Progress in Agricultural Engineering Sciences 9 (2013), 27–53
DOI: 10.1556/Progress.9.2013.2

Image Processing Based Method for Characterization of the Fat/Meat Ratio and Fat Distribution of Pork and Beef Samples

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Abstract. The fat content (fat distribution) of the pork and beef raw material is one of their most important quality characteristics. Image processing methods were applied to provide with quantitative parameters related to these properties. Different hardware tools were tested to select the appropriate imaging alternative. Statistical analysis of the RGB data was performed in order to find appropriate classification function for segmentation. Discriminant analysis of the RGB data of selected image regions (fat-meat-background) resulted in a good segmentation of the fat regions. Classification function was applied on the RGB images of the samples, to identify and measure the regions in question. The fat-meat ratio and textural parameters (entropy, contrast, etc.) were determined. Comparison of the image parameters with the sensory evaluation results showed an encouraging correlation.

Keywords: meat quality, marbling, image processing.

1. Introduction

Quality of meat depends on the muscle fiber and fat content, structure and distribution of these compounds. These features are also visible on the surface of meat slices. The characteristic pattern of muscle and fat is called marbling and usually connected with sensory score of palatability.

There are four dominant features that determine the meat quality and marketability: marbling score, muscle color, fat color and tightness of meat. Several studies examined the relationship of marbling structure and the quality characteristics of different meats, like beef (Jeremiah 1996; Li et al.

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1999) and pork (Brewer et al. 2001). Some paper found correlation between marbling and even the maturity of beef (Moon et al. 2006). Nowadays the relation of marbling scores and aging is also studied (Tania et al. 2012).

Researchers have to solve three problems to gain marbling properties. How to segment fat areas on grayscale, RGB, multispectral or hyperspectral images? How to interpret the imaging features? How to calibrate an industrial expert system by building statistical or neural network models?

To date, several studies on grading systems based on the marbling score have been reported. In the first studies, the marbling score was determined by simply calculating the percentage of fat on a segmented binary image (Kuchita et al. 1993). Others used grayscale image properties, like gray level co-occurrence matrix as a texture feature (Shiranita et al. 1998). Japanese researchers used a data reduction, compression method (Fluency Image Coding System) on binary images for beef marbling evaluation (Toraichi et al. 2002).

Hwang et al. (2010) analyzed *Longissimus dorsi* (LD), *Psoas major* (PM) and *Semimembranosus* (SM) muscles of well marbled Hanwoo steers. According to the evaluation of microscopic images, muscle types significantly differ in terms of fiber density (number of fibers in mm^2) and mean fiber diameter. The observed differences in structure and fat content resulted in higher L* (CIE standard luminosity) for LD and lower for SM muscles.

Pork of LD type was investigated by Barbin et al. (2012) using hyperspectral imaging. Six specific wavelengths (960, 1074, 1124, 1147, 1207 and 1341 nm) were selected in the acquired range of 900–1700 nm. Principal component analysis (PCA) was able to separate signals of fat and meat samples of three quality grades. It was estimated that classification may result in the accuracy above 96%.

Pre-sliced pork hams were evaluated for fat-connective tissue size distribution using color images and fractal analysis (Mendoza et al. 2009). Three different ham grades of high yield, medium yield and low yield (premium quality) were compared on the basis of entropy, fractal dimension and Rényi spectra. The multifractal analysis (MFA) was found to have the potential to discriminate ham grades according to their fat distribution. However, it was observed that extremes on the grade scale (low and high yield) were similar and closer to each other than medium yield ham slices.

Color images of pork marbling standard cards, in the grade range of 1.0–10.0, were evaluated and multiple linear regression (MLR) model was built for prediction (Liu et al. 2012). It was found that MLR model, based on edge detection (WLD) on color channels at 460 nm, 580 nm, and 720 nm, resulted in similar accuracy than the blue color channel alone using a simple linear model. The MLR model obtained $r^2 = 0.9992$ and RMSECV = 0.0938. This approach was later extended with other pattern analysis parameters extracted from gray-level co-occurrence matrix (GLCM) (Huang et al. 2013). It was observed that additional pattern analysis parameters could not exceed the accuracy of WLD model. Additionally, it was found in the second experiment that the green color channel contributed the most to successful prediction. This discrepancy between repeated experiments is interesting but might be logical and explained with the inverse position of red and green color directions on standard color planes, such as CIE La*b*, while blue is the complementary channel.

The GLCM method combined with hyperspectral imaging technique was able to successfully classify pork slices in the grade range of 3.0–5.0 (Qiao et al. 2007). Principal components calculated from wavelength range of 430–1000 nm were forwarded to artificial neural network (ANN). The ANN model using 10 principal components obtained 85% correct classification. Pre-sliced pork and turkey hams were classified using wavelet transform and genetic algorithm (Jackman et al. 2010b). Color information (such as a*, b*, brightness, saturation) and statistical parameters of gray-scale distribution (such as skewness, kurtosis) were included in the linear discriminant analysis (LDA). The optimal set of 10 features with LDA resulted in 100% accuracy in classification of ham grades. Tenderness of cooked beef steaks of *Longissimus thoracis* (LT), SM, *Biceps femoris* (BF) and *Supraspinatus* (SP) was predicted using color and multispectral texture features (Sun et al. 2012). Four different wavelengths of 440, 550, 710, and 810 nm were selected and used in multiple regression model and Support Vector Machine (SVM). It was observed that both color and multispectral data resulted in higher accuracy of tender steaks identification using SVM than multiple regression.

