Robust Extraction of Lean Tissue Contour from Beef Cut Surface Image

Heon Hwang, Y.K. Lee, and Y.R. Chen*

Sung Kyun Kwan University, College of Life Science and Natural Resources
Dept. of Bio-Mechatronic Eng., Suwon, Korea 440-746.
*USDA, Agricultural Research Service, Instrumentation and Sensing Laboratory
Beltsville, Maryland 20705-2350.

ABSTRACT

A hybrid image processing system which automatically distinguishes lean tissues in the image of a complex beef cut surface and generates the lean tissue contour has been developed. Because of the inhomogeneous distribution and fuzzy pattern of fat and lean tissues on the beef cut, conventional image segmentation and contour generation algorithms suffer from a heavy computing requirement, algorithm complexity and poor robustness. The proposed system utilizes an artificial neural network to enhance the robustness of processing. The system is composed of pre-network, network, and post-network processing stages. At the pre-network stage, gray level images of beef cuts were segmented and resized to be adequate to the network input. Features such as fat and bone were enhanced and the enhanced input image was converted to the grid pattern image, whose grid was formed as 4x4 pixel size. At the network stage, the normalized gray value of each grid image was taken as the network input. The pre-trained network generated the grid image output of the isolated lean tissue. A sequence of post-network processing was followed to obtain the detailed contour of the lean tissue. A training scheme of the network and the separating performance were presented and analyzed. The developed hybrid system showed the feasibility of the human like robust object segmentation and contour generation for the complex, fuzzy and irregular image.

Keywords: beef cut, lean tissue, contour generation, real time system, neural network, segmentation, automatic processing

INTRODUCTION

For the past several decades, the USDA quality and yield grades for beef have pursued to reduce the fat amount of the carcass associated with beef yield. In the U.S., beef carcass merit deals with evaluations of two different aspects: one is quality (marbling and maturity) and the other is composition (total lean, fat and bone, or lean with some acceptable level of external fatness, along with trimmable fat and bone). Recently, the beef industry drafted a plan for the research and development of an instrument capable of evaluating carcass leanness, marbling and maturity(Cross and Savell, 1994). The instrument should be able to predict the percentage of lean, marbling and maturity with a high degree of accuracy.

Development and installation of a system for instrumental assessment of carcass value would be critical because livestock producers are not sufficiently confident in current, subjective grading systems. Computer image analysis (CIA) has the potential to remove the subjectivity associated with visual composition measurement. CIA has been studied for predicting the lean and fat content of meat cuts and the composition of carcasses from measurements made on the cut surface.

An algorithm for the application of the Boolean random set model with convex primary grain in the description of the spatial distribution of marbling in beef ribeye was presented(McDonald and Chen, 1992). However, the automated separation of fat from lean and different degrees of fat cover for quantitative fatness assessment has not been achieved. Recently, the algorithm for rapid isolation of lean muscle from its surrounding fat in a beef carcass based on gray level intensity of the cut surface image was developed(Chen et al., 1995). However, executing such an algorithm required substantial processing time. In this study, an hybrid image processing algorithm was developed to automatically extract lean tissues in beef cut surface gray images and generate the contour.

MATERIALS AND METHODS

Ten ribeye beef cut surfaces were digitized by TM1000(PULNIX Inc., Sunnyvale, CA) B/W camera** which has a 1K by 1K high resolution and Oculus F/64 frame grabber(CORECO Inc., St. Laurent, CANADA). Then 20 beef cut surface images were artificially generated by manipulating the original digitized images. The automation process was simulated by writing a series of tasks into a file using "in-house" user friendly window-based software developed at the Instrumentation and Sensing Laboratory, Beltsville, Maryland. Algorithms have been developed considering real time on-line system implementation. The sequence of image processing algorithms were classified into three stages such as pre-network, network, and post-network processing stages.

At the pre-network stage, the gray image of beef cut was obtained from the prespecified measuring window and contrast was enhanced linearly. After background was segmented from the beef cut, X and Y processing ranges of the image were selected automatically by reducing background. Features such as fat and bone were segmented and the whole image was resized to 160 by 160 pixel image. Then the image was converted to the 40 by 40 grid pattern, where each grid was formed as square having 4 by 4 pixels. Finally gray values of pixels in each grid were averaged and normalized for the network input.

At the post-network processing, outputs of the network were thresholded first. And outputs of the network were converted to bitmapped image data resulting into 40 by 40 pixel size of binary image. After reducing noise of the original image, the size of the output image was restored to the image size of 160 by 160 pixels. This size restoration allowed the output image from the network to have the same size of the grid pattern as input grid image. And the grid pattern output image was converted to the detailed pixel based image. Then image smoothing was performed to remove jagged sections and isolated pixels.

At the network stage, a backpropagation network(Rumelhart et al., 1986) retaining two layers was adopted to identify the lean tissue from the beef cut surface image. The network was formed such as 1600 nodes(40 by 40 grid pattern image) for the input and the output layer respectively and 70 nodes in the hidden layer. Lean tissue identification via the neural network was composed of two operations, training along validation and execution. In both operations, the captured gray image was pre-processed and converted into the network input grid pattern. Since the neural network was trained based on a supervised learning algorithm, for a given input image, the associated desired lean tissue image was provided at the training stage. In this study, with the aid of computer image enhancement techniques the desired portions of the lean tissue in the beef cut image were specified interactively according to the human supervisory recognition results. Fig.1 shows the overall block diagram of the hybrid image processing to extract the lean tissue contour of the beef cut surfaces.

