EXTRACTION OF THE LEAN TISSUE BOUNDARY OF A BEEF CARCASS

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ABSTRACT

In this research, rule and neuro net based boundary extraction algorithm was developed. Extracting boundary of the interest, lean tissue, is essential for the quality evaluation of the beef based on color machine vision. Major quality features of the beef are size, marveling state of the lean tissue, color of the fat, and thickness of back fat. To evaluate the beef quality, extracting of loin parts from the sectional image of beef rib is crucial and the first step. Since its boundary is not clear and very difficult to trace, neural network model was developed to isolate loin parts from the entire image input. At the stage of training network, normalized color image data was used. Model reference of boundary was determined by binary feature extraction algorithm using R(red) channel. And 100 sub-images(selected from maximum extended boundary rectangle 11x11 masks) were used as training data set. Each mask has information on the curvature of boundary. The basic rule in boundary extraction is the adaptation of the known curvature of the boundary. The structured model reference and neural net based boundary extraction algorithm was developed and implemented to the beef image and results were analyzed.

Keyword: Lean Tissue, Beef Cut Image, Neural Network, Contour Generation, Quality Evaluation

INTRODUCTION

For the past several decades, the USDA quality and yield grades for beef have pursed to reduce the fat amount of the carcass associated with beef yield. In united states, beef carcass value depends upon two important aspects, one is quality such as marbling and maturity, the other is composition such as total lean tissue, fat and bone, or lean with some acceptable level of fat and bone to be trimmed. 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. Recently the beef industry drafted a plan for the research and development of an instrument capable of evaluating carcass lean tissue.

Automating beef quality evaluation process requires measurement of major attributes such as color, texture, distribution and ratio of fat, freshness of the sectioned beef carcass. Extracting boundary of the interest, lean tissue, is essential and the first step for the quality evaluation of the beef. Through this contour information of lean tissue, quantification of size, color, and marveling state of lean tissue is possible. However, the boundary of the lean tissue is sometimes very complex and obscure, it is very difficult to separate its boundary automatically.

Automatic lean tissue measurement using machine vision was performed in united states(Chen et. al.,1995). And recently, the algorithm for rapid and robust separation of lean tissue from its surrounding fat and other tissues in a beef carcass was developed based on the gray intensity of the cross sectioned cut image by Hwang et. al(Hwang, 1997). They utilized a neural network scheme to identify the boundary of the lean tissue. Though it worked in a robust way but it required a lot of work to prepare the training set for the network.

In this paper, rule and neural net based boundary extraction algorithm was developed by color computer vision techniques.

MATERIALS AND METHODS

The color computer vision system was used to measure the sample beef cut image. The measurement and analysis software was made with MFC library functions of Microsoft visual c++ version 6.0. Sample beefs were collected from the "Garak(slaughter house)" agricultural fresh market in Seoul. As shown in fig.1, beef samples were obtained at the 13^{th} rib.

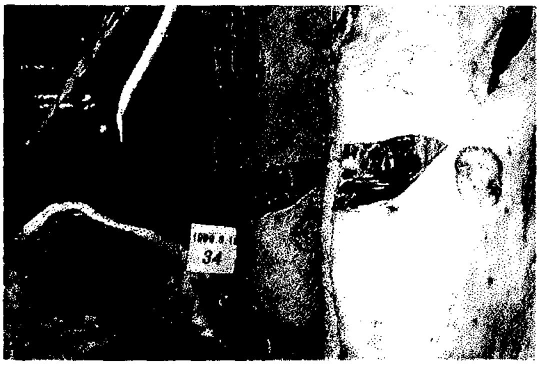


Fig. 1 Sampling sectioned beef at the modernized slaughter house in Seoul Garak fresh market.

2-1. Preprocessing for Network Input

To setup the network input image for training, true color image should be transformed into the binary image. HSI color format are known for more similar with human vision rather than RGB relatively. The mean value of average red, green and blue was measured by 202, 86, 150 for 60 sample images and variations were 0.0471, 0.0624, and 0.0918 respectively. Standard deviation was 0.2169, 0.2498, and 0.3030 respectively.

Thresholding was done by red channel, and then, color information was transformed to HSI values following formula, where I represents the intensity value.

