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A Fast Beef Marbling Segmentation Algorithm Based on Image Resampling

Bin Pang, Xiao Sun, Xin Sun, Kunjie Chen*
College of Engineering, Nanjing Agricultural University, Nanjing 210031, P. R. China
*Corresponding author, e-mail: chenkunjienau@163.com

Abstract

With the miniaturization and portability of online detection and grading equipment, traditional PC is being replaced with ARM or DSP embedded systems in beef quality grading industry. As the low basic frequency of embedded system, the traditional beef marbling segmentation method can not meet requirements of real-time performance. The fast segmentation algorithm of beef marbling based on image resampling is put forward aiming the disadvantages that the traditional method is time-consuming and does not apply to embedded systems. First, the entropies of the original image and resampling image were calculated according to the entropy principle to determine the image resampling rate based on entropy constraint according to the changes of relative information entropy of resampling image. Then fuzzy c-mean (FCM) cluster segmentation was conducted on the resampling image to calculate the beef image segmentation threshold. Finally, beef marbling area is segmented via morphological and logic operations on a series of images. The experimental results show that this proposed algorithm took 0.57s on average in beef marbling image segmentation under the constraints that the loss rate of relative information entropy ranged between 0.5-1.0%, which is only 6.43% of that of the traditional FCM cluster segmentation algorithm, indicating significantly augmented efficiency of segmentation.

Keywords*: beef, Image segmentation, marbling, calculation efficiency*

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1. Introduction

In available beef grading standards worldwide, the grade of beef marbling is determined based on the richness of intramuscular fat in the rib-eye section of beef carcass. As beef marbling grade is automatically determined using computer vision and image processing techniques, marbling image should be first segmented from the rib-eye image of beef carcass to extract the quantized characteristic value that can reflect the richness degree of marbling, and thereafter automatic determination is conducted on the beef marbling grade by mode identification according to the quantized characteristic value. Therefore, the segmentation of marbling from the rib-eye section image of beef carcass serves as the basis of automatic evaluation of beef marbling grade, while the accuracy and efficiency of marbling segmentation evidently influences the automatic evaluation of beef marbling grade.

Numerous methods for beef marbling image segmentation have been previously reported. For the first time, McDonald and Chen [1] segmented the image of beef rib-eye section into fat and muscle areas by image processing, then calculated the total area of fat, and obtained the relationship between fat area and the sensory evaluation results of beef quality. Shiranita et al. [2] extracted a rectangular black and white image with 340×212 pixels and 4-bit grayscale from a beef rib eye image, and performed region segmentation and binary treatment on its fat and muscle by neural network, aiming to acquire a beef marbling image that only contained white adipose pixel and black muscle pixel. Chen and Qin [3] proposed a beef marbling image segmentation method based on grader's vision thresholds and automatic thresholding. Jackman et al. [4] proposed a method of automatic beef marbling segmentation according to the marbling and color characteristics of one side of beef, which was adapted to different environments of image acquisition. Due to complex and changeable beef marbling, no clear boundary can be discerned between muscle and fat areas. Therefore, marbling can hardly be precisely segmented. The results of Subbiah et al. [5] show that fuzzy c-mean (FCM) algorithm functioned well in the segmentation of beef marbling image with high robustness. On this basis, Du et al. [6] proposed a KFCM algorithm which also worked in segmenting beef rib-

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eye image into background, muscle and fat regions. Qiu et al. [7] presented a fast modified FCM algorithm for beef marbling segmentation, suggesting that FCM is highly effective. As to the thresholding segmentation method, the shape of histogram apparently impacts the segmentation effects. If the beef image histogram is a single peak or peak-to-valley characteristics are unclear, the optimal threshold cannot be converged, leading to low segmentation accuracy or even segmentation failure. However, relatively good segmentation effect can be obtained by the FCM algorithm, regardless of the beef image histogram. Thus, FCM algorithm is ideal for beef marbling segmentation. Currently, real-time and online detection beef marbling is preferred. To meet the real-time requirements of online detection, image processing must be highly efficient and time-saving. However, although FCM image segmentation algorithm based on pixel classification has satisfactory segmentation effect and high robustness, it cannot meet the real-time requirements due to low efficiency and time-consuming issue.