2.1 Pre-network processing

The pre-network processing is part of the sequence of image processing to prepare for the appropriate network input. Fig.2 shows the block diagram of pre-network processing sequences. First of all, the size of the measuring window is prespecified considering the effect of nonlinear geometric distortion and processing time(Hwang and Lee, 1992). For the contrast of image, the linear contrast enhancement of the gray image was conducted such that

$$g(i,j) = \frac{255}{M-N}(f(i,j) - N)$$

, where f(i,j) and g(i,j) are gray values at pixel(i,j) of the original and resulting images after linear contrast enhancement respectively. M and N are the maximum and minimum gray values of f(i,j) respectively.

** Mention of any company or trade name does not imply endorsement of the products by the U.S. Department of Agriculture. It is for purpose of description only.

Then beef cut surface is separated from the background via automatic thresholding based on the window extension scheme. Various algorithms are known in determining the optimum threshold automatically such as an image statistical method which minimizes the weighted sum of group variances(Pratt, 1991), the moment preservation method(Tsai, 1985), maximum entropy method(Abutaleb, 1989), and window extension method(Hwang et al., 1992).

Since we can restrict the background to black, the background window extension scheme was quite simple and efficient in separating beef cuts from the background. The window extension method selects the threshold value by searching the starting point of the histogram variation of two images between the initial size and the extended size of the measuring window. Extending the window size enlarges the number of pixels of background which has somewhat uniform ranges of the gray level and keeps the number of object pixels unchanged.

Two histograms obtained from the initial and the extended windows are averaged at the specified gray interval to reduce noise effects. The gray value T_b is selected when the difference in probability density function between the two exceeds the predefined values. The segmented image is obtained such that

$$\begin{array}{ll} \text{if } g(i,j) < T_b, & g(i,j)=0 \\ \text{else,} & g(i,j)=g(i,j) \end{array}$$

where T_b is the threshold value and $g(i,j)$ is a gray value at the pixel coordinate (i,j).

Once the beef cut surface is segmented from the background, geometric features of the segmented beef cut are obtained via modified chain coding such as centroid and the contour information. The modified chain coding handles up to 3 pixel disconnectivity while preserving the tracing efficiency, 3 by 3 search mask was extended to 5 by 5, 7 by 7, and 9 by 9 based on the direction of the previous chain vector(Hwang et al., 1993). Rectangular boundary coordinates were utilized to assign the beef cut image area for the network input. The image was enhanced again by separating lean and fat tissues. A method based on the 6th moment difference was chosen to automatically separate fat from lean tissues since it gives consistent segmentation results even under the uneven lighting illumination.

The 6th moment difference can be computed from the co-occurrence matrix and is a modified version of average contrast(Chanda and Mjumder, 1985). Many investigators have applied the co-occurrence matrix techniques(Haralick et al., 1973) to find threshold values for segmentation purposes in many different ways such as busyness measure, conditional probability, entropy measure, average contrast measure(Chanda et. al, 1985; Chanda and Majumder, 1988; Weszka and Rosenfeld, 1978).

For a M by N pixel image with L levels of gray intensity, the elements of the gray level co-occurrence matrix [C] along the direction θ are defined as

$$C_{\theta\, m,n} = \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \#[g(i,j) = m \,/\, g(i-d\sin\theta, j+d\cos\theta) = n] \qquad (1)$$

where m is the gray level of pixel coordinates (i,j), n is the gray level of pixel coordinates $(i-d\sin\theta, j+d\cos\theta)$, and $i=0,1,2,..,M-1$ and $j=0,1,2,..,N-1$.

For our segmentation purpose, values of $d=1$, $\theta=0$ and $\theta = \pi/2$ were used. The resulting gray level co-occurrence matrix [C] is

$$[C] = \{ C_{m,n} \} = \frac{1}{2} ([C_0]+[C_{\pi/2}/2]) \qquad (2)$$

The busyness value B(t) is defined as

$$B(t) = \sum_{m=0}^{t} \sum_{n=t+1}^{L-1} C_{m,n} + \sum_{m=t+1}^{L-1} \sum_{n=0}^{t} C_{m,n} \qquad \text{for } t=0,1,2,..,L-2 \qquad (3)$$

The 6th moment difference $MD_6(t)$ is defined as

$$MD_6(t) = \frac{\sum_{m=t+1}^{L-1} \sum_{n=0}^{t} (m-n)^6 C_{m,n}}{B(t)} \quad \text{for } t=0,1,2,..,L-2 \qquad (4)$$

The gray value t which gives the largest value of $MD_6(t)$ is the optimum threshold to segment fat and bone from the beef cut.