Partial least squares regression (PLSR) model was also used to predict LD beef palatability and sensory scores on the basis of muscle color, marbling and surface pattern (Jackman et al. 2009, 2010a). The regression model was able to estimate likeability the best ($r^2 = 0.86$, RMSEP = 6%), followed by flavor, tenderness and juiciness. This approach is encouraging, especially because high and low quality grades were distinguished with 90% accuracy (Jackman et al. 2009).

Our objective was to test the imaging alternatives in different wavelength ranges and to develop methods and user-friendly software for the meat quality evaluation practice providing with quantitative parameters, comparable with standard (sensory) meat quality measures.

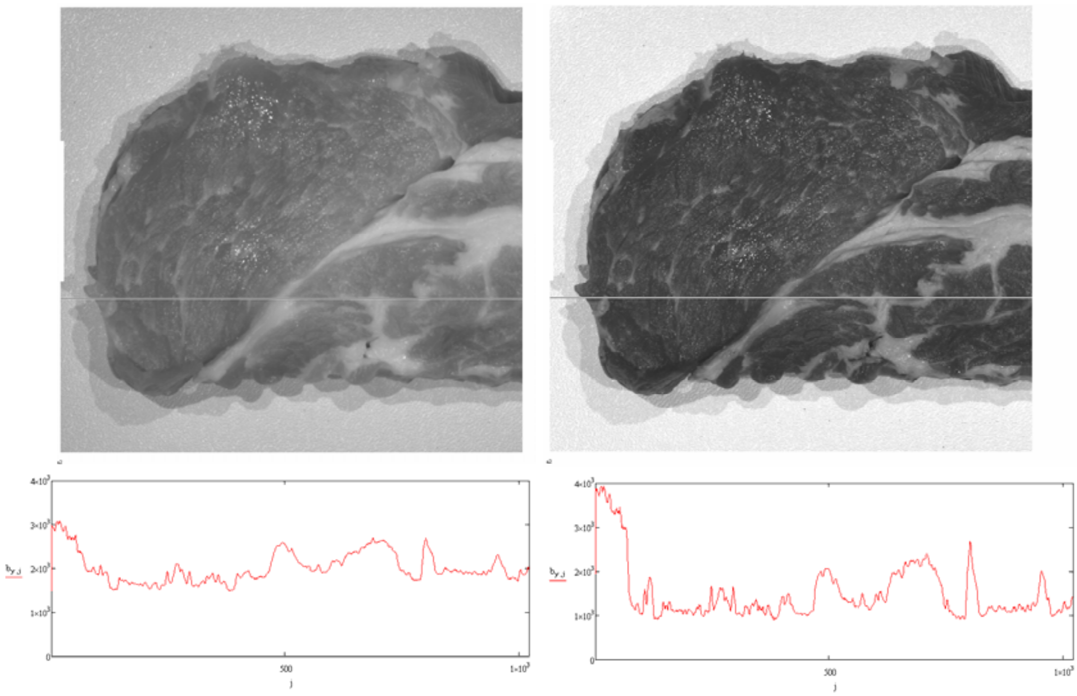
2. Material and Methods

2.1. Sampling

In preliminary experiments 6 to 12 slices of different types of pork and beef samples (from the local market) were used to test the applied recording and image processing methods.

In quality evaluation tests five bulls of Charolais cattle breed (age: 18–20 months) and five pigs of Hungarian Large White breed (age: 6 months) were slaughtered at the slaughterhouse of Lac-Hús Ltd. (Hajdúnánás, Hungary). The examined pork and beef meat was measured 2 days after slaughtering in ripened state.

Each bull and pig was subjected to the same pre-slaughter treatment, and carcasses of post-slaughter treatments were according to chilling