$I=0.3R+0.59G+0.11G$
$C_1=R-Y=0.7R-0.59G-0.11B$
$C_2=B-Y=-0.3R-0.59G+0.89B$
$Hue=\tan^{-1}(C_1/C_2)$
$Saturation=(C_1^2+C_2^2)^{0.5}$

To segment lean tissue from other fat and tissues of binary image, noisy factors were eliminated first using image shrinking(closing) process. Geometrical feature information was computed from the general moment method. Coordinates of the centroid were obtained from the formula.

$$\frac{1}{n}\sum_{i=0}^{n-1} xi,\ \frac{1}{n}\sum_{i=0}^{n-1} yi$$

In general, the pattern of beef cut image is rather obscure and complex boundary. Prewitt mask operation was used to find an outline contour of lean tissue. Among 8 masks as shown in Fig.2, maximum value and vector direction were selected as an intensity value and direction of edge component. Direction of 8 elements and its formula of vector elements from A to H are defined as following.

A={-1,1,1,-1,-2,1,-1,1,1} B={1,1,1,-1,-2,1,-1,-1,1}
C={1,1,1,1,-2,1,-1,-1,-1} D={1,1,1,1,-2,,-1,1,-1,-1}
E={1,1,-1,1,-2,-1,1,1,-1} F={1,-1,-1,1,-2,-1,1,1,1}
G={-1,-1,-1,1,-2,1,1,1,1} H={-1,-1,1,-1,-2,1,1,1,1}

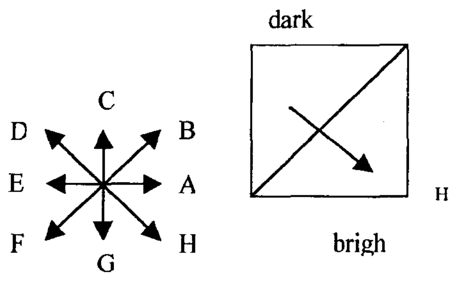
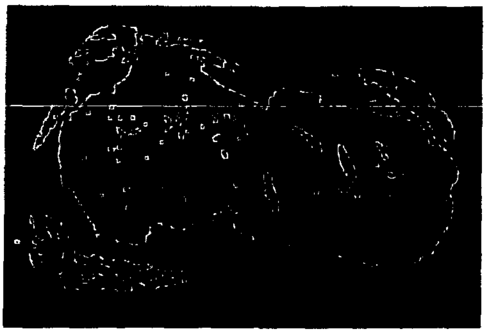


Fig. 2 Prewitt 8 mask operation (direction of dark to bright region's edge denoted with arrow).

After Prewitt mask operation, some of contour image has an unnecessary element such as noise. To remove unnecessary noise, image labeling was performed. Then, this image was all transformed with thinning(skeleton) image. This image has an one pixel boundary element, then Hilditch algorithm was adapted to obtain more clear skeleton image. And this resulting image was used as an input image of neural network training.

(a)original image

(b) image after shrinking



(c)Image after Prewitt mask operation

(d)Image after labeling

(e)Image after thinning

Fig.3 Sequence of preprocessing for network input.

2-2. Training Model

Generating lean tissue contour is difficult because of its uncertainty about the innumerable complex shapes. In this research, neural network was used to train the pattern of the lean tissue boundary. Input region was selected 100 small rectangular area having 20x20 pixel size from the whole beef image. The position of the sub-image was determined from the max/min coordinate and the centroid. The well known back propagation neural network was used to training this contour generation for lean tissue.

Since number of sampled beef images was 60, total number of input samples was 60 image x 100 sub-image. As shown un Fig.4, input neuron was composed of 20x20 pixel image and the number of the hidden neuron was set as 25. The number of output neuron was also composed of 20x20 pixel image. Training was successfully performed with 0.056 normalized system error. Training was performed with two sets of 100 images. One set was used for training and the other was used to prevent over training. Using the trained network, other images that were not used for training was tested through random input manner.

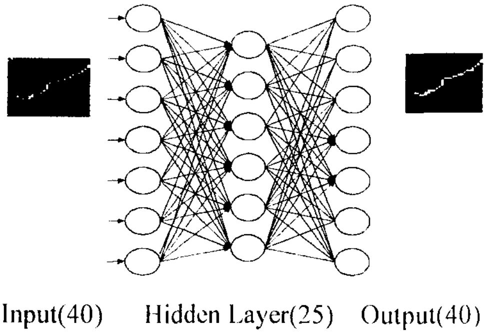


Fig. 4 Network structure of lean tissue contour generation.