To obtain the threshold value, the image intensity L is first scaled down from 256 gray levels to 64 levels and then co-occurrence matrix of the rescaled image is generated. The purpose of decreasing gray scale is for fast generation of the co-occurrence matrix. From this matrix, the optimum gray value is computed using the equation (4). The resulting binary image is obtained using T_f, the restored value from t_f, such that

$$\text{if } g(i,j) > T_f,\ g(i,j)=0$$
$$\text{else, } \quad g(i,j)=255$$

The image was resized to the 160 by 160 pixel square image and the scale factors for each X and Y direction were kept for later restoration. Then, the 160 by 160 pixel image was converted into 40 by 40 coarse grid image via averaging gray values of pixels in each 4 by 4 pixel grid. The average gray value of each grid was normalized for the neural network inputs. Fig.3 shows the results of pre-network processing.

2.2 Network processing

According to our previous experience, the conventional image processing techniques had the severe difficulty in eliminating the irregular or complex pattern of the extraneous tissues isolated or adhered to the lean tissue as shown in fig.4-a. However, this eliminating process is important because the extraneous regions cause errors in separating and selecting the longissimus muscle area. For beef cuts having simple patterns of the lean tissue and fat, morphological dilation and erosion of the image cooperated with some heuristic rules set up from the geometric characteristics of the lean tissue could successfully remove the adhered or isolated extraneous regions of the image. However, we experienced a difficulty in eliminating extraneous regions for the complicated and the irregular patterns. Fig.5 shows complicated and extraneous regions of the ribeye beef cut surface image which causes the wrong result of the lean tissue contour generation. Fig.5-b is one of the undesirable lean tissue contours and fig.5-c represents the desired one.

By the way, a human operator can easily eliminate the extraneous and isolated tissues and recognize the desired portion of lean tissue in a robust manner regardless of its pattern complexity. This was the motivation in employing the artificial neural network. Since the neural network can mimic the human decision making to some degree, the network was formed and trained to generate the binary image of lean tissue portions for the given input image of the beef cut surface. This is a major concept of this paper and the network was trained successfully to remove either adhered or isolated extraneous regions of lean tissue.

It is known that a structure of the network and the way of representing input and output are crucial to the success of the network application. In order to generate the proper lean tissue portions, the network should learn the gray intensity relationships between the input and the desired output images in the spatial domain using proper input and output representations. For the neural network model 1,600 nodes were assigned to the input and the output layer, respectively and 70 nodes were used in the hidden layer. A sigmoid function was used for the activation function of each node.

The variation of the beef cut size was automatically handled at the pre-network stage by adjusting the size of the input image grid to the network. Though the variation caused by the orientation of the beef cut was allowed, the rib bone side of the beef cut was restricted to lie in one direction. One beef cut image was utilized for 2 sample images including itself and the mirror image, whose bone laid in the same side. 60 sample images were formed from 10 beef cut samples via reflecting images and distorting images artificially. Fig.4 shows the original and artificially generated sample images. 40 sample images were used for training network and other 20 images were used for performance validation of the trained network.

As a desired output for the network, the binary contour grid image of the lean tissue was first tested. However, the contour grid output was so sensitive to the variation of input image and correcting the undesired portion of the output was not easy. It required rather complicated post-network processing to generate the detailed contour of the lean tissue. Instead of the grid contour of the lean tissue boundary shown in fig.6-c, the overall binary image of the lean tissue portion was adopted as a desired network output as shown in fig.6-d.

Fig.7 shows the block diagram of the training operation. After pre-network processing, an image was recomposed to 40 by 40 grid image. The gray value of each grid was obtained from averaging 4 by 4 pixel size part of the enhanced binary image. Then gray value of each grid was normalized and input to the network. The network generated real valued outputs ranging from 0 to 1. Network outputs were compared with gray values of the desired binary image.

The desired binary images of lean tissue portion were formed manually from the 40 by 40 grid images. Portions except the lean tissue were forced to be white leaving lean tissue portions as black. White and black areas of desired image were converted to real values of 1 and 0 respectively before comparing with network outputs.

2.3 Post-network processing

At the post-network processing, output values generated from the network are thresholded to 0 and 1 and then converted to binary image data resulting in 40 by 40 pixel size. At this point each pixel of the output image generated by the network corresponds to the 4 by 4 pixel grid. After passing noise removal which removes undesired pixels such as isolated islands and holes, the coordinates of the boundary grid of the lean tissue output image were generated via morphology contour generation and the output image of the network was restored to 160 by 160 pixel size by duplicating each pixel to 4 by 4 pixels with same gray values.

The coarse grid image generated by the pre-trained network was converted to the detailed pixel based image by switching pixels of the grids of the lean tissue generated from the network to corresponding pixels of the input binary image. Then once again a smoothing process was performed to remove jagged sections and isolated islands and holes using morphology opening algorithm. Then the detail contour of the lean tissue was generated. Fig.8 shows the block diagram of the post-network processing. Fig.9 shows the sequence of the resulting images obtained from the post-network processing.

RESULTS AND DISCUSSION

In order to test the performance of the proposed algorithms, 60 sample images of beef cut surfaces were used. Since the objective of the network training was isolating certain portions of the given image, performance of the network training was monitored by the Root Mean Squared Error (RMSE) such that

$$\mathrm{RMSE} = \sqrt{\frac{\Sigma(D(i,j) - F(i,j))^2}{n}}$$

, where n is total number of pixels in the image. F(i,j) and D(i,j) represent the network output and the desired output respectively. D(i,j) has values of 1 and 0.