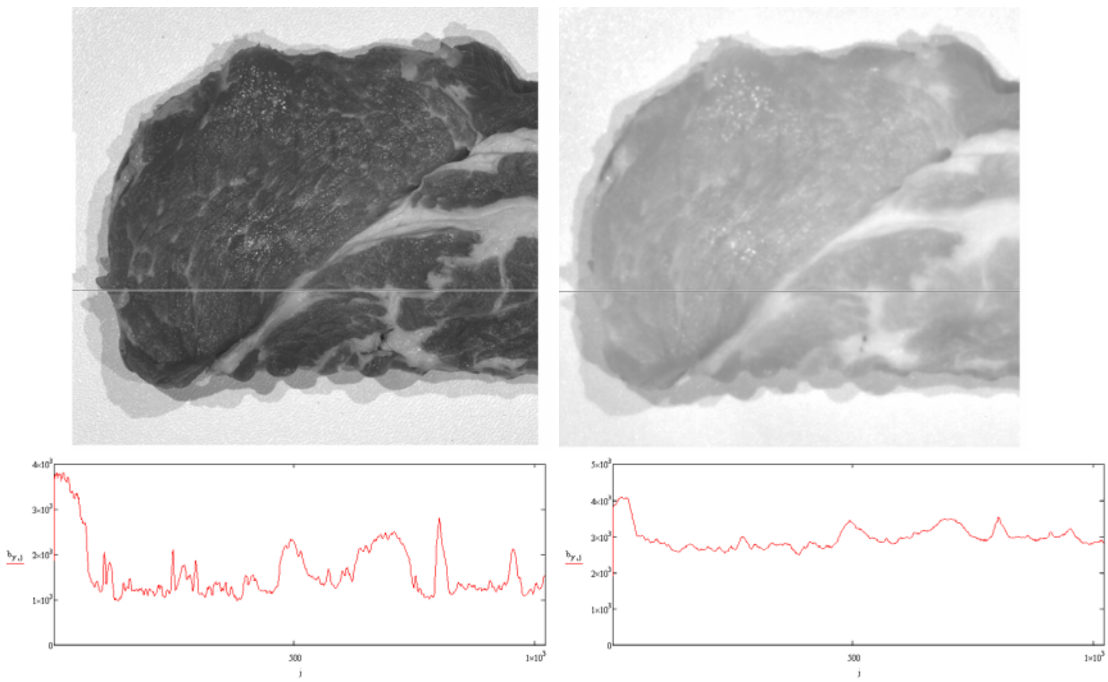
Red 625 nm +/– 10 nm

Blue 470 nm +/– 12 nm

Figure 1. A high resolution image of a rib sample recorded applying quasi-monochromatic illumination alternatives (LED modules) with the corresponding intensity diagrams of the multispectral rib images at the marked image-row

conditions found in many abattoirs. Carcasses were dressed, centrally split and chilled after 1 day post-mortem under normal conditions at around 2 °C. The classification of the pork carcasses was performed according to SEUROP system and in case of beef the meat was classified according to fatness in classes from 1 (low) to 5 (very high) (Council Regulation (EC) 2007). The range of the examined pork meat was of S, E, U, R, and O quality and the beef derived from a range of 1–5 class (hereafter: “Carcass Classification”).

In the case of beef, the samples were taken from the muscle bundles of *longissimus dorsi* (origin: 1st-5th lumbar). For pork samples the total chop was used, meaning the muscle bundles of thoracic and lumbar. The samples of sirloin were cut into 3 parts, which were carved to 2 cm thick slices. In this way 3–5 slices were obtained from one part and 9–13 slices from one sirloin.



Green 525 nm +/– 12 nm InfraRed 850 nm +/– 20 nm

Figure 1. (continued)

The pork chop was cut into 4 uniform pieces and these were sliced also into 3 cm thick slices, which resulted in 21–23 samples.

The sensory evaluation and the machine vision measurement were performed by examination of both sides of the slices, which resulted in a number of 106 samples for beef and 220 samples for pork (150 samples were selected for further analysis in order to decrease inconsistency of the sensory scoring – see later). Each steak was immediately vacuum-packed and transferred to a 4 °C fridge until investigation.

In quality evaluation tests the rib and sirloin samples were qualified according to their marbling quality. The evaluation of marbling was performed on a 1–5 scale (hereafter: "Sensory Quality") by an expert panel (8 persons, one trained meat expert – governing the evaluation process – and 7 members, expert in food, but not trained for meat quality evaluation).

After the sensory evaluation, the recorded images of the samples were given to the image processing team for development of classification method.

2.2. Image recording

Different approaches were applied for the image recording:

2.2.1. High resolution industrial

B&W camera (MV1–D1312(I) Gigabit Ethernet Series, CMOS Area Scan Camera) was used with multispectral illumination system. The applied light source alternatives were as follows

– White:	4 pcs 1 W Power LED
– Red:	625 nm +/– 10 nm (4 pcs 1 W LED)
– Green:	525 nm +/– 12 nm (4 pcs 1 W LED)
– Blue:	470 nm +/– 12 nm (4 pcs 1 W LED)
– InfraRed:	850 nm +/– 20 nm (4 pcs 70 mW/sr infrared power LED)

The multispectral images were recorded in the same position of the samples, this way the records of different wavelength ranges can be investigated in arbitrary combination as well. Images of high dynamic range (12 bit) and 1024*1024 pixel spatial resolution were recorded and stored as lossless BIN files.

2.2.2. Hyperspectral system

Headwall Photonic Hyperspec™ NIR XS-I320C1-100 imaging spectrometer was used to record meat sample images in 1000–1700 nm range. The push-broom system recorded the projected line of the sample with 320 pixel spatial resolution and scanned the whole surface of the sample by moving the sample-holder table by 0.5 mm steps. The records were stored in hypercubes, containing the spatial and spectral information.

2.2.3. In industrial environment

Images of samples (previously qualified by experts) were recorded with a commercial, SLR digital camera (CANON EOS 450D). In order of the reproducibility, the camera was applied with fixed recording parameters (shutter time, aperture and white balance). Special measurement setup with diffuse, homogenous illumination was used to avoid the disturbing effects of the shiny or shadowed details.

2.3. Image processing

2.3.1 Preliminary tests

The images of the multispectral system were recorded by the software of the MV1-D1312(I) camera as monochromatic 12-bit images and they were stored in "bin" files. The images were visualized and analyzed in Mathcad (V11.0). In the preliminary tests, our aim was the visual evaluation of the contrast of the images and the extraction of the intensity values of the different regions of the images (identified manually).

The spectral hypercube of samples were taken by HeadWall hyperspectral system in the range of 900 nm to 1700 nm with 4,75 nm spectral resolution and 14 bit AD resolution. The optics were set to 160 mm spatial view that meant 0,5 mm/px spatial resolution. Argus hyperspectral data acquisition software (Firtha, 2007; Firtha et al. 2012) was used to control the calibration and measurements. Hyperspectral images were segmented by ENVI algorithm, a supervised classification method (Spectral Angle Mapper), retrieving the average spectra of pure meat and fat tissues. The subtraction of 1300nm and 1200nm images shows the optimal difference of two tissue types.

