Grade Prediction of Meat Quality for Ultrasound Images using Feature Extraction and Multi SVM Algorithm

Accepted 4th March, 2016

ABSTRACT

This paper proposes a grade prediction method to measure meat quality in beef using classification and feature extraction algorithms with ultrasound images obtained using a measuring device. The applied classification algorithm is a multi-class support vector machine (multi-SVM). The texture features of the given ultrasound images are extracted using segmentation based fractal texture analysis (SFTA). In this paper, as an initial phase, we selected ultrasound images of cattle for verifying experimental results; however, we ultimately aimed to develop a diagnostic decision support system for human body scan using ultrasound images. The advantages of using ultrasound images of cattle are: accurate grade prediction without butchery, optimizing shipping and feeding schedule and economic benefits. Researches on grade prediction using biometric data such as ultrasound images have been studied in countries like USA, Japan, and Korea. Studies have been based on accurate prediction method of different images obtained from different machines. However, the prediction accuracy is low. Hence, we proposed a prediction method of meat quality using feature extraction and classification algorithms with ultrasound images of the cattle. From the experimental results compared with that of the real grades, it is determined that the total prediction accuracy of the proposed method is 92.86%.

Key words: Grade prediction, feature extraction, texture information, classification.

INTRODUCTION

The amount of meat consumption per capita in Korea has been increasing steadily at 19.9 kg in 1990, 31.9 kg in 2000 and 40.6 kg in 2011. In addition, amount of beef consumption per capita in Korea is comprised of a large proportion and has been constantly rising. Amount of cattle consumption was 4.1 kg in 1990, 8.5 kg in 2002 and 10.7 kg in 2011 (Animal, Plant and Fisheries Quarantine and Inspection Agency in Korea, year).

For high quality beef production, various methods were developed and applied over 30 years. There are systematic and genetic improvement through modernized breeding, assorted feed, improvement of environment and feeding method. According to livestock research, average weight and the circumference of the chest (eighteen-month-old) of Korean native bulls are 567 kg and 197 cm respectively. In addition, average weight and the circumference of the chest of Korean native cows which are considered as capital resource are 357 kg and 167 cm respectively. In recent time, genetic improvement of Korean native cattle has improved based on biometric data of a bull. However, there is a growing interest in devising an improvement method using a cow. Currently, applied breeding technologies for producing high quality beef are: high quality feed, castration of bulls and ultrasound scanning analysis, etc (Korea Institute for Animal Products Quality Evaluation in Korea, year) (Gresham et al., 1994; Haley et al., 1992; Hartjen et al., 1993; Robinson et al., 1992; Song et al., 2002).

Among those technologies, the ultrasound scanning analysis is widely used for feed adjustment in accordance with the status quo and optimal scheduling of shipments by beef.
quality and amount of beef. When applying the early prediction technology for improving business of beef industry in livestock industry, there were advantages such as a reduction of cost, judgment of optimal shipping schedule, and so on. In foreign countries, many research based on image analyses using ultrasound scanning apparatus has been actively studied.

In foreign studies, there are many reports of the real time ultrasound (RTU) for beef quality prediction. However, Korean native cattle have a characteristic of late variety and lower deposition time of marbling score than foreign cattle. Therefore, decision of the assessment time for an accurate prediction and prediction rate of the beef quality are highly important. In Korea, since 1990 research based on early prediction technology of beef quality using an ultrasound scanning apparatus is being done in Livestock Sanitation Office and various institutions (Rhee et al., 2005; Kim et al., 2003, 2012; Ko et al., 2013; Oh et al., 2006; Lee and Yeo, 2011).

However, information analysis using biometric data obtained from ultrasound image is widely used for high quality beef production. However, due to difficulties in analyzing ultrasound images, the marbling degree in the images is not easily determined for evaluating beef quality. In other words, the beef quality determined by ultrasound image is interpreted by diagnostic manual which derives highly subjective, biased the result based on experts' experience. Therefore, this paper proposes the early prediction of beef quality in Korean native cattle using feature extraction algorithms (Segmentation based Fractal Texture Analysis and Texture information of an ultrasound image) and classification algorithm (Multi-class Support Vector Machine).