The network was trained by repetitively presenting 40 sample patterns in a random order. Network output error was accumulated at every 8 sample presentations resulting the learning epoch of 8 presentations and back-propagated. The learning coefficient of the network was set initially to 0.2 and decreased by half at every 1000 presentations. The network performance before and after learning was shown in Table 1 based on RMSE. The RMSE of the network for 40 training samples was 0.217 and after 5000 random presentation of 40 samples it was reduced to 0.044. Here, one presentation means presentation of one sample to the network. The output RMSE decreased most to 0.067 during the first 1000 random presentations. The RMSE of the trained network for 20 unknown samples was 0.079. However, the network error could be further reduced after passing a sequence of post-processing such as thresholding network output, noise removal, grid template merging, and morphological smoothing.

Fig 10 and 11 illustrate typical results of proposed algorithms for the samples used for the network training. Sample of fig.10 had a relatively simple lean tissue pattern compared with that of fig.11. Fig.12 and 13 illustrate typical results of proposed algorithms for the samples not used for the network training.

CONCLUSIONS

Proposed hybrid processing algorithm successfully separated the portion of the lean tissue from the beef cut surface in a robust manner without human intervention. The extracted ribeye images could be used to measure the ribeye area and marbling for yield and quality grading. Though for unknown samples the trained network generated the contour of lean tissue portion not accurate enough but it assigned the desired lean tissue portions quite successfully for a complex pattern of beef cut surface image. It seems that introducing more beef sample images could improve the performance of the network.

However, since a sequence of image processing algorithms with some heuristic rules successfully segment a lean tissue with a simple pattern, it is strongly suggested to introduce some heuristic rules to compensate the network based lean tissue segmentation. Instead of generating the lean tissue directly via artificial neural network, research is on-going currently to utilize the neural network as a decision supporting subsystem.

REFERENCES

1. Abutaleb, A.S. 1989. "Automatic Thresholding of Gray Level Pictures Using Two Dimensional Entropy" *Computer Vision, Graphics and Image Processing*, Vol.47: 22-32.
2. Chanda, B., B.Chaudhuri, and D. D. Majumder. 1985. "On image enhancement and threshold selection using the gray level co-occurrence matrix" *Pattern Recognition* letters: 243-251.
3. Chanda, B. and D.D. 1988. "A note on the use of the gray level co-occurrence matrix in threshold selection" *Signal Processing*: 149-167.
4. Chen, Y.R., M. Nguyen, and B. Park. 1995. An image processing algorithm for separation of fat and lean tissues on beef cut surface. ASAE Paper No. 953680. ASAE St. Joseph, MI.
5. Cross, H.R. and J.W. Savell. 1994. "What do we need for a value-based beef marketing system" *Meat Science* 36: 19-27.
6. Haralick, K., I. Shanmugam, and I. Dinstein. 1973. "Textural features for image classification" *IEEE Trans. SMC*, Vol SMC-3: 610-621
7. Hwang, H. and C.H. Lee. 1992. "Computer Vision Based Measurement, Error Analysis and Compensation" *Trans. of KSAM*, Vol.17, No.1: 65-78.
8. Hwang, H. and C.H. Lee and Y.K. Lee. 1993. "Automatic Visual Feature Extraction and Measurement of Mushroom(Lentinus Edodes L.)" *Int. Conf. on Agricultural Machinery and Process Engineering '93* Oct. 19-22, Seoul, Korea Vol.4: 1232-1243.
9. McDonald, T.P. and Y.R. Chen. 1992. "A geometric model of marbling in beef longissimus dorsi" *Trans. of the ASAE* 35(3): 1057-1062.
10. Pratt, W.K. 1991. "Digital Image Processing" John Wiley & Sons Inc.
11. Rumelhart, D.E., G.E. Hinton, and R.J. Williams. 1986. Learning internal representations by error propagation. In D.E. Rumelhart and J.L. McClelland (Eds.), *Parallel Distributed Processing: Explorations in the Microstructures of Cognition*. Vol. 1: *Foundations*, pp.318-362, MIT Press, Cambridge, MA.
12. Tsai, W.H. 1985. "Moment Preserving Thresholding: A New Approach. Computer Vision" *Computer Vision, Graphics and Image Processing*, Vol.29: 377-392.
13. Weszka and A. Rosenfeld. 1978. "Thresholding evaluation techniques" *IEEE Trans. SMC*, Vol. SMC-8: 622-629.

Table 1 RMSE of the network during the learning process for 40 training samples of beef cuts

No. of Presentations	RMSE for 40 Training samples
initial (untrained network)	0.217
1,000 presentations	0.067
5,000 presentations	0.044

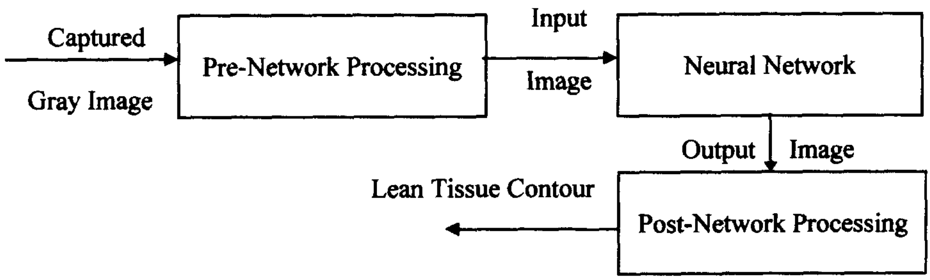


Fig.1 Overall block diagram of the proposed hybrid image processing .