Resampling is a process of transforming a discrete image which is defined at one set of coordinate locations to a new set of coordinate points. Image resampling method can be utilized to reduce the dimensionality of the original image, reserve effective pixels, remove redundant pixels, and decrease the amount of image processing data, thereby accelerating image processing. To ensure the information and quality of images, resampling can be conducted by entropy constraint [8-11] to minimize the loss of useful information, to simultaneously lower image dimensionality, and to decrease the data volume of image processing, thus reducing the time required for image processing.

The application of embdded microprocessor in beef image acquisition and processing as well as quality grade determination enables related equipment to be miniaturized and portable, thus realizing online detection and classification of beef quality. Nevertheless, compared with PC, ARM and DSP microprocessors are disadvantageous in the lack of arithmetic capability, and longtime consumption in image processing and computation of large data volume [12]. Therefore, to optimize the existing beef image processing algorithm and to develop a novel one suitable for the ARM or DSP microprocessors lay a technological foundation for the future research on miniaturized beef quality grading system to allow online detection and grading of beef quality. This study targets to analyze the influence of resampling rate on image quality and image segmentation efficiency, based on which a fast segmentation algorithm of beef marbling images for embdded system was established relying on information entropy constraints and resampling.

2. Segmentation Algorithm Based on Entropy Constraint and Resampling

2.1. Image Preprocessing

Beef image preprocessing refers to an operation of removing the background of beef image. The beef target area after background removal can be obtained via threshold, region growth and morphological operations [13]. As this study focuses on developing a fast segmentation algorithm of beef marbling, the operation of background removal is not described herein.

2.2. Image Resampling

Uniformly-space resampling can be performed in the digital image-forming principle. The sampling transformation is described as follows:

$$\begin{cases} x_1 = \eta x_0 \\ y_1 = \eta y_0 \end{cases} \tag{1}$$

Where (x_0, y_0) is coordinate of the original image pixel, and (x_1, y_1) is calculated pixel coordinate. $0 < \eta < 1$ is image resampling rate. A lower η indicates lower image sample size after resampling, but more loss of image information and more serious image distortion. The beef grayscale images at different resampling rates η are shown in Figure 1.

Figure 1 exhibits that when $\eta = 0.5$, the image remains unchanged; when $\eta = 0.1$, the image suffers from significant detail loss; when $\eta = 0.05$, the image is severely distorted. To compare the changes of image histogram at different resampling rates, $Hist$ and $Hist_\eta$ were set as the original image histogram and the histogram of resampling image respectively. The following equation can be used first to normalize $Hist$ and $Hist_\eta$ respectively.

$$Hist' = \frac{Hist - \min(Hist)}{\max(Hist) - \min(Hist)} \tag{2}$$

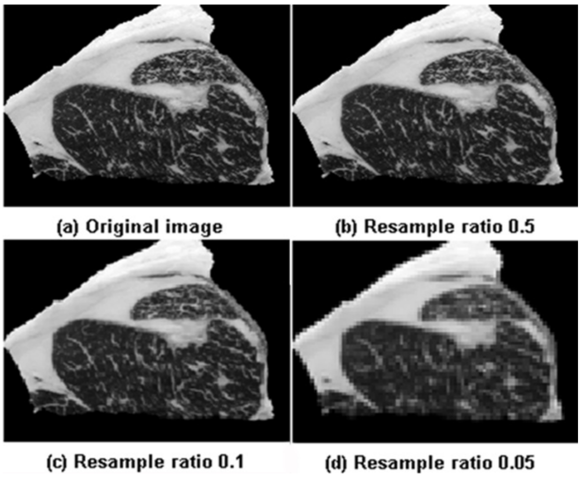

Figure 1. Beef Grayscale Images at Different Resampling Rates

Thereafter the histograms of the four images in Figure 1 are displayed in Figure 2. As shown in Figure 2, with changing sampling rate, the basic shape of resampling image histograms remains intact, but they are subject to detail variations. When $\eta = 0.5$, the histograms of the resampling image and the original image almost resemble; when $\eta = 0.1$, they begin to differ obviously; but when $\eta = 0.05$, the differences between them are extremely significant. The results suggest that as the sampling rate decreases, the differences between the histograms of two images are increased, which is mainly attributed to the loss of image information. Therefore, to ensure the quality of image, an appropriate resampling rate is prerequisite for image resampling to control the loss of image information.

