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A nonintrusive beef grading evaluation based on marbling fat imaging by using K-Means Clustering Technique

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Abstract An alternative technique of beef quality assessment and grading was proposed using image analysis based on the K-means clustering algorithm as a semi-automated and nonintrusive approach. An input image of the rib-eye meat area was converted into L*a*b* color space, followed by classifying groups of features over the spatial domain. By performing a search and cluster, iterating the features of the target image in a*b* axes resulted in several distinct image zones categorized by different K-groups of features. Marbling fat was estimated in conjunction with quality assessment as an arbitrary grading system. Experimental testing on both synthetic and real image data suggested accuracy better than 95% of averaged. As comparison to conventional methods, this technique is nonintrusive, nondestructive, fast and economic for application and implementation as a measuring tool in the meat research industry.

Keywords: Nonintrusive, Beef grading, Marbling fat, Imaging, K-Means clustering

Introduction

Quality is a key factor in the beef production industry from the upstream supply chain down to the end consumers. Morgan *et al.* (2002) defined quality by a set of indices. Meat quality determination was initiated by in-house experts with a long history of knowledge and experience to make rating decisions (Kushida *et al.,*1999). Quality assessments based on inspection by visual appraisal and compared to standard templates are still performed in many countries (Meat Technology Update: Newsletter 2/04, 2004). To determine meat quality using quantitative and comparative parameters, pre-defined scientific indices, and definitions together with numerical descriptions are required (Jean-

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Louis and Sylvie, 2008). There are many approaches to define meat deterministic parameters, for example apparent color measurements (Wulf and Wise, 1999), sensory and juiciness measurements (Vote *et al*., 2003), tenderness or toughness of muscle fiber by shear force measurements (Chrystall *et al*., 1994) and intramuscular or marbling fat measurements (Sapp *et al*., 2002). Quality probing on a part of meat called the rib-eye can be used to predict and represent the whole quality (Kushida *et al*., 1999). A promising technique to measure marbling fat accurately is by chemical analysis of meat samples; however, this process is time-consuming and cost-intensive (Herrero, 2008), inevitably intrusive and destructive. Moreover, chemical analysis cannot be used to determine the quality of meat instantly and requires cutting, grading, and labeling processes (Japan Meat Grading Association, 1998).

Visualization by experts starts with inspection of a sample part of the rib-eye and comparison with a set of standard templates, i.e., a set of images taken from many rib-eye parts with different degrees of marbling fat priori-categorized into distinct numerical scores. The experts then search for an image that best matches the sample and assign a score.

This grading process depends on the skill and experience of the experts. Accuracy and precision are by nature inconsistent and prone to human error (Sadasivan and Gramopadhye, 2007). To enhance measurement accuracy and precision, computer vision techniques can be applied to perform automatically, economically, and fast, while removing human error. Computer vision techniques for food quality inspection were introduced by Brosnan and Sun (2004), with applications on meat processing initiated by Slosarz *et al*. (2004) to determine marbling fat in lamb. Tan (2004) proposed computer techniques to evaluate quality grading of meat.

In 2008, more advanced computer vision techniques were developed and proposed by Murasawa *et al*. (2008) and used to measure marbling fat of beef without chemical analysis. The principles of operation consisted of analyzing and dividing the contents of the image; referred to as features generation and classification. By categorizing pixels of the image into two different groups of intensities, a single threshold value was introduced, with pixel values separated by inter-modal histogram peaks (Daniel and Neelima, 2012). Final results present pixels labeled in two groups of low intensity (black) and high intensity (white) to display two areas of red meat and marbling fat, respectively. Other advanced research applications incorporating artificial intelligence techniques (AI) are now used as vision systems to analyze and classify images of the rib-eye area using artificial neural networks (ANNs), as proposed by Shiranita *et al.* (2000). These processing techniques operate using binary labeling, i.e., categorizing image pixels by value into two groups, lower or higher than the threshold level; hence all image features are classified into two parts, whereas other details are neglected (Lee and Chung, 1990).

To obtain higher accuracy and precision, a powerful classifier together with an appropriate domain of more distinguishable features is required. Therefore, here, the application of a statistical method as K-means clustering (Harikumar *et al*., 2012) was proposed to analyze and classify marbling fat from beef images.

The objective was to apply a non-destructive and non-physical contact approach to determine beef marbling fat and beef quality grading by using computer vision and statistical K-means clustering method.

Materials and methods

The method relied on image analysis tasks that represented as four consecutive steps of data processing as shown in Figure 1. Process flows and algorithms in each block were coded and scripted using computer vision, image processing together with statistics and machine learning toolboxes of scientific and engineering computing software (MATLAB R2023a, 2023). The processing platform consisted of hardware and software, Intel Core-I7, 64 bits CPU, and Windows 10 operating system, respectively. The process and block diagram details are described in the following sections.