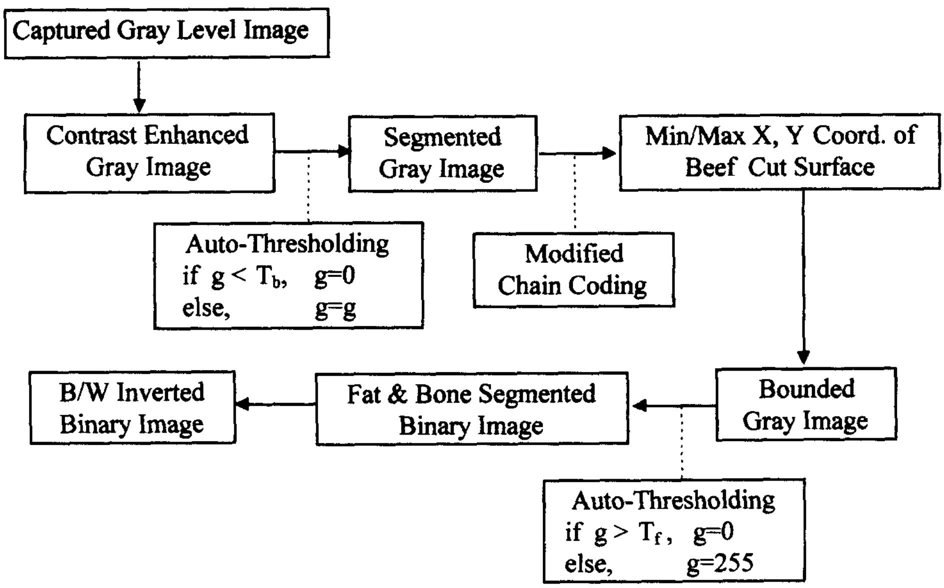
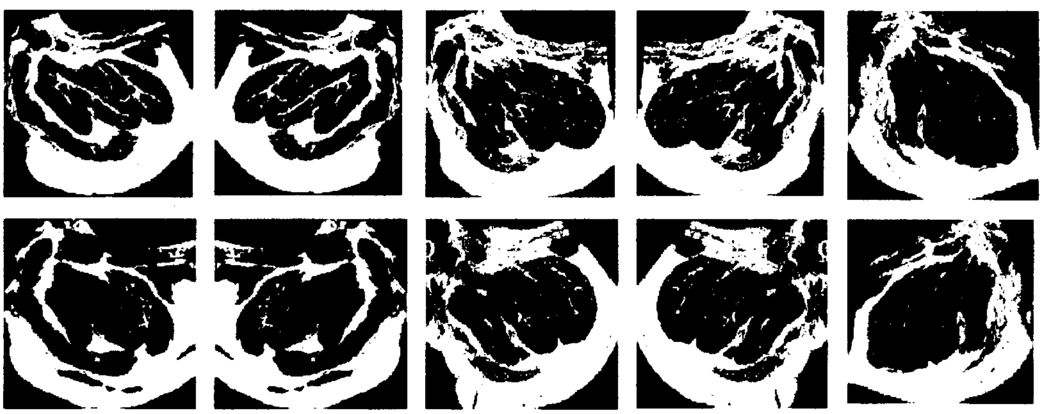


Fig.2 Block diagram of pre-network processing.

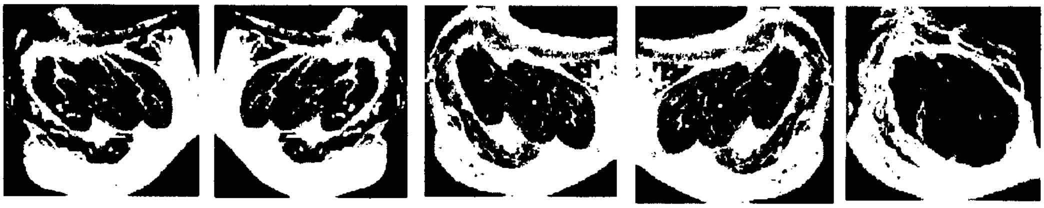
(a) (b) (c)

(d) (e) (f)

Fig.3 Sequence of the intermediate images obtained from pre-network processing; (a) original image : 400x320 pixels (b) linearly contrast enhanced image: 400x320 pixels (c) background segmented and bounded image: 400x320 pixels (d) fat segmented binary image: 400x320 pixels (e) resized and inverted binary image: 160x160 pixels (f) grid input image for the network after averaging gray values of 4x4 pixels: 40x40 grids(1 grid = 4x4 pixels).