2.3.2. Quality evaluation test and statistical analysis

Good signal-to-noise levels of the green and blue channels in the preliminary experiments were found to be encouraging from the point of view of applying an RGB color camera, as an alternative image recording tool. To extract the fat content or fat distribution information from the images, two different approaches were used in the further steps:

- the segmentation of the fat/meat/background regions of the images to characterize the fat/meat ratio of the tested sample
- to enhance the image from the point of view of fat "highlighting" and measure the image-texture properties, possibly suitable to characterize the fat distribution.

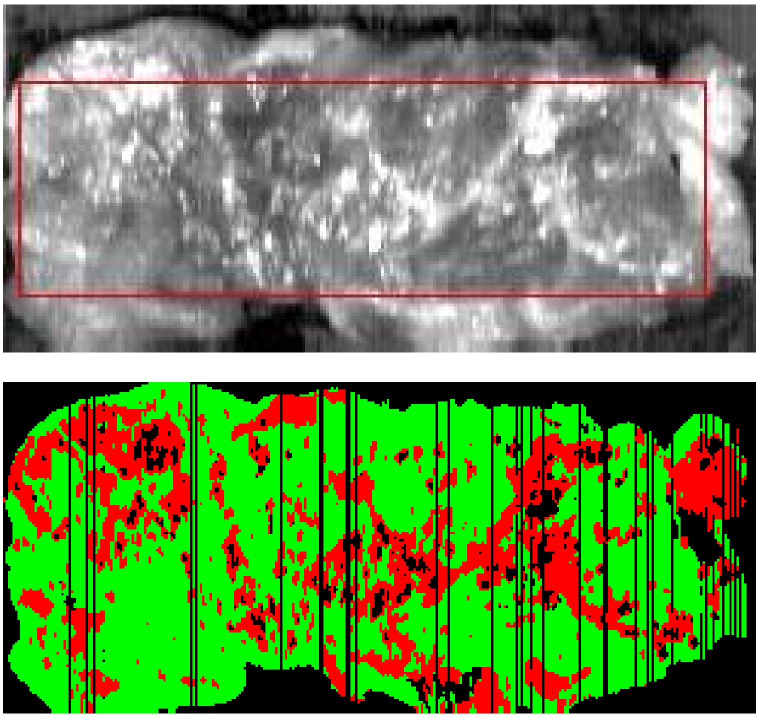


Figure 2. Spatial projection of the hypercube of a sirloin sample at a given wavelength and the result of the fat/meat segmentation

Figure 3 illustrates the distribution of the color points of a sirloin sample in the RGB-space (RED: pixels of the fat region, BLUE: pixels of the meat region) with significant overlapping in either color channel. The diagram confirms the conclusion of the preliminary tests: for individual slices of either beef or pork samples, the simple segmentation methods, applied to RGB values or given transformed channels of the RGB images (namely the BLUE, CYAN or SATURATION transformations) can result in acceptable, but specific segmentation of the fat and meat regions. To achieve a more general, flexible method, suitable for processing of wide range of sample types, it was necessary to develop more general algorithm and software for the segmentation task.

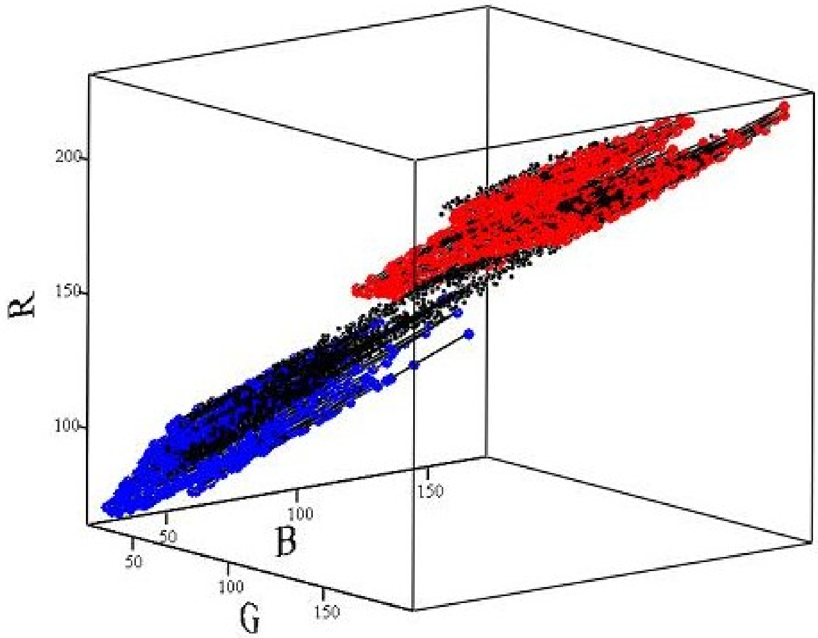


Figure 3. Distribution of the color points of a sirloin sample in the RGB-space (RED: pixels of the fat region, BLUE: pixels of the meat region)