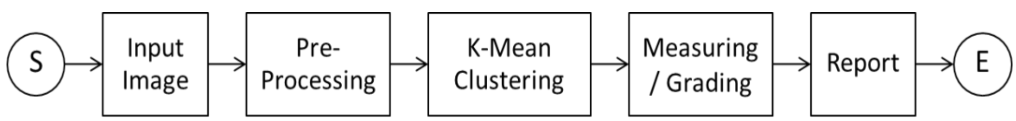


Figure 1. Processing flow diagram

Input data

Input data used in this application consisted of a set of still images taken by a consumer grade digital camera. Each image was captured by a CCD sensor and recorded as jpeg file format in size of 1125 (width) x 750 (height) pixels, with three monochromatic colors of RGB, i.e., red, green and blue components, respectively. This data format can be handled and processed easily with MATLAB with an abundance of functions and supporting provided.

Preprocessing

In this step, the image in RGB color space preselected a region of interest (ROI) manually, i.e., confining the target area to be analyzed, by an embedded adjustable rectangular cropping tool in the image processing toolbox. Then, the

ROI was separated into three monochromatic color images that were represented as three individual grayscale images. Each monochromatic ROI was parsed to perform median filtering to attenuate point-wise noise from circumferential natural light or other artifacts. The final task of the pre-processing step was recombined the three, noise-attenuated, monochromatic ROI images and then convert them into L*a*b* color space as another standard of device independent color space that was defined by CIE (Colorimetry-Part4, CIE 1976 L*a*b Color Space, 1976), as shown in Figure 2.

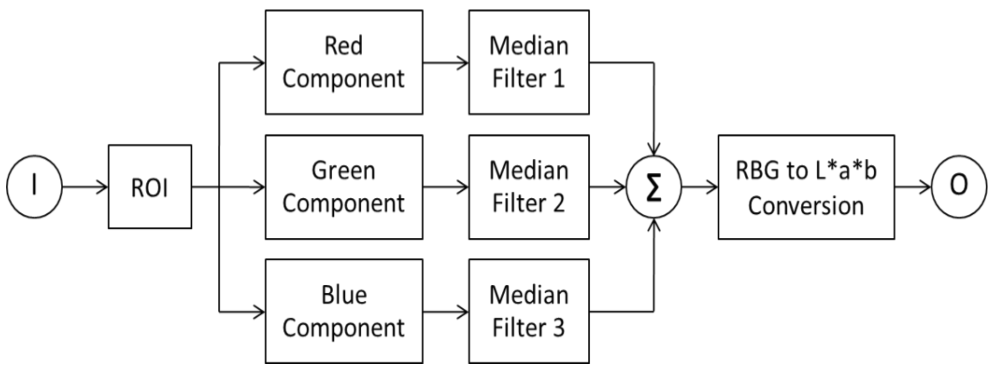


Figure 2. Median filtering

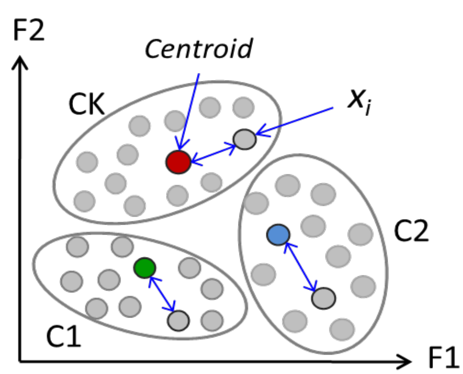


Figure 3. Object classification by K-means

Processing algorithm: K-Means classification

The preprocessed target ROI in L*a*b* color space was fed to a statistical based classification algorithm, namely K-means clustering (Statistics and Machine Learning Toolbox, 2023). By omitting the luminosity component, i.e., L*, out of the L*a*b* space, the remain components a*b* of the image were minimized or freed of any artifacts from uneven lighting. This spatial domain in alternate color space was appropriate to perform classification and grouping by K-means. The principle of classifying objects is depicted by several clusters of data samples in Figure 3.

The process of K-means attempts to consolidate all data samples over the F1-F2 features domain into K-mutually exclusive groups. In brief, resemblance feature values are collected around its centroid, i.e., a group mean, by reassigning the centroid of each group iteratively. If it performs successfully with a finite number of iterations, the domain is then separated into K partitions. The total distance between the data centroid to the rest of the samples within each group is minimal and can be measured by the objective function J,

$$\min\ J = \sum_{j=1}^{K} \sum_{i=1}^{N} \left\| x_i^j - c_j \right\|^n$$

$$when\ \ x_i^j \to c_j$$

where xij is an object or data sample and cj is a centroid or sample mean of cluster j. This is a general form of objective function of K-means. To measure total distance of all groups without absolute value calculation, squared error is taken into account by replacing the quadratic function. Therefore, J can be rewritten as

$$\min\ \ J = \sum_{j=1}^{K} \sum_{i=1}^{N} \left(x_i^j - c_j\right)^2$$

$$when\ \ x_i^j \to c_j$$

This occurrence exists theoretically with the condition of convergent, i.e., each group has its exact centroid or sample mean. A general form of optimization employed in statistical K-means is defined by

$$\left(\frac{\partial J}{\partial x_i^j} \right) = 0$$

$$when\ \ \ c_j = \mu_j$$

where µj is population mean of cluster j

In practical applications, this condition is rigorous, and the objective function may not be minimized to zero because the data domain from the digital image is in a discrete manner. Therefore, to allow the condition of convergence to exist, a nonzero value of J is utilized. This can be summarized conceptually by the procedural steps as shown in Figure 4.