2-3. Post Processing

Generated contour of the trained network sometimes showed disconnectivity. Simple digital differential analyzer(SDDA), which is a well known scan line conversion algorithm and Overhauser curve generation algorithm were used in order to regenerate missing contour of the network output. SDDA was used for disconnected pixels of small size regions. And Overhauser curve generation was used for large size regions. Based on the linear differential solution about $dy/dx = \Delta y/\Delta x$, this formula could written by intermediate expression as below. Where, the "s" is a stepping variable.

$$x = x_0 + \Delta x \cdot s$$
$$x = y_0 + \Delta y \cdot s$$

The recursive expression above formula can be replace with below formula.

$$x_i + 1 = x_i + \varepsilon \cdot \Delta x$$
$$y_i + 1 = y_i + \varepsilon \cdot \Delta y$$

where, ε is percentage of linear element defined by Δx and Δy. If $|\Delta x| > |\Delta y|$, this formula can assume that $\varepsilon \cdot \Delta x = 1$ and ε is also replace with $1/\Delta x$.

$$x_i + 1 = x_i + 1$$
$$y_i + 1 = y_i + \Delta y/\Delta x$$

In opposite cases, assume that $\varepsilon \cdot \Delta y$ equal to 1. Therefore, ε can be replaced with $1/\Delta y$.

$$x_i + 1 = x_i + \Delta x/\Delta y$$
$$y_i + 1 = y_i + 1$$

All values were initially set to be zero and initial coordinate value X_0 and Y_0 were set as 0.5. Coordinates of boundary pixels were already computed and stored in the memory and these coordinates will be substituted for previous recursive expression. Finally, new contour was generated via iterative computation.

In order to escape the unstable contour generation effect caused by this algorithm, Overhauser curve generation algorithm was utilized The generated curve C(t) is expressed as

$C(t)=[a][b][c]$.
where, $[a]=[t^3,t^2,t,1]$

$$[b]=\begin{vmatrix} -0.5 & 1.5 & -1.5 & 0.5 \\ 1 & -2.5 & 2 & -0.5 \\ -0.5 & 0 & 0.5 & 0 \\ 0 & 1 & 0 & 0 \end{vmatrix}, \quad [c]=\begin{vmatrix} p1 \\ p2 \\ p3 \\ p4 \end{vmatrix}$$

This algorithm easily can generate a smoothing curve (2^{nd} derivative continuity) between disconnected two pixel points p_2 and p_3 using p_1, p_2, p_3, and p_4 as shown in Fig.5.

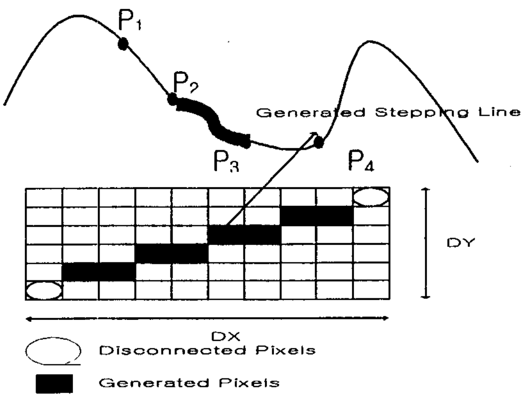


Fig.5 Overhauser and SDDA line-curve conversion.

RESULTS AND DISCUSSION

Neural network based training simulation has been performed using the 60 beef cut images and each image is composed of 100 sub-images. Size of each sub-image was specified as 20x20 pixels. After training, the normalized system error was converged to 0.056, and this training was performed by each 1000 training times for input image sample to avoid its serious computation time and verification of learning performance. Contour generation results showed perfect result about trained sample images.

In order to testify the generalization effect of neural network, 20 untrained beef image was tested in random input manner. Contour was generated completely for only 8 samples and other 12 beef images showed some disconnected points among the sub-images. The average number of disconnected sub-images for 12 beef images showed as 4.67(total 56 undesirably generated sub-images among the 12 beef samples:56/12).

From the result, each undesirably generated contour image from network has at least disconnection ratio of 5% for one sample image. To enhance the performance of contour generation network model, another compensation algorithm must be necessary to build more precisely results. In this research, basic line conversion algorithm(simple digital differential analyzer:SDDA) and a graphic curve generation algorithm(Overhauser curve generation algorithm) were adopted to regenerate disconnected contour. First, SDDA algorithm was performed and if the connectivity was not acquired from SDDA, Overhauser curve generation algorithm was used.

After this two step conversion processing, all 56 undesirably generated sub-images could make a new closed curve boundary. This two-step algorithm contributes to enhance contour generation of complex lean tissue. However, this algorithm has a complex computation loads and making training set required a serious time consuming work. To solve this problem, it is necessary to develop more convenient training methods such as auto association memory or new adaptation of input-output structure.

CONCLUSIONS

Contour extraction of lean tissue is critical to automatically evaluate the beef quality. Based on this generated contour information, marbling state, fat composition ratio and color grade were determined. Proposed contour generation algorithm consisted of preprocessing, network training, and post processing. Proposed neural network based contour generation algorithm successfully separated the portion of the lean tissue from the beef cut image through three step processing. Contour generation via network output could eliminate the random or complex pattern of the extraneous lean tissue isolated or adhered to the lean tissue.

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