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쇠고기의 절단면 영상을 이용한 육량 및 육질 평가

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Robust Identification of Lean Tissue Quality from Beef Cut Surface Image

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Abstract

A neuro-net aided image processing system which automatically identifies lean tissue state from the image of a complex beef cut surface. The proposed system utilized an artificial neural network to enhance the robust segmentation of lean tissue. The system was composed of pre-network, network, and post-network processing stages. At the pre-network stage, gray level image of the beef cut was segmented from the background and converted to the network input. At the network stage, the coarse grid pattern image of the segmented lean tissue was generated. A sequence of post-network processing was followed to obtain details of the lean tissue state. Developed system showed the feasibility of the human like robust object segmentation for the complex and fuzzy pattern image.

Key words: beef cut, lean tissue, quality, yield, segmentation, neural net, image 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 fat and bone to be trimmed). 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. Machine vision (MV) has the potential to remove the subjectivity associated with visual composition measurement. MV 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.

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, it showed the lack of the robustness in separating lean tissues with complex pattern and executing such an algorithm required substantial processing time. In this study, a neuro-net aided image processing algorithms were developed to automatically identify the state of the lean tissue from the beef cut surface gray image.

Materials and Methods

Ten ribeye beef cut surfaces were digitized by TM1000 (PULNIX Inc., USA) B/W camera which has a 1K by 1K high resolution and Oculus F/64 frame grabber (CORECO Inc., CANADA). Then

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20 beef cut surface images were artificially generated by manipulating the original digitized images. The sequence of image processing algorithms were classified into three stages i.e. pre-network, network, and post-network processing.

Pre-network Processing

The pre-network processing is a sequence of image processing to prepare for the appropriate network input. First of all, the size of the measuring window was pre-specified and linear contrast enhancement of the gray image was conducted.

Then beef cut surface was separated from the background via automatic thresholding. Various algorithms are known in determining the optimum threshold automatically such as an image statistical method (Pratt, 1991), the moment preservation method (Tsai, 1985), maximum entropy method (Abutaleb, 1989). Since the background could be restricted to be black arbitrarily, the window extension scheme was quite simple and efficient.

Window extension method selects threshold value by searching the starting point of the histogram variations of two images between the initial and extended sizes of the measuring window. Extending window size enlarges the number of pixels in the background which has somewhat uniform ranges of the gray level and kept the number of object pixels unchanged. Two histograms obtained from the initial and the extended windows were averaged at the specified gray interval to reduce noise effects. The threshold value was selected when the difference in probability density function between the two exceeded the predefined value.

Once the beef cut surface was segmented from the background, rectangular boundary coordinates of the beef cut image were obtained to assign the image area for the network input. And the method based on the 6th moment difference (MD_6) was utilized to automatically separate fat and bone from lean tissues since it gave consistent segmentation results even under the uneven lighting illumination.

MD_6 can be computed from the co-occurrence matrix and is a modified version of average contrast (Chanda and Mjumder, 1985). 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 q are defined as

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

where m is the gray level of pixel coordinates (i,j), n is the gray level of pixel coordinates (i-dsinq, j+dcosq), and i=0,1,2,..,M-1, j=0,1,2,..,N-1.
For the segmentation purpose, values of d=1, q=0 and q=$\pi/2$ were used. The resulting gray level co-occurrence matrix [C] is

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

The busyness value B(t) was defined as

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

and $MD_6(t)$ is defined as

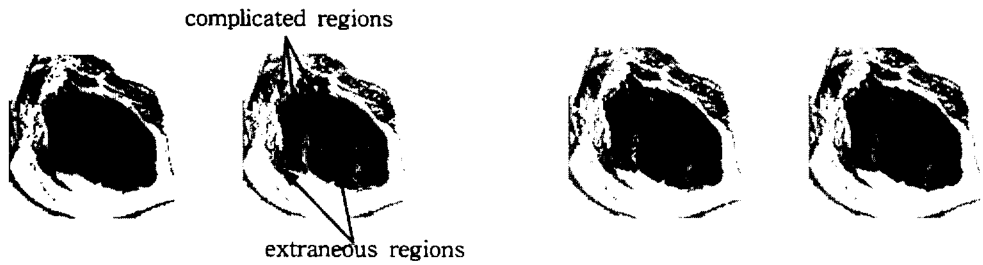
$$MD_6(t) = \frac{\sum_{m=0}^{L-1}\sum_{n=t+1}^{t} (m-n)^6 C_{m,n}}{B(t)} \quad \text{for } t=0,1,2,..,L-2$$