Step 1: Predefine number of clusters (K)
Step 2: Randomly assign centroid of each cluster (K centroids for K clusters)
Step 3: Assign data point to cluster by minimum distance measured between the data point to the K-centrods
Step 4: Do Step 3 for all data points (N)
Step 5: Measure total distance between K-centroids and its neighborhood
Step 6: Check for minimum value of distances both of each cluster and total of all K-clusters
Step 7: Re-assign new K-centroids of each cluster and do Step 3 to Step 6 untill it meets criterion
Step 8: Classification complete

Figure 4. Procedural steps of data processing

After running the K-means and convergence exists, the post-processing data turns out K clusters of different physical values of a*b* and exhibits different K zones within ROI. These are further interpreted by semantic meaning. Their quantitative indices are calculated in the next step.

Determination of marbling fat

The result of the K-means algorithm appeared as a piecewise ROI in K-clusters. Each cluster had its own averaged features and population of samples around its centroid. From a statistical point of view, the whole population within ROI comprised stratified samples in different K subgroups, means and frequencies, respectively.

To determine the marbling fat in the application of meat quality measurement, a basic knowledge of meat structure and colors is necessary. In this study, meat color in reddish areas is referred to as muscle microfibrils, whereas the white area is intramuscular fat or marbling fat (Anne *et al.,* 2016). By inferring such knowledge to an apparent image of meat cutting, the numerical value of K becomes 2, which represents two clusters of red and white areas. Those have different features in a*b* space and different mean values. Additionally, the population of white and red areas can be obtained directly from K-frequencies. The data format used in this study was in RGB and L*a*b* color spaces and each feature was an unsigned integer of 8 bits depth. Therefore, the magnitude was between 0 and 255, i.e.,

$$F_1 = [0, 255]$$
$$F_2 = [0, 255]$$

where F1 and F2 stand for the coordinate axis of the feature in a* and b*, respectively.

Results

Testing of the technique was carried out by two experiments by running the script firstly on synthetic image data and then on a set of real image data of rib-eye area from beef cutting.

Synthetic image data

The aim of testing on synthetic data was evaluated the existing accuracy and precision of the technique before applying real data. Synthetic data were synthesized by the paintbrush program and built up from image pads of a squared checkerboard. With predefined sizing and colors, the technique of K-means was classified features in ROI with accuracy better than 90%. In these trials, combinations of ROI in five different sizes and colors were tested repetitively five times each. Moreover, the technique was tested comparatively with normal and blurred data. The test results of K-means are shown in Figure 5 for an example image of checkerboard, whereas its accuracy was tested using a technique of bimodal threshold with results summarized in Table 1.

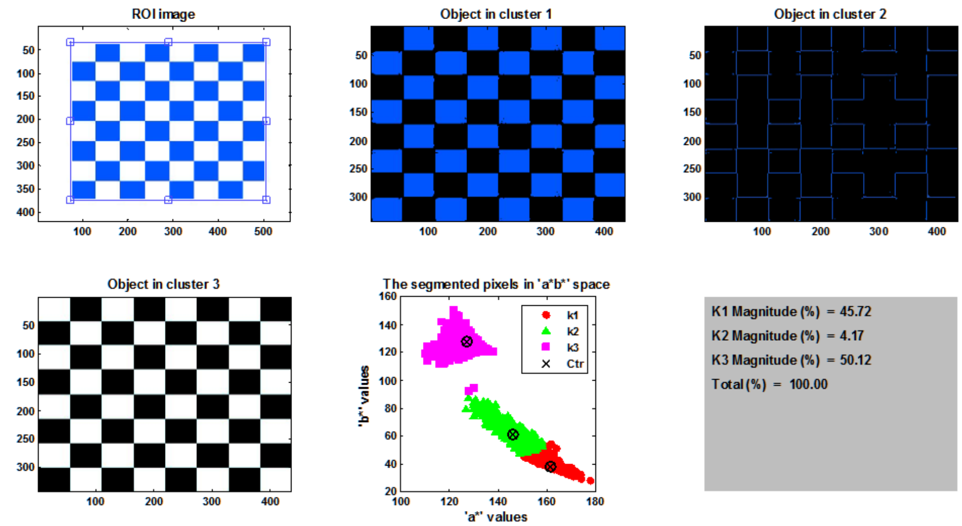


Figure 5. Test result of synthetic data-IV: image of the chess board with 50:50

Table 1. Accuracy test on synthetic data-I

Case	*Ratio (%)*	*K-Means (avg)*		*Bimodal Threshold (avg.)*	
		Normal (%)	*Blurred (%)*	*Normal (%)*	*Blurred (%)*
1	20	20.15±2.26	20.62±2.44	20.20±1.94	21.03±10.30
2	20	19.68±2.37	19.55±2.19	20.51±0.58	21.37±9.26
3	20	19.32±3.14	19.87±3.02	19.13±1.74	20.69±8.62
4	20	20.29±2.81	20.14±3.42	21.14±1.79	21.52±8.69
5	20	20.16±2.30	20.30±2.16	21.01±1.42	21.36±9.12