**MATERIALS AND METHODS**

**Ultrasound image for grade prediction**

Distinction standards of a cattle quality is the quality and the yield grade of the meat. The quality grade of cattle is divided into 5 grades (1++, 1+, 1, 2 and 3). The yield grade is classified as A, B and C in accordance with the amount of meat. The quality grade of cattle is classified into numbers from 1 to 9, according to Beef Marbling Score (BMS).

The BMS is computed by measuring the fat which is located in the gap between the first and the second muscles. BMS is an important factor to determine the quality of the meat and it is closely related with the flavor of the meat. The higher the rank the wider is the marbling distributed. Butchery is necessary to classify the meat grade based on its two colors. One is the cross section of the longissimus muscle. Another is the fat.

Therefore, the grade cannot be predicted in advance (Perkins et al., 1992; Crews and Kemp, 2001). Hence, the ultrasonic image of cattle is effective to predict the grade of the cattle. Figure 1 shows the BMS of cattle. Generally, an ultrasound image is used to predict the meat quality and the range of ultrasound for prediction is 2 to 3.5 MHz. Figure 2 shows the measuring part for the classification of grade and Figure 3 shows the measurement device in the proposed method for early prediction of meat quality for each grade. Figure 4 shows samples of each grade.

Features of images in each grade are: The white color range in the image increases at a higher grade and roughness of an ultrasound image is lower. The reason for a higher grade is due to a detailed reflection wave from sirloin in the cattle. In other words, a higher grade of a high quality reflects a detailed reflection wave and a lower grade reflects a strong reflection wave. Figure 5 shows the histogram of each grade image (5 grades).

**Grade prediction of meat quality using proposed method**

The grade prediction of the beef is described using analysis of the ultrasound image. Figure 6 shows the flowchart of the proposed method including wavelet transform for noise re
Figure 2. Measuring part.

Figure 3. Measuring device.

Figure 4. Ultrasound images; (a) 1++ grade, (b) 1 grade (c) 3 grade.
Figure 5. Histogram of each grade from left to right; 1++, 1+, 1, 2, 3.

Figure 6. The proposed method.

Pre-process step

The pre-process step eliminates unnecessary ranges such as the verge of the image and the muscle range. The verge range presents the measurement device and the depth information. The muscle range appears very bright (almost white color) in all images. The muscle range is eliminated after elimination of the verge range in the image.

Wavelet transform

Wavelet transform and histogram equalization are applied to the ultrasound image for noise rejection and feature extraction using the equalized image of color information from the result image of the pre-process step (http://en.wikipedia.org/wiki/Daubechies_wavelet, year; Lawrence et al, 1996; Maarten, 2001; Jan et al, 2012).

Histogram equalization algorithm is applied to a pre-
processed image for equalization of an image level. The third step is to apply a wavelet transform algorithm to make it easier to classify (Karami et al., 2012; Suranai and Xiao, 2013; Jianzhao et al., 2012).

A wavelet transform algorithm is a non-decimated algorithm and a wavelet filter in a wavelet transform algorithm is Daubechies filter. The result of a wavelet transform algorithm restores only LL filter in sub-bands using LL, LH, HL, HH. Figure 7 shows the structure of the non-decimated wavelet transform algorithm and Figure 8 shows the wavelet function and the scaling function.

**Figure 7.** Structure of the non-decimated wavelet transform algorithm.

**Figure 8.** Wavelet function and scaling function of Daubechies 6 filter; (a) Wavelet function, (b) Scaling function.

**Feature extraction**

For the grade prediction, this step extracts features of the noise removed image (Saraswathi et al., 2014; Ilackiya and Perumal, 2015). In addition, this step is classified as the SFTA for the feature extraction and the texture information of the image.

The SFTA extracts feature by dividing the color of the image. The structure of the SFTA is shown in Figure 9. The SFTA comprises of two steps: 1) The division step using the Two-Threshold Binary Decomposition (TTBD), and 2) The Extraction step using the calculated vector information.