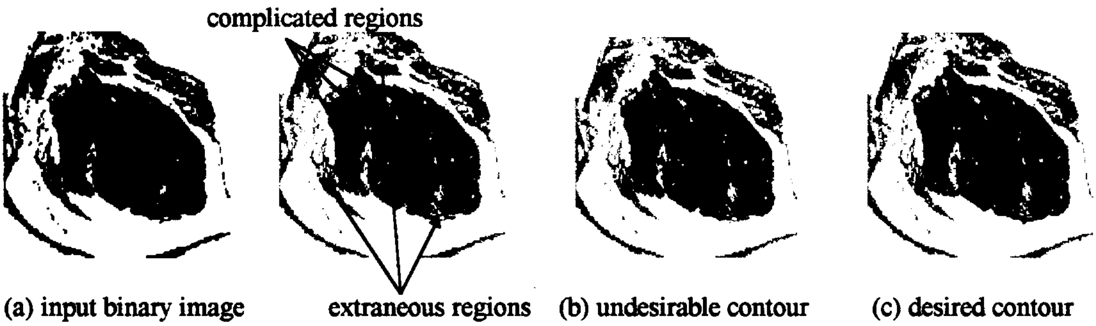


(a) original and reflected samples



(b) artificially generated samples

Fig.4 Part of original and artificially generated sample images.



(a) input binary image (b) undesirable contour (c) desired contour

Fig.5 Typical beef cut having a complex lean tissue pattern and generated contours.

(a) (b) (c) (d)

Fig.6 Input and desired output images for network training; (a) enhanced binary image: 160x160 pixels
(b) input grid image for the network after averaging 4 by 4 pixels of the binary image: 40x40 grids
(c) desired network output I: 40x40 grids (d) desired network output II.: 40x40 grids.

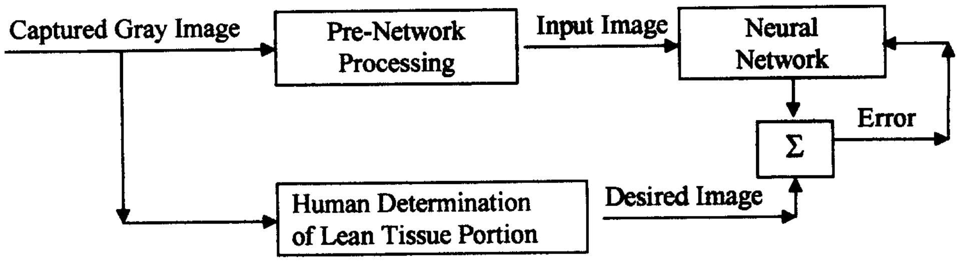


Fig.7 Block diagram of neural network training.

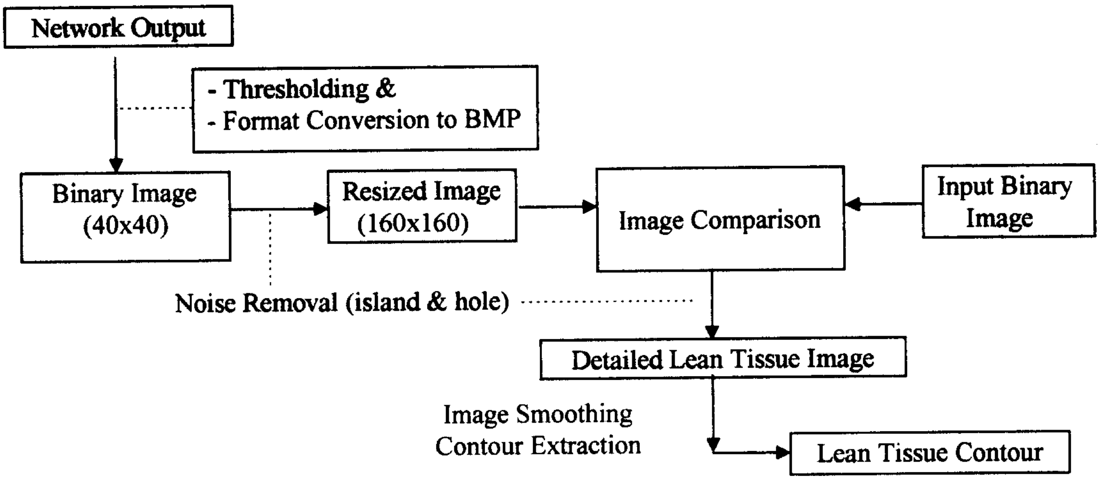


Fig.8 Block diagram of the post-network processing.