Table 2. Accuracy test on synthetic data-II

Case	*Ratio (%)*	*K-Means (avg)*		*Bimodal Threshold (avg.)*	
		Normal (%)	*Blurred (%)*	*Normal (%)*	*Blurred (%)*
1	30	30.28±2.19	30.56±2.13	30.20±1.22	30.54±9.60
2	30	30.64±2.52	30.48±2.09	30.51±1.07	31.37±9.32
3	30	31.38±3.02	31.72±2.32	31.19±1.87	32.24±8.72
4	30	31.25±2.58	30.14±3.02	31.05±1.92	31.52±8.34
5	30	30.30±2.55	30.31±3.04	30.84±1.15	31.85±9.74

Table 3. Accuracy test on synthetic data-III

Case	*Ratio (%)*	*K-Means (avg)*		*Bimodal Threshold (avg.)*	
		Normal (%)	*Blurred (%)*	*Normal (%)*	*Blurred (%)*
1	40	39.62±2.24	39.56±2.88	39.20±2.60	41.85±10.30
2	40	39.38±2.57	39.24±2.90	39.51±2.58	41.37±9.26
3	40	40.21±2.44	41.19±2.01	41.63±2.74	42.69±10.62
4	40	40.59±2.89	40.12±2.62	40.05±2.09	42.52±6.69
5	40	40.16±2.64	40.30±2.25	40.84±2.28	42.15±6.12

Table 4. Accuracy test on synthetic data-IV

Case	*Ratio (%)*	*K-Means (avg)*		*Bimodal Threshold (avg.)*	
		Normal (%)	*Blurred (%)*	*Normal (%)*	*Blurred (%)*
1	50	49.32±2.76	47.56±2.88	49.20±1.60	44.85±10.30
2	50	49.18±2.94	48.55±2.90	49.51±0.58	45.37±9.26
3	50	49.31±3.58	48.14±3.72	49.13±1.74	44.69±10.62
4	50	50.14±2.71	49.12±3.62	52.05±0.09	48.52±6.69
5	50	52.17±2.50	52.27±2.25	52.87±1.28	53.39±6.12

The checkerboard was designed by the squared aspect ratio of pixels in width and height, and two area ratios as 1:1 or 50 % as seen in Fig.5. By defining K equal to 3, i.e., assuming that there were three clusters, the post running of K-means classifier showed that the checkerboards were classified into two major groups of two different color areas and the rest. As a result, there were three clusters of data samples that had mutually exclusive areas of 49%, 48% and 3%, respectively. The same scenario occurred in other examples, but slightly different numerical values were obtained. The accuracy test showed that K-means classifier was able to classify features in normal as well as in bimodal images but was noticeably better in the case of blurred images (Table 1). Particularly, for this test, K-means had an overall accuracy performance of slightly over 90%.

To confirm existence of its accuracy between the K-means classification technique, further numerical ratios beyond 50% had been synthesized and tested. The results of synthetic data testing as shown in Table 1-4 had been performed to check accuracy of the K-means comparatively to the bimodal thresholding classification technique. Since synthetic images have precise numerical percentage, which can be made or assigned to any arbitrary number of ratios, i.e., 20%, 30%, 40%, and 50% as shown in Table 1, 2, 3, and 4 respectively. Whenever the technique measured all synthetic images with various numerical percentages accurately, it can also measure marbling fat on a beef image accurately. In addition, all synthetic data had been made and separated into two types, i.e., normal, and blurred images, which can be used to test both accuracy and robustness of the technique when applied to noisy or low-quality images.

Rib-eye image data

Testing on numerous sets of real data was performed on images of the rib-eye to further investigate the capability of the technique. All sample images were taken by a consumer-graded digital camera, Canon EOS 450D, covered with a wideband-circular polarized filter. Foreground illumination was from fluorescent light sources in daylight color temperature. Each sample image was captured under unique settings of the camera, i.e., focal length, exposure time and field of view. The test results are shown in Figure 6 and Figure 7 for different images from different cutting samples.

The original image format was in RGB color space, and the target area was manually selected by an adjustable ROI cropping tool (Figure 6). The selected ROI was then preprocessed and fed to the K-means classifier with predefined K equal to 3. After running the classifier in the final step, the obtained result became three clusters corresponding to K, i.e., red meat, marbling fat and residue that could be a miniature part of intramuscular fat or other including noise. Qualitative contents within ROI were labeled by three distinct colors and quantitative indices were measured by a set of numerical values, respectively.