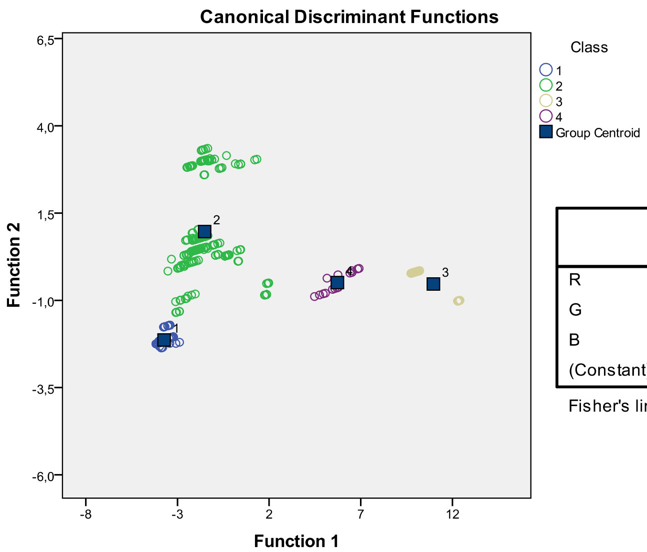
The method for effective segmentation of the fat and meat fractions of an arbitrary type meat sample was based on an interactive teaching process:

– The first step was the interactive selection of characteristic image regions to collect RGB database of the fractions to segment:
  - o meat fraction
  - o fat fraction
  - o background area
  - o shiny spots

– Statistical analysis of the RGB data was performed in order to find appropriate classification function for segmentation. Discriminant analysis (IBM SPSS Statistics, Version 20) of the RGB data of selected image regions (fat-meat-background) resulted in a good segmentation of the fat regions *(Figure 4)*.

– Coefficients of the Fischer classification function were determined

– Classification function was applied on the RGB images of the samples to identify and measure the regions is question *(Figures 5* and *6)*. The number of pixels, belonging to the different identified regions of the images, was determined (meat area, fat area).



Classification Function Coefficients

	cl			
	1	2	3	4
R	6,619	6,214	3,368	5,294
G	-9,551	-8,568	-5,418	-8,026
B	4,078	3,612	3,755	4,475
(Constant)	-192,012	-187,719	-173,013	-208,368

Fisher's linear discriminant functions

Figure 4. Result of the Discriminant Analysis (DA) of the teaching RGB data base (classes: 1: meat, 2: fat, 3: background, 4: shiny spots) with the classification coefficients (BEEF samples)

Figure 5. Original image of a sirloin sample

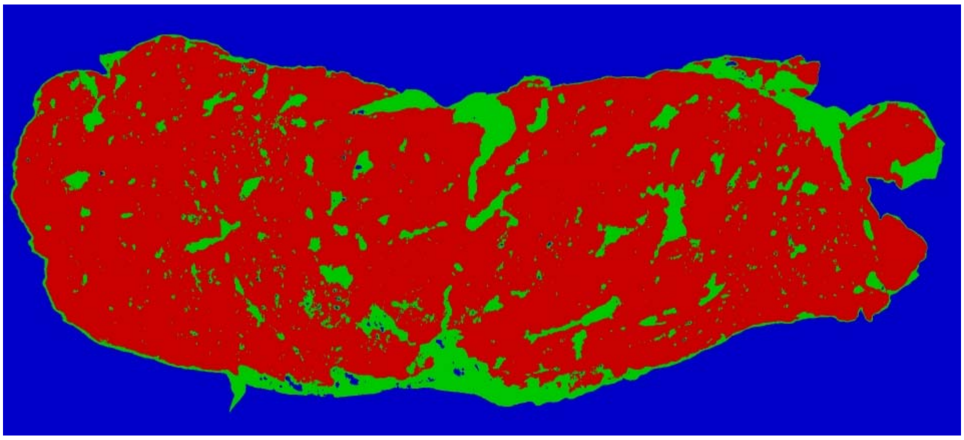


Figure 6. Application of the classification function of the Discriminant Analysis on the sample image: (blue: background and shiny spots, red: meat fraction, green: fat fraction)

In case of the samples qualified by experts, the Fischer classification function was used to produce the binary images of the samples, representing the fat distribution *(Figure 7).* These images – after morphological transformation (namely OPENING) to eliminate the noise of the binary images – can be the base of the further work on identification and characterization of the fibre-structure of this fat content.