In the first step, the image is decomposed to a set of binary images by the TTBD algorithm. The TTBD algorithm divides the feature range in the image using 3 ranges according to 2 threshold values and it converts the set of the binary images from the gray image. The color information of 3 range means 0 (value < lower threshold or value > upper threshold) and 1 (lower threshold < value < upper threshold). Hence, the result of the TTBD algorithm is a binary image. Figure 10 shows the structure of the TTBD algorithm. After that, the second step extracts features of the image using calculated feature vectors by the edge range of the binary image. Feature vectors are composed of an area, a mean and a fractal dimension, which is calculated by a box counting algorithm. The box counting algorithm used in the first step calculates the number of matrices containing the object after
dividing matrices of the regular size from the image. On the other hand, the box counting algorithm in the second step calculates the gradient of the linear using the approximation information of the line fitting method. The gradient of the result derived by the line fitting method is the fractal dimension. Area is the size of the binary image and mean is the average gray color information according to the matched value, the extracted binary image and the result image described in the chapter of the wavelet transform. Figure 11 shows the algorithm structure for the feature vector.

**Texture information**

The next step is to extract the feature from the ultrasound image using a Co-occurrence matrix. The matrix describes the relative frequencies in which two pixels are separated by a distance on the image in the direction specified by an angle between the gray-tone \( i \) and the gray-tone \( j \). The calculated process of co-occurrence is shown in Figure 12. Equation (1) is the normalization of the co-occurrence matrix where \( n \) is the sum of elements.

\[
\hat{c_{ij}} = \frac{o_{ij}}{n} 
\]  

(1)

Co-occurrence matrix provides useful information, but the matrix is not available to classify the features of the meat. Therefore, to reduce the computational complexity, the proposed method is used to find the following five features:
energy, entropy, contrast, homogeneity and correlation. These five values are calculated using Equations 2 to 6 (Hernan et al., 2014; Seifzadeh and Faez, 2014; Oh, 2014). The five features are explained as follows:

- Energy calculates the uniformity of texture on the image, the more the images are homogenous, the larger is the resulted value.
- Entropy measures the disorder of an image and it achieves the largest value when all elements in the co-occurrence matrix are equal.
- Contrast measures the amount of local variations in an image.
- Homogeneity achieves its largest value when the most of occurrences in Co-occurrence matrix are concentrated on the main diagonal.
- Correlation provides a correlation coefficient of the rows and columns of a normalized co-occurrence matrix.

Parameters associated with the image gradient analysis describes the local differences in intensity. The parameters are based on the absolute value of the gradient calculated from pixels adjacent to the pixel of interest.

\[
\text{Energy} = \sum_{j=0}^{g-1} \sum_{i=0}^{g-1} o_{ji}^2
\]  

\hspace{1cm} (2)
Entropy = \sum_{j=0}^{q-1} \sum_{i=0}^{q-1} \hat{\rho}_{ji} \log_2 \hat{\rho}_{ji} \tag{3}

Contrast = \sum_{j=0}^{q-1} \sum_{i=0}^{q-1} (j-i)^2 \hat{\rho}_{ji} \tag{4}

Homogeneity = \sum_{j=0}^{q-1} \sum_{i=0}^{q-1} \hat{\rho}_{ji} / \{1 + |j-i|\} \tag{5}

Correlation = \sum_{j=0}^{q-1} \sum_{i=0}^{q-1} (j-\mu_j)(i-\mu_i) \hat{\rho}_{ji} / \sigma_j \sigma_i \tag{6}

In these equations, q is a constant of quantization. If q is 8 then 0 to 31 gray values are changed to 0 and 32 to 63 values are changed to 1. The q of the proposed method is 8. i and j are indices of the Co-occurrence matrix.

Classification for prediction

This paper applies the Multi-SVM as a classification algorithm for grade prediction using the extracted information. The other types of classification algorithms are the decision tree, artificial neural network and support vector machine (SVM) etc (Wong et al., 2014; Boyang et al., 2013). Among the many algorithms, the SVM algorithm classifies data using the hyperplane of the linear information. It separates data into classes and then converts the dimensions of the data. Therefore, the SVM algorithm has advantages such as high accuracy and low rate of overfitting, etc when compared to other algorithms. However, the learning time is longer than the other classifiers (Moustakidis et al., 2011; Peijun et al., 2012; Lee and Kim, 2015).

However, considering the fact that the system dealt in this paper is not a real time system, the longer learning time has a lower impact. In the proposed method, we used the multi-SVM algorithm as it needs category 5 grades. The structure of the Multi-SVM is shown in Figure 13.