In addition, extensive testing on numerous images from two kinds of local meat products of Thailand as Thai French and KU beef were examined.

The two kinds of meat showed significant differences in marbling fat since they had differed in muscular structure and breeding (Figure 8). The distinct features were obviously seen by the appraisal test as part of the test procedures in many standards. The quality of meat was pre-categorized based on marbling fat by the expert, and a particular grading system was set up by NBACFS (National Bureau of Agricultural Commodity and Food Standards).

To perform further testing the technique on image of meat samples, the quality of meat that was graded by the expert using NBACFS standard, had been tested comparatively with the proposed technique. In Table 5, the meat samples were obtained from two different kinds of breeding, KU-beef, and Thai French beef, which gathered from retail butcher shops. Those had been pre-classified into four classes of grade by the in-house experts individually using NBACFS. All meat sample images had been used as input data for testing of the proposed technique. The post-tested is shown in Table 6, which it is illustrated that beef marbling fat measured and graded by the expert, i.e., visual inspection (VI), was ambiguity and resulted in miss-classification or overlapping between quality classes as illustrated by the box plots in Figure 8. It is clearly seen that there was overlapped between contiguous quality classes both KU-beef and Thai French beef. After applying the technique, the post-processing results are illustrated by statistical analysis in Table 6 and shown by the box plots in Figure 9. In contradictory to the results which were obtained by the experts, it is obviously seen in Figure 9 that there was overlapped-free between quality classes, and they had been separated into four groups independently. In addition, when considering numerical percentages of the measured marbling fat contents in each class, the post-processing results turned out lower error bounds in all classes.

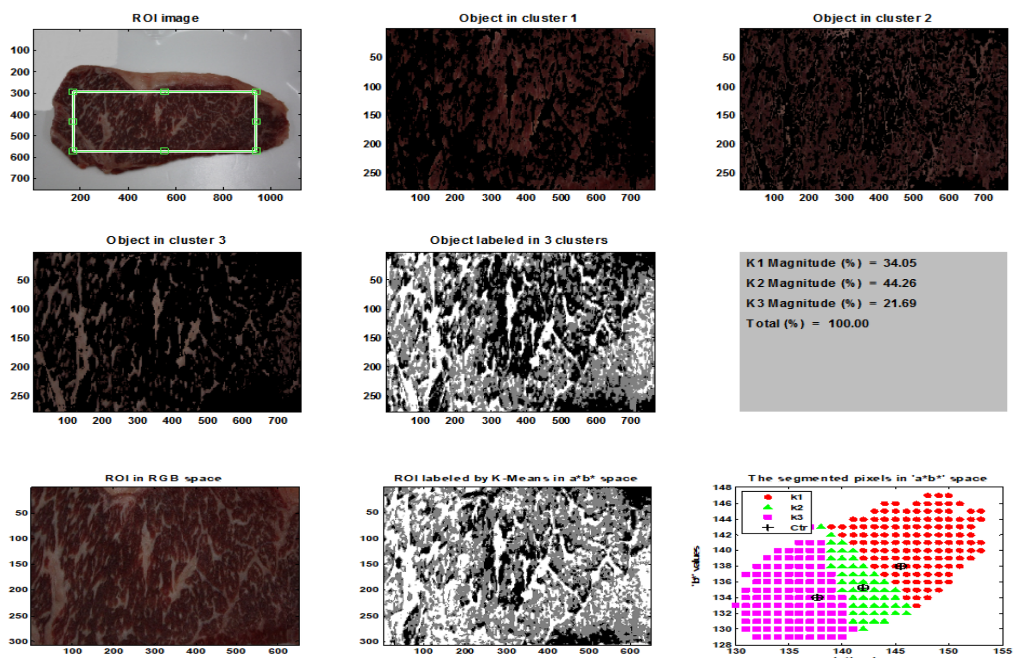


Figure 6. Test result of image from rib-eye sample1

Table 5. Trial test on images from different cutting samples

Type	*Class1*	*Class2*	*Class3*	*Class4*
TF-Meat	S = 10 T = 40	S = 10 T = 40	S = 10 T = 40	S = 7 T = 28
KU-Beef	S = 2 T = 8	S = 10 T = 40	S = 10 T = 40	- -

S: Number of samples, T: Total number of K-means running test,
Class1-4: Level of marbling fat

