acoustics *27* (2008), No. 4, 179–182.

[20] C. Rother, V. Kolmogorov, A. Blake: *Grabcut, Interactive foreground extraction using iterated graph cuts.* ACM transactions on graphics *23* (2004), Nos. 3, 304–314.

[21] C. C. Yi, B. Wu, H. Y. Zhang: *An Improved Grabcut Image Segmentation Method.* J Chinese Institute of Engineers *35* (2014), No. 5, 1164–1168.

[22] H. P. Mao, Y. C. Zhang, B. Hu: *Segmentation of crop disease leaf images using fuzzy C-means clustering algorithm.* Transactions of the Chinese Society of Agricultural Engineering *24* (2008), No. 9, 163–140.

[23] L. M. Wang: *FCM algorithm with adaptive weighted spatial information for medical image segmentation.* Microcomputer & Its Applications *30* (2011), No. 22, 42–45.

[24] Y. P. Hu, H. Xiang, D. J. Luo: *Clothing image retrieval method based on improved GrabCut algorithm.* Computer Science *43* (2016), No. S2, 242–246.

[25] L. F. Zhou, J. N. He: *Improved image segmentation algorithm based on GrabCut.* Journal of Computer Applications *33* (2013), No. 1, 49–52.

[26] V. Vezhnevets, V. Konouchine: *GrowCut: Interactive multi-label ND image segmentation by cellular automata.* Graphicon-2005 (2006), No. 1,231–234.

[27] S. D. Han, Y. Zhao, W. B. Tao: *Gaussian Super-pixel Based Fast Image Segmentation Using Graph Cuts.* Acta Automatica Sinica *37* (2011), No. 1, 11–20.

[28] S. Han, W. Tao, X. Wu: *Texture segmentation using independent-scale component-wise Riemannian-covariance Gaussian mixture model in KL measure based paper13multi−scale nonlinear structure tensor space.* Pattern Recognition *44* (2011), No. 3, 503–518.

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