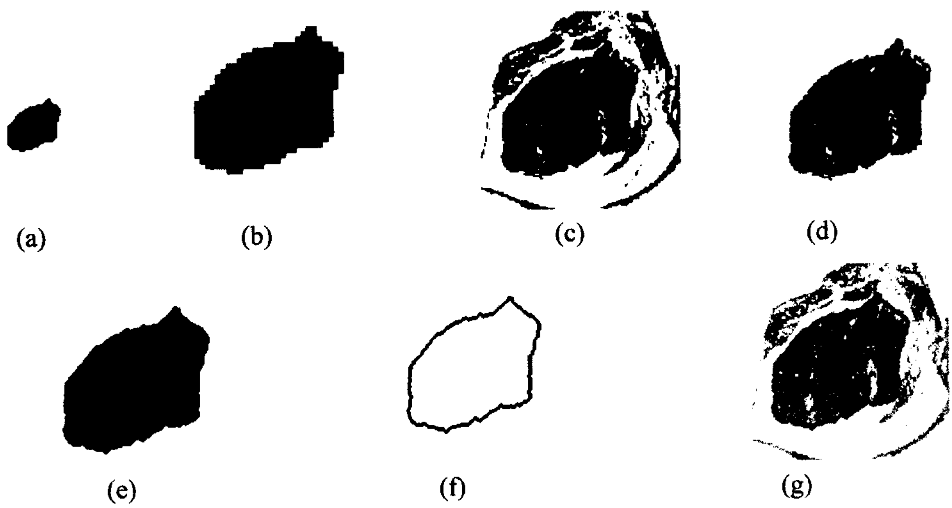


Fig.9 Sequence of the resulting images obtained from post-network processing; (a) network output image:40x40 grids (b) resized image: 160x160 pixels (c) input binary image: 160x160 pixels (d) merged lean tissue with input binary image (e) image after morphology opening (f) lean tissue contour (g) merging contour to the beef cut image

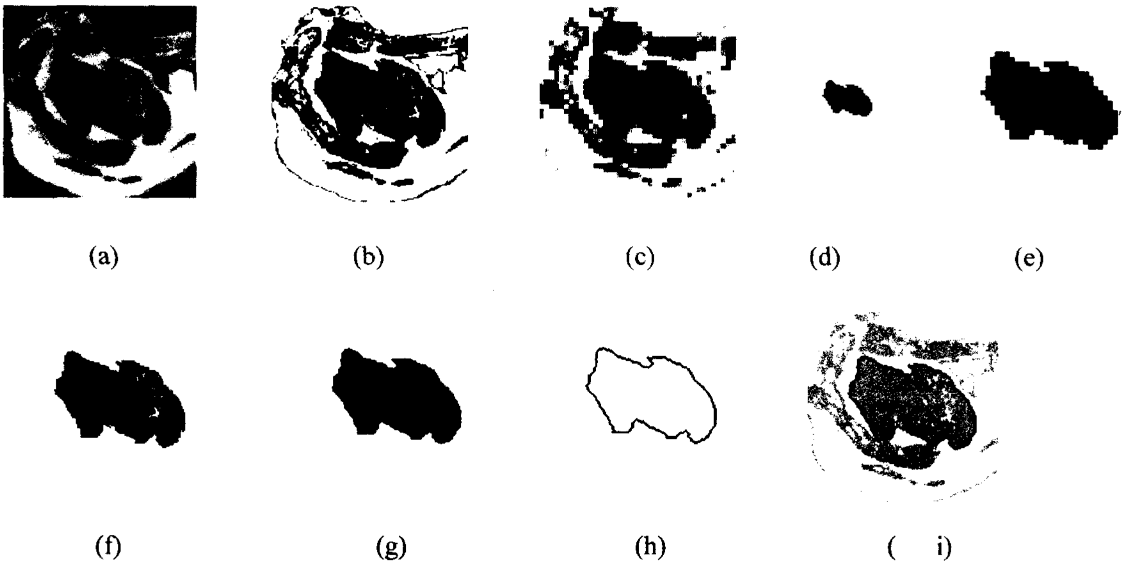


Fig.10 Results of processing for the trained sample with simple pattern; (a) contrast enhanced input image: 160x160 pixels (b) segmented binary input image (c) input grid image to the network: 40x40 grids (d) network output: 40x40 grids (e) resized image: 160x 160 pixels (f) detailed lean tissue image (g) image after morphology opening (h) contour of the lean tissue (I) input image merged with contour.

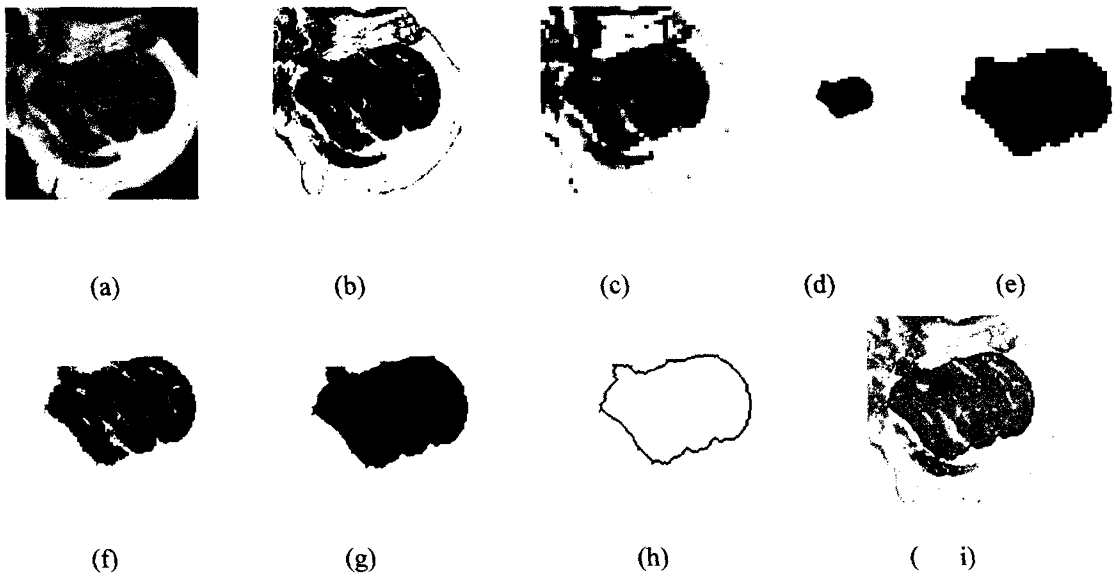


Fig.11 Results of processing for the trained sample with complex pattern; (a) contrast enhanced input image: 160x160 pixels (b) segmented binary image (c) input grid image to the network : 40x40 grids (d) network output:40x40 grids (e) resized image:160x160 pixels (f) detailed lean tissue image (g) image after morphology opening (h) contour of the lean tissue (I) input image merged with contour.