To obtain the threshold value, the image intensity L was first scaled down from 256 to 64 gray levels for the fast generation of the co-occurrence matrix. From this matrix, the optimum threshold value which gave the largest value of $MD_6(t)$ was computed and the binary image was obtained.

After separating fat and bone from lean tissue, 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 pattern image, where each grid was formed as a square having 4 by 4 pixels. And then gray values of pixels in each 4 by 4 pixel grid were averaged. The average gray value of each grid was normalized for the neural network inputs.

Network Processing

According to the previous experience, the conventional image processing techniques used to have the severe difficulty in eliminating the irregular or complex pattern of the extraneous tissues isolated or adhered to the lean tissue. However, this eliminating process is important because the extran-



(a) binary image (b) complex lean tissue pattern (c) undesirable contour (d) desired contour

Fig. 1. Typical beef cut having a complex lean tissue pattern and results of segmentation.

eous 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 based on the geometric characteristics of the lean tissue could successfully remove the simple adhered or isolated regions of the image.

However, there was a difficulty in eliminating extraneous and complicated regions as shown in Fig. 1(b) ,which caused the wrong result of the lean tissue segmentation. Fig. 1(c) is one of the undesirable lean tissue contours and Fig. 1(d) 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.

A backpropagation network (Rumelhart *et al.*, 1986) retaining two layers was adopted to identify the lean tissue from the beef cut surface image. 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.

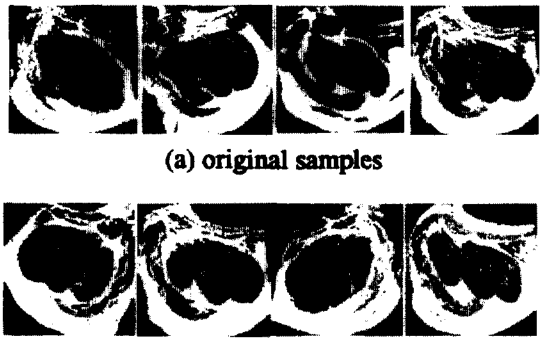
For a given input image, the associated desired lean tissue image was provided at the training stage. The desired binary images of lean tissue portion were specified interactively from the 40 by 40 grid images according to the human supervisory recognition results. Portions except the lean tissue were forced to be white leaving lean tissue portions as black.

For the neural network model 1,600 nodes (40 by 40 grid pattern image) were assigned to the input and the output layer, respectively and 70 nodes to the hidden layer. A sigmoid function was used for the activation function of each node.

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 to generate 2 sample images (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. 2 shows parts of 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, the overall binary image of the lean tissue portion was adopted as a desired network output as shown in Fig. 3.

The network generated real valued outputs rang-



(a) original samples

(b) artificial samples

Fig. 2. Part of original and artificially generated sample images.

ing from 0 to 1 in ASCII format. Network outputs were compared with gray values of the desired binary image. White and black areas of desired image were converted to real values of 1 and 0 respectively before comparing with network outputs.

Post-network Processing

At the post-network processing, ASCII formatted output values generated from the network were thresholded to 0 and 1 and then converted to 40 by 40 pixel size of binary image. 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 undesirable pixels such as isolated islands and holes, 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 grid pixels 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, isolated islands and holes using morphology opening algorithm.

Then the detail contour of the lean tissue was generated from the resultant binary lean tissue image. After adding resulting binary image to the input gray level image, details of gray level images of the segmented lean tissue was obtained. And quantitative texture data of the lean tissue were computed using co-occurrence matrix of the detail gray image of the lean tissue. Fig. 4 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).