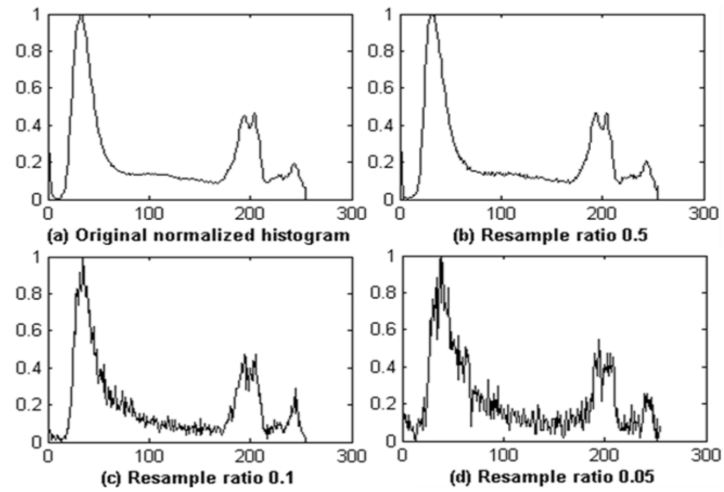

Figure 2. Normalized Histograms at Different Resampling Rates

2.3. Image Information Entropy Calculation

The amount of image information is generally expressed by information entropy, of which Shannon entropy is used most commonly. Its basic form is:

$$H = -\sum_{i=1}^{m} P(\omega_i|x)\log P(\omega_i|x) \tag{3}$$

Where m is number of categories, x is the element, and ω_i is the i category. For an image with the size of $M \times N$, its information entropy is defined as:

$$\begin{aligned}
&H = -\sum_{k=1}^{T} P_k \log P_k, \\
&P_k = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\delta_{ij}(k), \\
&\delta_{ij}(k) = \begin{cases} 1, I(i,j) = k \\ 0, else \end{cases}, \\
&k = 0,1,\ldots,T
\end{aligned} \tag{4}$$

Where $T = 255$ is the grayscale level, and P_k meets the following conditions:

$$\sum_{k=0}^{T} P_k = 1 \tag{5}$$

The information entropy of the original image is set as H_1, and the information entropy of image with the sampling rate of η is set as H_η. Its relative loss of information is defined as:

$$\sigma_{1-\eta} = \left|\frac{H_1 - H_2}{H_1}\right| \tag{6}$$

2.4. Determination of Resampling Rate

The resampling rate that met the information loss interval of $[\sigma_{\min}, \sigma_{\max}]$ was searched within the range of the resampling rate of $(0,1)$.

According to the relationship between image η and $\sigma_{1-\eta}$, it is supposed that the resampling rate of the last step is η_0 for the current search of the step size and resampling rate to be h and η respectively, the following equations are derived:

$$\sigma_{1-\eta} < \sigma_{\min},\ h = \eta_0 k, \eta = \eta_0 - h \tag{7}$$

$$\sigma_{1-\eta} > \sigma_{\max},\ h = \eta_0(1-k/2), \eta = \eta_0 + h \tag{8}$$

Where k is the parameter characterizing the change rate of search, which is the binary search method in case of $k = 0.5$. After the appropriate sampling rate meeting the relative information entropy constraint $[\sigma_{\min}, \sigma_{\max}]$ was found, sampling image was utilized for segmentation threshold calculation that was applied thereafter.

2.5. Proposed Image Segmentation Algorithm

The steps of threshold segmentation algorithm based on the criteria of information entropy are as follows:

Step 1: Give the initial step size in the search of h, the initial k value and the initial sampling rate $\eta_0 = 1$. Assign $\eta = \eta_0 - h$, set the sampling state to calculate the information entropy H_1 of the original beef grayscale image.

Step 2: Use η to sample the original beef grayscale image, calculate the information entropy H_η of sampling image, and calculate the relative loss of information $\sigma_{1-\eta}$ according to Equation (4), (5) and (6).

Step 3: If $\sigma_{1-\eta} < \sigma_{\min}$, make $\eta_0 = \eta$, calculate the resampling rate of the next step using Equation (7), and follow Step 2.

Step 4 If $\sigma_{1-\eta} > \sigma_{\max}$, make $\eta = \eta_0$, calculate the resampling rate of the next step using Equation (8), and follow Step 2.