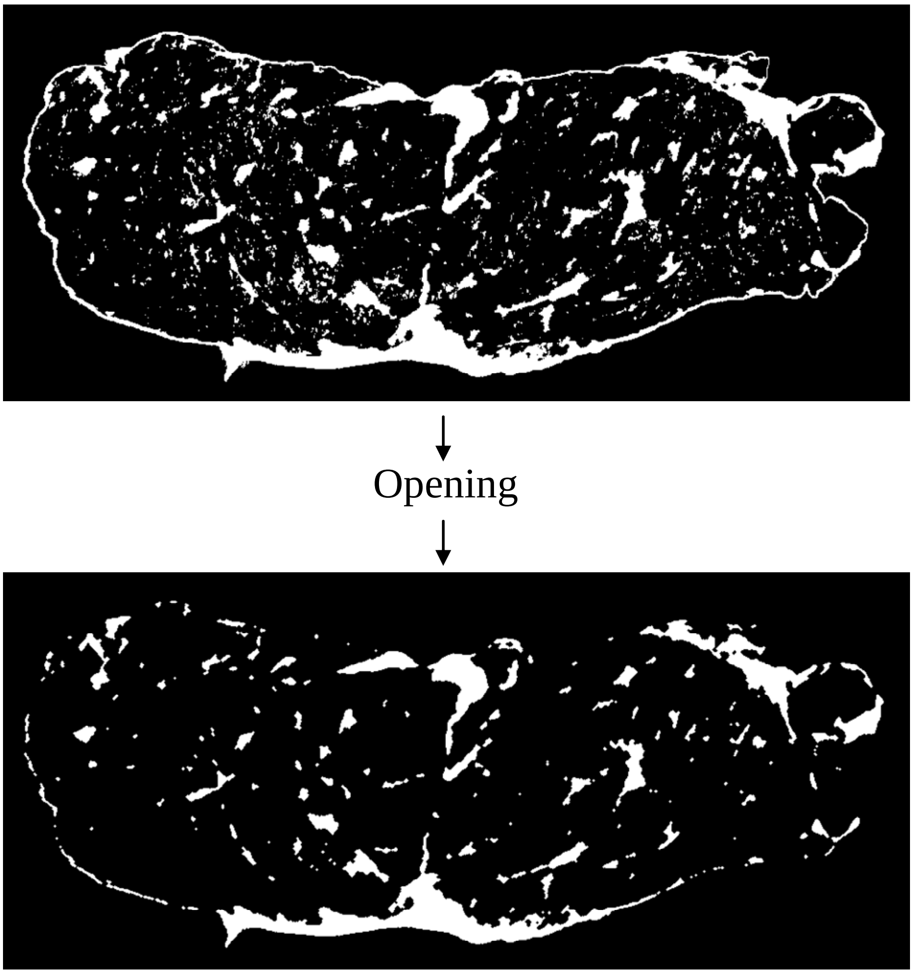


Figure 7. Binarised "fat-image" corrected by morphological transformation to remove the noise

To characterize the pattern structure of the samples, the images were transformed to reach the maximum fat/meat contrast: gray level images were calculated, where the background and shiny pixels were excluded (zero intensity) and the intensity of any object pixel was determined according to their position along the meat-to-fat axis in the Discriminant Function space. The image texture parameters (entropy, energy, homogeneity, contrast) were determined based on the $C_{i,j}$ Gray-level Co-occurrence Matrix of the normalized images, according to the following formulas:

$$Entropy := \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} C_{i,j} \cdot \log_2(C_{i,j})$$

$$Energy := \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} {C_{i,j}}^2$$

$$Homogeneity := \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{C_{i,j}}{1+|i-j|}$$

$$Contrast := \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} C_{i,j} \cdot (i-j)^2$$

where i and j are the intensity levels in the gray-level image, N is the number of the levels (in our case, 256). The transformations were performed, and the parameters were calculated in the Mathcad program (Mathcad, Ver14).

3. Results and Discussion

3.1. Preliminary experiments – Multispectral system

The tests resulted in four-channel images of the samples. In case of a rib sample, a typical image-set is illustrated in *Figure 1*, together with the intensity diagrams of the multispectral rib images at a marked image-row. Very similar images were recorded with beef samples as well.

According to the evaluation of the image records we can conclude that the best meat-to-fat contrast (conclusively the best signal-to-noise ratio, resulting in the most effective segmentation) can be achieved by applying the blue (470 nm) or the green (525 nm) light sources. This conclusion was confirmed by the shown intensity diagrams. These intensity ratios provide with sufficient information for the further image processing steps, the tested camera with the appropriate illumination (monochromatic blue or green light source) was found to be technically suitable for the image recording. However, the main advantage of this system of relatively high cost (very high dynamic range) is not really needed for processing of the tested meat sample images (the natural variability of the intensity of a meat surface – even within a practically homogenous picture detail – is far above the camera noise).

3.2. Preliminary experiments – Hyperspectral system

The measurements resulted in hypercubes, containing the spatial and spectral information about the tested sample. The spatial projection of a sirloin sample at the wavelength, selected by statistical analysis in order to produce effective fat/meat segmentation and the results of the segmentation are shown in *Figure 2* (subtraction of 1300 nm and 1200 nm images). For the pork samples, we got similar images at the same wavelength values (not shown).

Summarizing the experiences of the tests with hyperspectral system, we can conclude that the hyperspectral measurements in the 1000–1700 nm range resulted in no really significant wavelength, enhancing the fat-meat discrimination power. Furthermore, the spatial resolution of the applied instrumentation was at the edge of the technical applicability (approx. 0.5 mm/pixel in case of inspection of a whole slice). Conclusively, the hyperspectral system was excluded from the further investigations.

3.3. Quality evaluation

3.3.1. Sensory evaluation

The members of the sensory board were compared pair wise by cross tabulation (IBM SPSS Statistics, Version 20). In good accordance with the practice and the literature (e.g. as Liu wrote: "…such subjective procedure is not easy and has poor repeatability in addition to the environmental factors that can also influence the grader …(Liu et al. (2012))), relatively low Contingency Coefficients were typical between the evaluator pairs, due to the uncertainty of the interpretation of the marbling quality. Evaluators with Contingency Coefficient, lower than 0.5 in any comparison were excluded from the further analysis, and the average classification of the remaining members (applying 2* weight for the results of the trained expert) was used to determine the Sensory Quality classes.

3.3.2. Segmentation

The resulted segmented pseudo-color images (as it is illustrated in *Figure 6*) were visually evaluated by the image processing team and one meat expert. According to the assessment, several general conclusions can be drawn:

- the pixel-classification based on Discriminant Analysis of appropriate teaching image data base (different for beef and pork samples) was found to be effective
- the presence of connective tissue was found to be a disturbing factor: based on RGB data, there was no effective method found to perfectly distinguish between the fat and connective tissue areas; it can cause overestimation of the fat regions
- the presence of reflections was found to be a disturbing factor: the shiny spots can be excluded according to the DA-classification, however, they cover the possible fatty areas; it can cause underestimation of the fat regions.