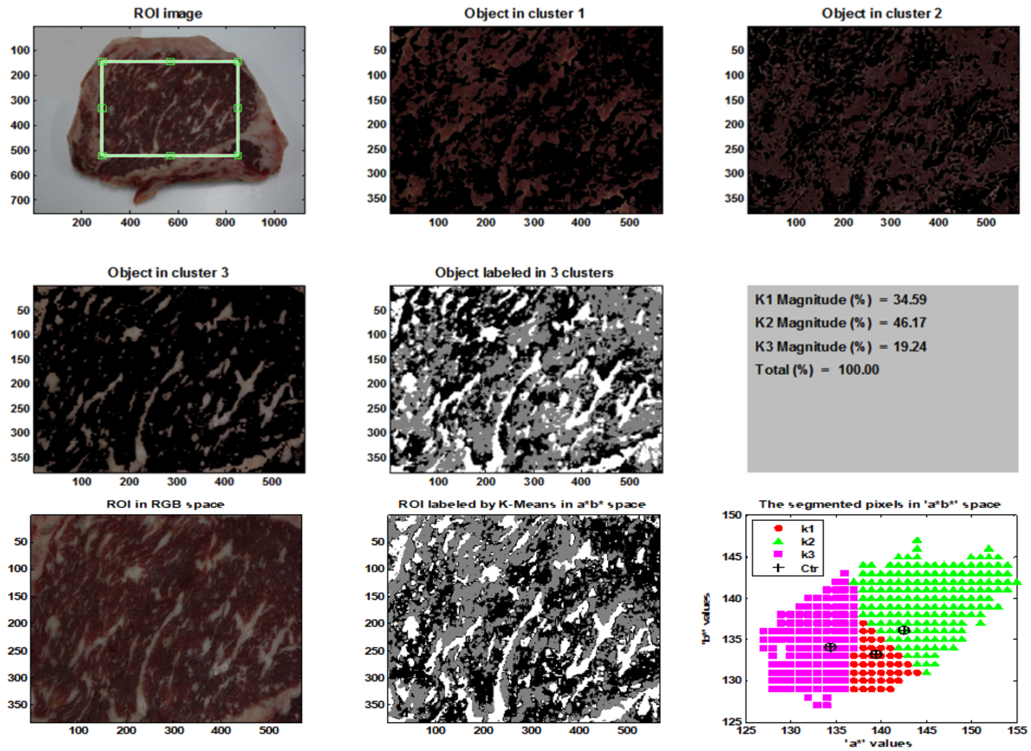
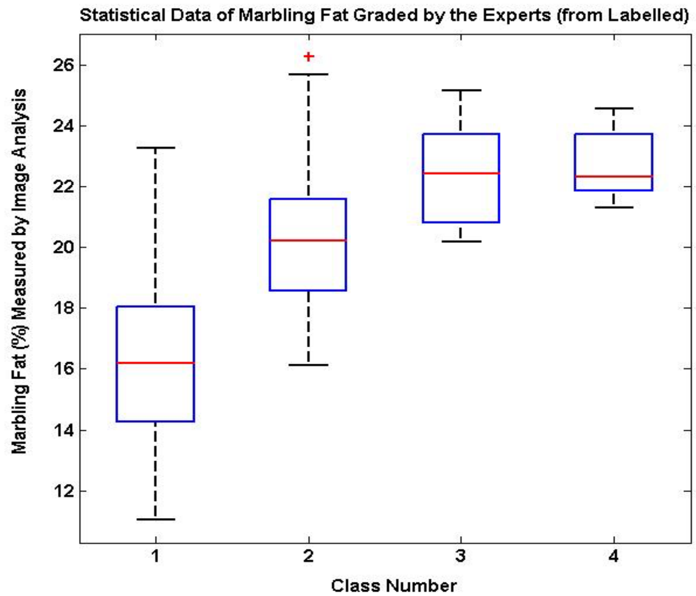


Figure 7. Test result of image from rib-eye sample2

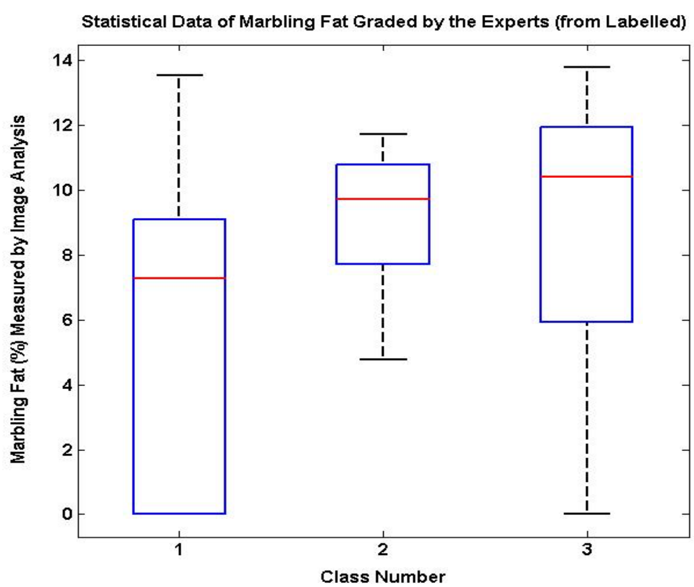
Table 6. Statistical analysis results of the cutting samples

Type	*Measurement*	*Class1*	*Class2*	*Class3*	*Class4*
TF-Meat	VI	16.28±7.05	20.28±2.51	22.31±2.25	22.71±1.37
	K-means	15.36±0.99	17.93±1.62	22.06±1.85	25.07±0.13
KU-Beef	VI	9.02±4.29	9.34±3.30	11.01±2.27	-
	K-means	4.07±0.01	8.21±0.91	11.32±0.81	-

VI: Visual inspection by the experts,
K-means: Computer vision using K-means classification.