Step 5: When $\sigma_{1-\eta} \in [\sigma_{\min}, \sigma_{\max}]$, end this search, and return the resampling rate η.

Step 6: Take the sampling image with the resampling rate of η as the input dataset, and use the FCM algorithm to calculate the beef image segmentation threshold whose cluster number is 2.

Step 7: Use the segmentation threshold obtained in Step 6 for threshold segmentation on the original beef grayscale image, and acquire the beef fat and muscle regions.

2.6. Marbling Segmentation

The steps of beef marbling segmentation are as follows [13]: First, logical XOR algorithm was conducted on the target region (Figure 3(a)) and the fat region (Figure 3(b)) derived from Section 2.1 and 2.4 respectively, and the results are displayed in Figure 3(c). After the omnidirectional corrosion of Figure 3(c), small areas were removed once again, and then the image was expanded omnidirectionally to obtain a complete muscle region, as shown in Figure 3(d). As the structure of rib-eye section image of beef carcass is available, and the longissimus dorsi was the largest muscle connected region in the image, Figure 3(d) was subjected to cavity filling, and the largest connected region was reserved to obtain the mask of longissimus dorsi region, as shown in Figure 3(e). Figure 3(b) and Figure 3(e) were then subjected to logic "and" operations to acquire the beef marbling region, as shown in Figure 3(f).

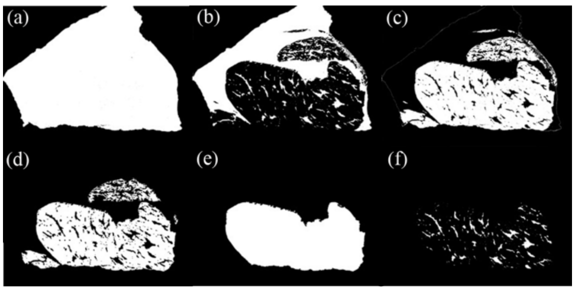

Figure 3. Segmentation of Marbling from a Representative Beef Image

2.7. Apparatus and Data Processing

A digital camera, Dimage Z1, Minolta Co. Ltd, was used in image capture. The output images were stored in red-green-blue format. The computer used in this study is a 2.6GHz PC equipped with a 40 GB hard drive and 2.0G DDR2 of RAM.

All image processing algorithms were implemented with Matlab. SPSS 18 was used for data analysis.

3. Results and Analysis

3.1. Effects of Resampling Rate on the Relative Loss of Information

To study the relationship between the relative loss of information and the resampling rate, the rate of relative information loss of the beef images (1600×1200 pixels) at different resampling rates shown in Figure 1(a) was calculated within the sampling rate range of $\eta\in\left(0,1.0\right]$ according to Equation (6) (Figure 4).

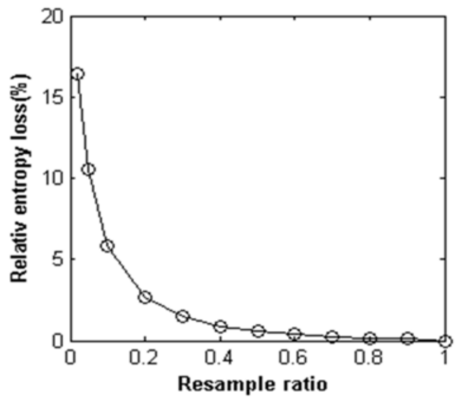

Figure 4. Relative Loss of Information at Different Resampling Rates

As shown in Figure 4, when 0.4<η ≤1.0, $\sigma_{1-\eta}$ is slowly elevated with decreasing η , and the loss of image information was gradually increased. When η =0.4, the corresponding rate of relative information loss is 0.88%. The resampling image retains more than 99% of the original image information, indicating only mild loss and the unobvious affected image quality at the resampling rate of 0.4. The loss of image information $\sigma_{1-\eta}$ start to increase rapidly as η decreases within the range of 0<η <0.4. When η =0.1, the relative loss of information reaches 5.87%, suggesting a relatively large loss of image information. At this time, the histogram of resampling image undergoes significant deformation (Figure 2c), indicating that the quality of resampling image is significantly affected by the resampling rate. Therefore, when resampling image is used for segmentation, the resampling rate should not be lower than 0.4. Otherwise, there will be serious loss of image information, which may severely influence the accuracy of image segmentation.