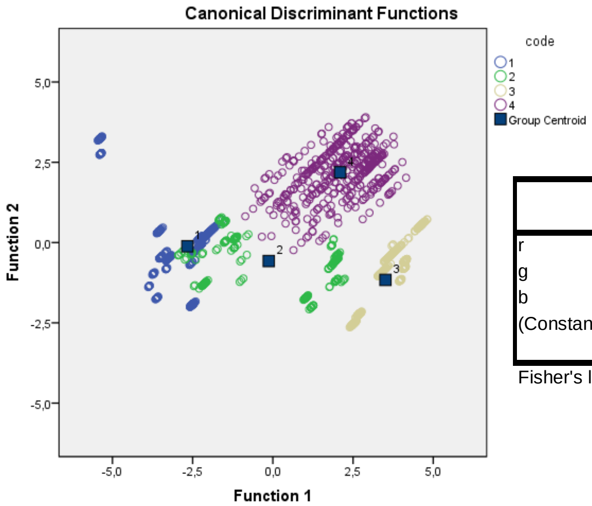
3.3.3. Beef samples

Altogether 107 sirloin images were processed. According to the Carcass Classification, measured in the slaughterhouse on the carcasses, the classes of 1/2/3/4/5 included 17/18/26/22/24 sample images, respectively. The sensory evaluation of the marbling resulted in Sensory Quality of the samples in the range of 1–5 in the distribution, included in *Table 1*.

Table 1. Cross tabulation of the Carcass Classification vs. the Sensory Quality (BEEF)

		Sensory Quality (Marbling)					Total
		1	2	3	4	5	
Carcass Classification	1	17	0	0	0	0	17
	2	0	8	10	0	0	18
	3	0	0	21	5	0	26
	4	0	0	15	7	0	22
	5	0	0	1	19	4	24
Total		17	8	47	31	4	107

The marbling quality was increasing with the Carcass Classification of the carcasses *(Figure 8* and *9)*. The difference of the sensory marbling scores between the Carcass Classification classes was significant (at 95% probability level), excluded between the 3rd and 4th class, where the confidence intervals overlapped.



Classification Function Coefficients

	code			
	1	2	3	4
r	1,070	0,735	0,150	0,705
g	-0,884	-0,507	-0,076	-1,143
b	-0,086	-0,076	0,109	0,654
(Constant)	-21,083	-16,847	-14,796	-24,301

Fisher's linear discriminant functions

Figure 8. Result of the Discriminant Analysis (DA) of the teaching RGB data base (classes: 1: meat, 2: fat, 3: background, 4: shiny spots) with the classification coefficients (PORK samples)

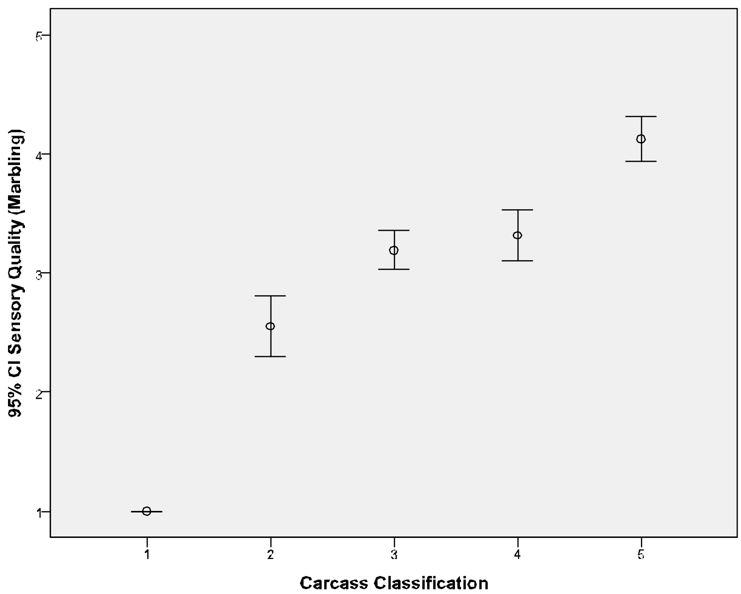


Figure 9. Average values and 95% Confidence Intervals of Sensory Quality scores vs. the Carcass Classification

The processing of the sirloin images resulted in quantitative characteristics of the samples as follows:

– the Discriminant Analysis of the images, and the application of the Fisher Classification Functions to classify the pixels into meat/fat/background/reflections categories, resulted in the

– meat area (pixels)
– fat area (pixels)
– fat-to-total area ratio

– the image pattern structure characterization of the normalized images resulted in the following parameters:

– Entropy
– Energy
– Homogeneity
– Contrast

The results (average values for a given class, and their standard deviation values) are summarized in *Tables 2* and *3*.