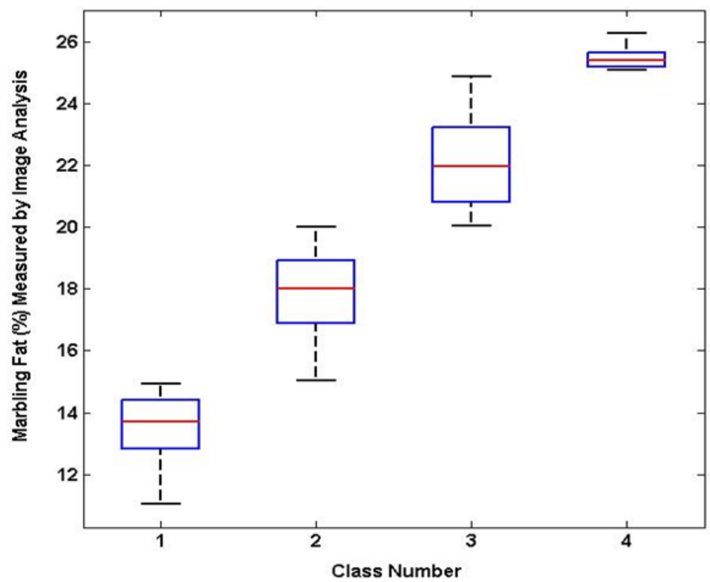


a. Thai-French Meat

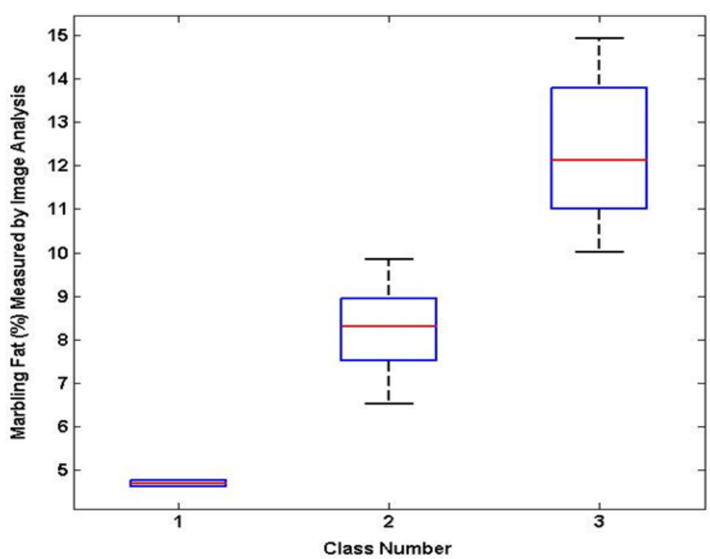


b. KU-Beef

Figure 8. Marbling fat measurement by visual inspection



a. Thai-French Meat



b. KU-Beef

Figure 9. Marbling fat measurement by computer vision and using K-means classification

The cutting samples from two varieties were pre-defined quality by grading into 4 classes by marbling fat levels (Table 3). All samples of those classes were graded by the expert and then proceeded to test using the K-means classification technique. Each cutting sample was tested 4 times and thus resulted in 4 sets of numerical indices. Finally, those numerical indices of each class were performed statistical analysis and, the results are plotted in the box-chart histogram as shown in Fig.8 a, b for TF-meat and KU-beef respectively.

It was remarkably seen that two kinds of meat had distinct levels of marbling fat, i.e., 20.2% and 9.0% for TF-Meats and KU-Beefs in averaged and, ranged from 10.5% to 25.5% and 0.2% to 14% for TF-Meats and KU-Beefs, respectively. The boxplot of histograms was obviously seen that marbling fat level of KU-Beefs had vast dispersion and overlapped in all classes. Those resulted in vague or even mis-classified quality in a process of meat grading and labeling. In the case of TF-Meats, there was better quality classification when compared to the case of KU-Beefs. It could come from that TF-Meats having a clear and distinct trace between the red fibril and the white fat of intra-muscular area. As a result, a better classification can be obtained whereas some overlaps still occurred among the quality class 2, 3 and 4. However, those methods were the basis of visual inspection by the experts, therefore the results are inherently prone to human-error.

The post-processing results of running K-means on those data sets of two variant meat products were illustrated by the box-plot histogram (Figure 9 a, b). It was clearly seen that both two data sets of marbling fat percentage had been measured and classified exclusively without overlaps. Moreover, those quality classes can be re-defined to standard, i.e., both percentage of marbling fat levels and number of classes before running the K-means. In this study, quality classes of two variants had been set to the same number, both the pre-and post-processing, i.e., 4 and 3 classes for TF-Meats and KU-Beefs, respectively. As a result, the post processing results illustrated that all 4 classes quality of TF-Meats were clearly excluded to each other without overlaps and lower variances. The technique of K-means was effective to the case of KU-Beefs, i.e., all 3 quality classes were clearly separated with overlap-free whereas the apparent variances were narrow dispersion.