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 RMSE 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 1 sample to the network. The output RMSE decreased most to 0.067 during the first 1000 random presentations. The RMSE of the train-

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

Fig. 3. Input and desired output images for network training; (a) enhanced binary image: 160×160 pixels input grid image for the network after averaging 4 by 4 pixels of the binary image: 40×40 grids desired network output I: 40×40 grids (d) desired network output II.: 40×40 grids.

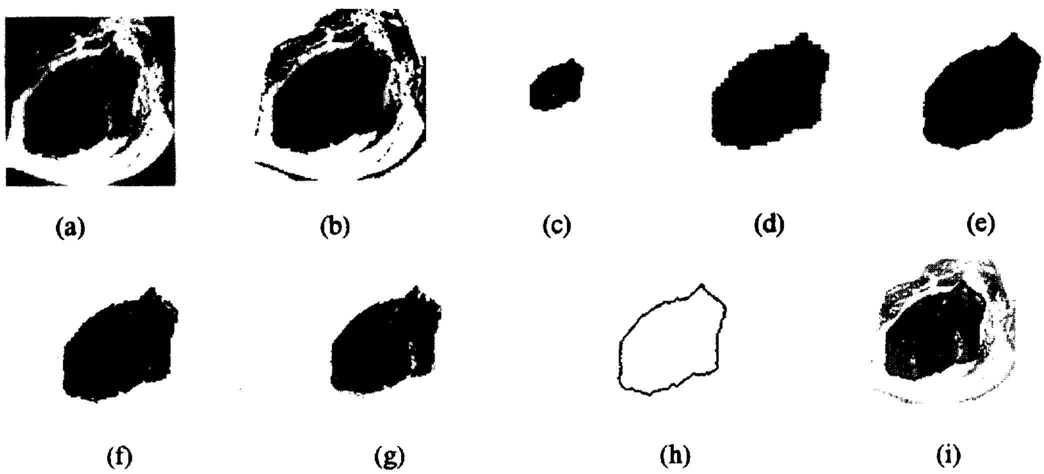


Fig. 4. Sequence of the resulting images obtained from post-network processing; (a) enhanced gray level image (b) segmented binary image (c) network output image:40×40 grids (d) resized image: 160×160 pixels (e) binary image after noise removal and morphology processing (f) detail binary image of segmented lean tissue (g) detail gray image of segmented lean tissue (h) lean tissue contour (i) merged contour to the beef cut image.

ed network for 20 untrained samples was 0.079. When all of 60 samples were trained, the initial and final RMSE after 5000 random presentations were 0.214 and 0.056, respectively.

However, the network error was further reduced after passing a sequence of post-processing such as thresholding network output, noise removal, grid template merging, and morphological smoothing. Fig. 5 illustrates results of processing for typical training samples. Fig. 6 illustrates results of processing for untrained samples.

Conclusions

Proposed neuro-net aided processing algorithm successfully separated the portion of the lean tis-