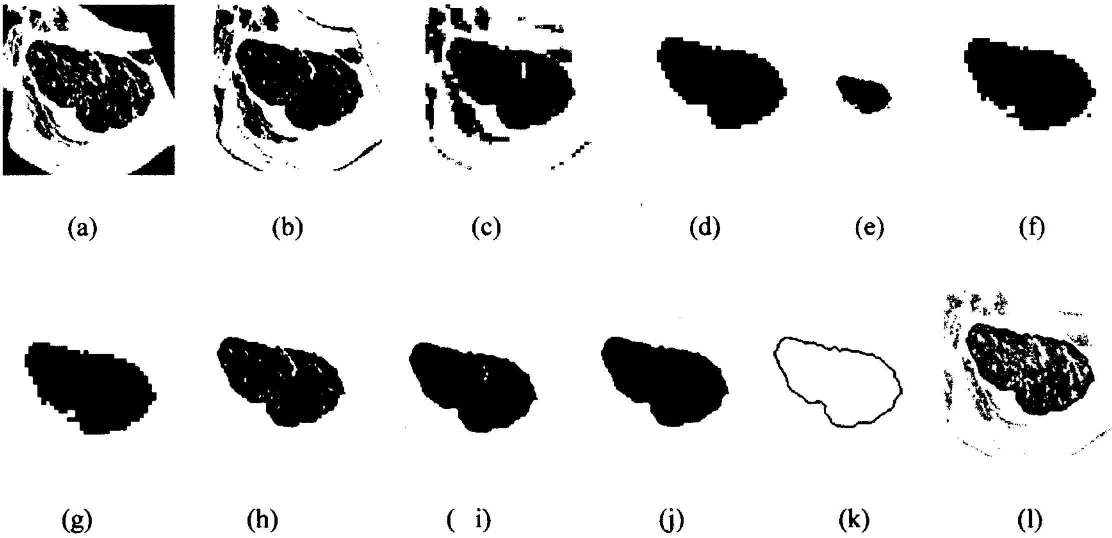


Fig.12 Results of processing for unknown sample I; (a) contrast enhanced input image: 160x160 pixels (b) enhanced input image (c) input grid image to the network: 40x40 grids (d) desired network output: 40x40 grids (e) network output: 40x40 grids (f) resized image: 160x160 pixels (g) image after noise removal (h) detailed lean tissue image (i) image after noise removal (j) image after morphology opening (k) contour of the lean tissue (l) input image merged with contour.

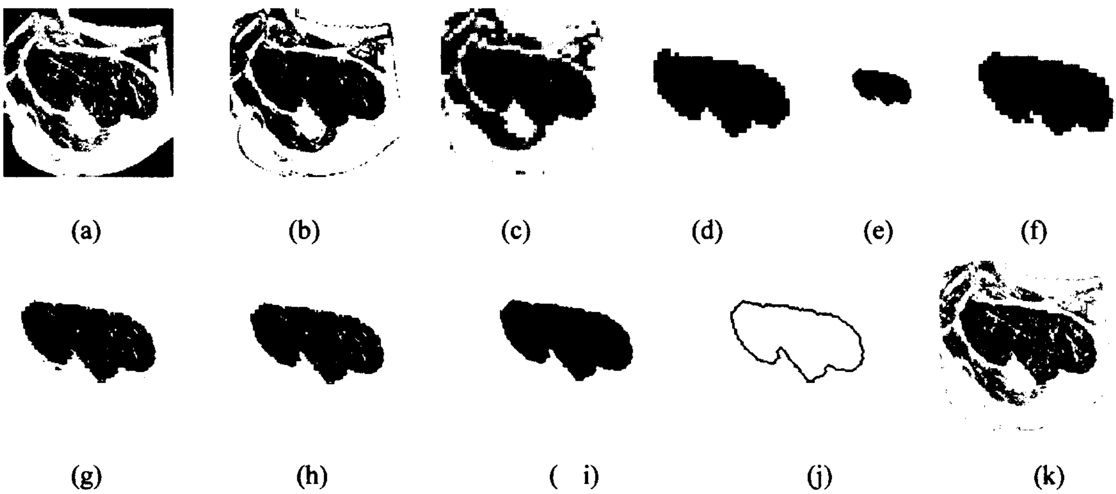


Fig.13 Results of processing for unknown sample II; (a) contrast enhanced input image: 160x160 pixels (b) enhanced input image (c) input grid image to the network: 40x40 grids (d) desired network output: 40x40 grids (e) network output: 40x40 grids (f) resized image: 160x160 pixels (g) detailed lean tissue image (h) image after noise removal (i) image after morphology opening (j) contour of the lean tissue (k) input image merged with contour.