Convergent tests

When running the computerized classifier iteratively, the condition of convergent is a crucial factor. Particularly to the K-means, criterion of convergence met between a finite number of iterations, and minimum error of total intra-class distance. In this testing, three different sizes of image data, which is represented in number of pixels, i.e., N1 = 197,800, N2 = 205,712, and N3 = 217,634 for IM1, IM2, and IM3 respectively, were used and the result is shown in Fig.10.

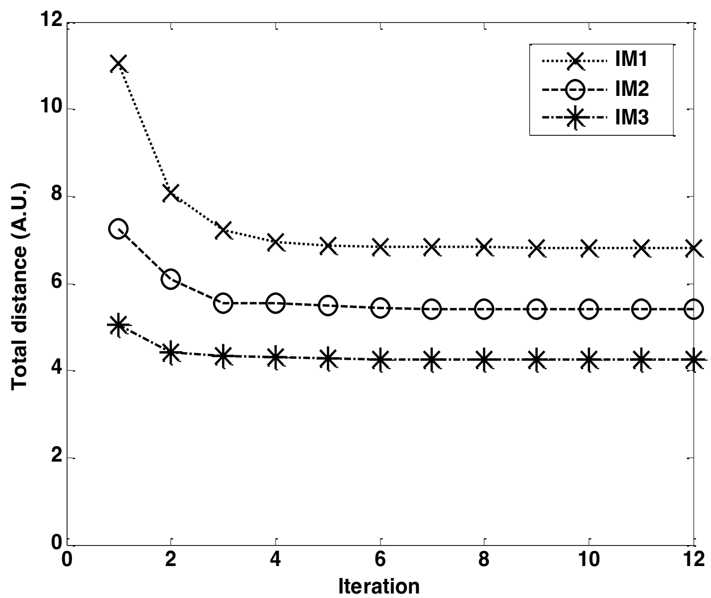


Figure 10. Convergent test of different sizes of image data

The classification process converged within 8 iterations and was bounded with three finite SODs, i.e., sum of distances of all subgroups, corresponding to three sizes of image. The larger the image size, the higher the sum of distances and vice versa. As a result, classification process converged within 8 iterations and was bounded with three finite total intra-class distances, i.e., sum of distances (SODs), of all subgroups, which is corresponded to three sizes of image. The larger the image size, the higher the sum of distances and vice versa. In brief of this testing, a successful of running K-means classifier was measured by a finite and minimum number of iterations together with a limited or bounded SODs.

Discussion

This research proposes a method of beef quality assessment using computer vision-based and K-means clustering technique which is a non-destructive approach. In contradictory to conventional approaches, for examples, determine tenderness of meat by shear force measurement (Chrystall *et al.,* 1994), sensory measurement (Vote *et al*., 2003), intramuscular measurement (Sapp *et al*., 2002) or chemical analysis (Herrero, 2008), the proposed technique can alternately determine beef quality without destroying or even physical contact to the beef sample. By applying the proposed technique instead of those conventional approaches, it can solve the problem of meat quality assessment simultaneously, i.e., not only quantitative determination of meat quality by marbling fat measurement but also qualitatively grading with the pre-defined standard.

The implemented computer vision technique in this research comprises of two parts, firstly the pre-processing part which comprises of median filtering and color space conversion, secondly the K-means clustering part which is the classification algorithm. By applying these techniques, the K-means can automatically consolidate, grouping and counting pixel members of each cluster individually and correctly when compared to conventional computer vision method using bi-modal classification technique, i.e., black, and white pixels thresholding technique. As a result, marbling fat content in meat can be measured quantitatively and precisely without inferiority of accuracy even applied it to a low-quality image as it was happened to the technique based on black, and white pixels separation. To examine consistency of the technique, it had been tested with synthetic images with different ratios of dark and light pixels ranging from 20% to 50% which mimics to various red and white pixels in real meat images. Moreover, those synthetic images were synthesized into normal images and low-quality ones, i.e., blurred images. The tested results showed that the K-means technique can classify those synthetic images accurately with lower error in averaged to 0.5% of all ratios when compared to 1.8% of one when using bi-modal thresholding technique (Murasawa *et al*., 2008).

In addition, the conventional classification method using AI that proposed by Shiranita *et al.* (2000), i.e., Artificial Neural Networks (ANNs) suffered from a situation of lacking quantity and low quality of beef image whereas the K-means is freed off. As a result, the post processing of the beef marbling assessment is then followed by a process of qualitative grading by ranking of marbling fat contents. This process can be applied to any arbitrary number of grading levels and interval of marbling fat percentages which depends on the pre-defined standards and breeding of beef. However, the technique needs to be improved its accuracy and tested extensional to much more images of meat cuts from other beef breeding. Moreover, the software itself needs to be further developed and embedded with a fully automatic ROI selecting tools inside the software and can operate on mobile application platforms. Through this development, the software is much more versatile and user-friendly.

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