RESULTS AND DISCUSSION

In an ultrasound image, a right number between numbers means real grade which is marked by cattle experts. Therefore, the prediction result of the proposed method can be compared to the real number and it is compared to various experimental results. The total number of ultrasound images is 42 (1++ grade: 1, 1+ grade: 1, 1 grade: 9, 2 grade: 15, 3 grade: 16). All ultrasound images are used in the learning step and the verification step of the classification algorithm due to the small number of images.

Table 1 shows results of the proposed method using the wavelet transform, SFTA, texture information and Multi-SVM. Table 2 shows results of the compared method using the low-pass filter instead of the wavelet transform for noise rejection. In addition, Table 3 shows results using the neural network instead of the Multi-SVM. Different parts of the compared method is equal to the algorithm of the proposed method. Figure 14 shows graph results of experiments and Figure 15 shows results of each step in the proposed method.

According to the experiment, the result obtained is the average prediction rate of 92.86% (1++ grade: 100.00%, 1+ grade: 100.00%, 1 grade: 100.00%, 2 grade: 86.67%, 3 grade: 93.75%). The prediction rate of the 1++ and the 1+ grade is 100.00%. This result is difficult to trust as the sample count is very small. However, the results of 1, 2 and 3 grades improved when evaluated with respect to the compared method.
Table 2. Prediction rate of the low-pass filter instead of wavelet transform (%).

<table>
<thead>
<tr>
<th>Grade</th>
<th>1++</th>
<th>1+</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1++</td>
<td>100.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>1+</td>
<td>0.00</td>
<td>100.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>1</td>
<td>0.00</td>
<td>0.00</td>
<td>55.56</td>
<td>20.00</td>
<td>25.00</td>
</tr>
<tr>
<td>2</td>
<td>0.00</td>
<td>0.00</td>
<td>33.33</td>
<td>66.67</td>
<td>25.00</td>
</tr>
<tr>
<td>3</td>
<td>0.00</td>
<td>0.00</td>
<td>11.11</td>
<td>13.33</td>
<td>50.00</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td>59.52%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3. Prediction rate of the neural network instead of SVM (%).

<table>
<thead>
<tr>
<th>Grade</th>
<th>1++</th>
<th>1+</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1++</td>
<td>100.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>1+</td>
<td>0.00</td>
<td>100.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>1</td>
<td>0.00</td>
<td>0.00</td>
<td>66.67</td>
<td>13.33</td>
<td>12.50</td>
</tr>
<tr>
<td>2</td>
<td>0.00</td>
<td>0.00</td>
<td>22.22</td>
<td>60.00</td>
<td>31.25</td>
</tr>
<tr>
<td>3</td>
<td>0.00</td>
<td>0.00</td>
<td>11.11</td>
<td>26.67</td>
<td>56.25</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td>61.90%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 14. Result of experiments.

The partial images in 2nd and 3rd grade failed to grade the prediction because of their similar characteristic. Hence, if the algorithm to express features supplements to the proposed method we can expect high performance.

Conclusion

This paper presents the grade prediction of beef using feature extraction algorithms (the wavelet transform for the noise rejection, the SFTA feature extraction algorithm and the texture information for the feature extraction) and the classification algorithms (the Multi-SVM for beef grade prediction with extracted features). The experimental results of the proposed method is the prediction rate of 92.86% (1++ grade: 100.00%, 1+ grade: 100.00%, 1 grade: 100.00%, 2 grade: 86.67% and 3 grade: 93.75%), and the proposed method is compared with various methods using the different algorithms. The experimental results verify that the proposed method is superior to other methods. In the future, more experiments must be done and the research extended to the process of analyzing
the ultrasound image of the human body.

ACKNOWLEDGMENTS

This work was supported by BK21PLUS, Creative Human Resource Development Program for IT Convergence and was supported by the MOTIE (Ministry of Trade, Industry and Energy), Korea, under the Industry Convergence Liaison Robotics Creative Graduates Education Program supervised by the KIAT (N0001126).

REFERENCES


Cite this article as:


Submit your manuscript at
http://www.academiapublishing.org/journals/ajar