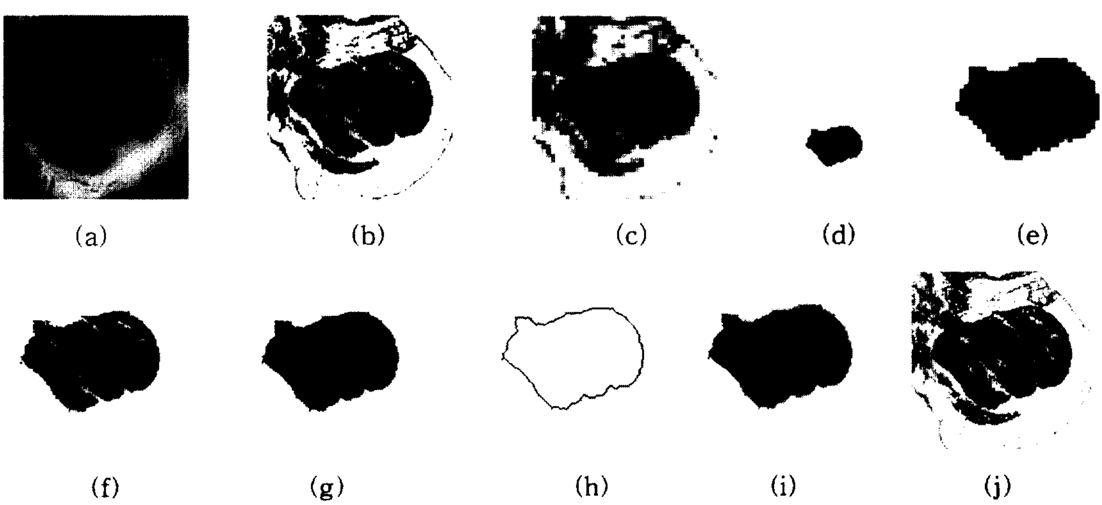


Fig. 5. Results of processing for the trained sample with complex pattern; (a) contrast enhanced input image: 160×160 pixels (b) segmented binary image (c) input grid image to the network: 40×40 grids (d) network output:40×40 grids (e) resized image:160×160 pixels (f) details of binary lean tissue image (g) image after noise removal and morphology opening (h) contour of the lean tissue (i) details of gray level lean tissue image (j) input image merged with contour.

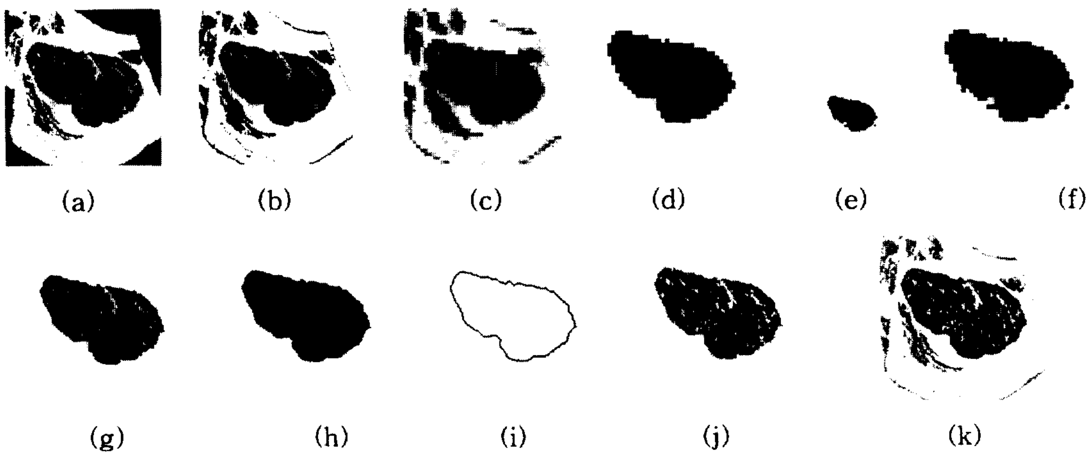


Fig. 6. Results of processing for unknown sample; (a) contrast enhanced input image: 160x160 pixels (b) segmented binary image (c) input grid image to the network: 40x40 grids (d) desired network output: 40x40 grids (e) network output: 40x40 grids (f) resized image: 160x160 pixels (g) detail binary image of lean tissue (h) image after noise removal and morphology opening (i) contour of lean tissue (j) detail gray level image of lean tissue (k) input image merged with contour.

sue from the beef cut surface in a robust manner without human intervention. The extracted lean tissue gray images could be used for yield and quality grading. Though the trained network could not generate the contour of lean tissue for certain untrained samples as accurate as trained ones, it assigned the desired lean tissue portions quite successfully for a complex pattern of beef cut surface image. It seemed that introducing more beef sample images could improve the performance of the network. Research is on-going currently to utilize the neural network as a decision supporting subsystem instead of generating the lean tissue directly.

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