3.2. Effects of Resampling Rate on the Efficiency of Image Segmentation

To study the efficiency of image segmentation at different resampling rates, the traditional FCM image segmentation algorithm was used for the marbling segmentation of beef images with different η values to record the consuming time of computer in segmentation processing as an indicator to evaluate the segmentation efficiency. The changes of time consumption of computer for segmentation on beef images in Figure 1a at different resampling rates are shown in Figure 5.

As presented in Figure 5, the FCM algorithm spends nearly 8 s on the marbling segmentation of the original image, but with reducing resampling rate, the time consumption of computer is rapidly lowered. When η =0.4, the time consumption drops to 1.242 s, only one-sixth of that when η =1.0. Resampling rate remarkably affects the efficiency of beef image segmentation, and reducing the resampling rate can significantly augment the operational efficiency of beef image segmentation.

In addition, the segmentation thresholds given by the FCM algorithm at different resampling rates were compared, and when $\eta\geq0.4$, the segmentation thresholds of the resampling and original images are identical at 103. The results infer that when $\eta\geq0.4$, the segmentation effects regarding the original and resampling images should be similar on the basis of the traditional FCM algorithm segmentation. When $0.05 < \eta < 0.4$, the segmentation thresholds are slightly different, while when $\eta \leq 0.05$, the segmentation thresholds differ distinctly. The results imply that the effect of resampling image segmentation may be significantly different from that of original one.

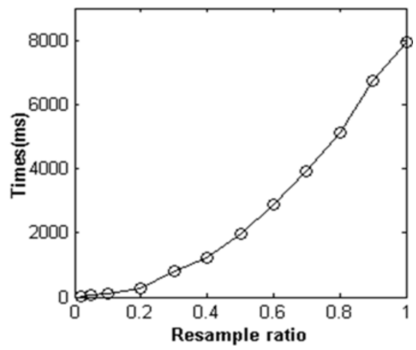

Figure 5. Image Segmentation Time at Different Resampling Rates

3.3. Beef Marbling Image Segmentation in Case of Entropy Constraint

The above experiments show that resampling rate exerts a significant impact on the beef image information loss and segmentation efficiency. A lower resampling rate boosts the segmentation efficiency at the cost of aggravated loss of image information. Therefore, it is imperative to find out a suitable resampling rate that not only controls the loss of image information within an acceptable range to ensure the quality of image segmentation, but also reduced the time consumption of computer, thereby improving the efficiency of image segmentation. As is shown above, when $\eta \geq 0.4$, the loss of resampling image information was less than 1% without significantly jeopardized image quality, while the computer for segmentation operation took only 1.242 s, indicating a significantly improved segmentation efficiency. Therefore, if the loss of relative information entropy is constrained within 1% to select the resampling rate between 0.4-1.0, it is possible to reduce the computer time consumption and to maintain the quality of image segmentation. Thus, under the constraints of relative information entropy loss of $\sigma \in [0.005, 0.01]$, the 126 beef images acquired were segmented using the methods described in sections 2.4 and 2.5, which were compared with the traditional beef marbling segmentation method of FCM [7]. The results are summarized in Table 1.

Table 1. Comparison of Calculation Efficiency between Traditional FCM Algorithm and Proposed Algorithm

	Maximum	Minimum	Mean	Standard derivation
Time of FCM algorithm (ms)	8974	7855	8532	345
Time of algorithm herein (ms)	722	473	570	77

Table 1 shows that this algorithm herein spent 0.57 s on average on beef marbling image segmentation constrained by the loss rates of relative information entropy ranging between 0.5-1.0% (only 6.43% of that of the traditional FCM cluster segmentation algorithm), which significantly raises the efficiency of segmentation and ensures the image quality as well.

4. Conclusion

Resampling rate exerts a significant influence on the information loss and segmentation efficiency of beef image. The image segmentation efficiency was significantly boosted as the resampling rate decreased, and the relative loss of information only subtly increased when the resampling rate dropped from 1.0 to 0.4, but it thereafter rapidly increased with further reduction of resampling rate. Being constrained by the loss of relative information entropy ranging between 0.5-1%, the FMC image segmentation method based on entropy constraint and resampling proposed in this study substantially enhanced the efficiency of beef image segmentation and maintained the image quality simultaneously, which lay a technological foundation for the future research on miniaturized beef quality grading system to enable online detection and grading of beef quality.

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