Table 2. Average and standard deviation values of fatness parameters of the Carcass Classification and the Sensory Quality classes (BEEF)

Carcass Classification	Fat area (pix)		Meat area (pix)		Fat/Total ratio	
	avg	std	avg	std	avg	std
1	10066	3475	104161	14644	0,0878	0,0279
2	19840	8611	118501	15861	0,1434	0,0598
3	12051	3879	103502	23322	0,1082	0,0404
4	12219	3509	127655	19229	0,0886	0,0265
5	12191	4336	121198	25099	0,0932	0,0320

Sensory Quality	Fat area (pix)		Meat area (pix)		Fat/Total ratio	
	avg	std	avg	std	avg	std
1	10066	3475	104161	14644	0,0878	0,0279
2	20539	7695	119163	19141	0,1485	0,0576
3	13573	6106	114773	23856	0,1080	0,0454
4	12809	4148	121775	24028	0,0977	0,0345
5	8131	1857	104638	7652	0,0721	0,0158

Table 3. Average and standard deviation values of image texture parameters of the Carcass Classification and the Sensory Quality classes (BEEF)

Carcass Classification	Entropy		Energy		Homogeneity		Contrast	
	avg	std	avg	std	avg	std	avg	std
1	-7,596	0,771	0,1769	0,0560	0,5656	0,0549	176,4	36,1
2	-7,836	0,444	0,1651	0,0333	0,5541	0,0304	220,0	64,6
3	-7,476	0,544	0,1863	0,0433	0,5675	0,0368	268,2	88,0
4	-8,110	0,540	0,1390	0,0336	0,5189	0,0366	290,1	87,3
5	-8,043	0,450	0,1440	0,0359	0,5206	0,0366	279,6	58,7

Sensory Quality	Entropy		Energy		Homogeneity		Contrast	
	avg	std	avg	std	avg	std	avg	std
1	-7,596	0,771	0,1769	0,0560	0,5656	0,0549	176,4	36,1
2	-7,595	0,398	0,1800	0,0319	0,5703	0,0218	213,1	78,9
3	-7,758	0,561	0,1665	0,0408	0,5479	0,0396	271,6	91,9
4	-8,054	0,568	0,1446	0,0434	0,5239	0,0429	270,2	55,1
5	-7,963	0,105	0,1451	0,0042	0,5209	0,0079	295,1	54,4

For quality assessment, the possibility of classification, based on image texture parameters (Entropy, Energy, Homogeneity and Contrast) to predict either the Carcass Classification or the Sensory Quality (marbling score) was evaluated.

Table 4. Classification results (predicted Carcass Classification, based on image texture parameters) (BEEF)

Carcass Classification			Predicted Group Membership					Total
			1	2	3	4	5	
Original	Count	1	13	3	0	0	1	17
		2	3	13	2	0	0	18
		3	1	4	14	4	3	26
		4	2	2	2	12	4	22
		5	2	2	2	10	8	24
	%	1	76,5	17,6	0,0	0,0	5,9	100,0
		2	16,7	72,2	11,1	0,0	0,0	100,0
		3	3,8	15,4	53,8	15,4	11,5	100,0
		4	9,1	9,1	9,1	54,5	18,2	100,0
		5	8,3	8,3	8,3	41,7	33,3	100,0

Linear Discriminant Analysis was applied (IBM SPSS Statistics, Version 20) to find the classification model and to classify the samples (described by the texture characteristics) into given quality classes. The results are shown in *Tables 4* and *5*. *Table 6* contains the Classification Function Coefficients (Fisher's linear discriminant functions) for the calculation of the Carcass Classification or the Sensory Quality score for an unknown sample.

Table 5. Classification results (predicted Sensory Quality (Marbling values), based on image texture parameters) (BEEF)

Sensory Quality (Marbling)			Predicted Group Membership					Total
			1	2	3	4	5	
Original	Count	1	12	3	0	2	0	17
		2	1	6	1	0	0	8
		3	4	11	16	7	9	47
		4	3	3	8	15	2	31
		5	0	0	1	0	3	4
	%	1	70,6	17,6	0,0	11,8	0,0	100,0
		2	12,5	75,0	12,5	0,0	0,0	100,0
		3	8,5	23,4	34,0	14,9	19,1	100,0
		4	9,7	9,7	25,8	48,4	6,5	100,0
		5	0,0	0,0	25,0	0,0	75,0	100,0

Table 6. Classification Function Coefficients (Fisher's linear Discriminant functions) (BEEF)

	Carcass Classification				
	1	2	3	4	5
Entropy	-11004	-11071	-11028	-11055	-11045
Energy	28849	28941	28896	28994	28977
Homogeneity	45992	46024	45824	45689	45711
Contrast	-,032	-,082	-,065	-,098	-,084
(Constant)	-36577	-36735	-36463	-36410	-36413

	Sensory Quality (Marbling)				
	1	2	3	4	5
Entropy	-10963	-11015	-10995	-11013	-10981
Energy	31860	31909	31905	32004	31856
Homogeneity	44920	44934	44732	44781	44438
Contrast	,738	,694	,689	,699	,646
(Constant)	-36784	-36886	-36659	-36778	-36327

The efficiency of the classification is usually characterized by the percentage of original grouped cases classified correctly. In the present case, it shows relatively weak results:

- 56.1 % of original grouped cases classified correctly in case of prediction of the Carcass Classification;
- 48.6 % of original grouped cases classified correctly in case of prediction of the Sensory Quality (Marbling).

However, it is not in real contradiction with the everyday praxis of the meat quality evaluation or the published research experiences. We cannot expect much better results even from the sensory evaluation. Taking into account the mentioned relatively low Contingency Coefficients between the evaluators, we have to conclude that the uncertainty of the sensory classification is similar.

If we do not punish the misclassification into the *neighboring classes*, the percentage of original grouped cases *classified acceptably* will be 86% for Carcass Classification prediction and 79.4% for Sensory Quality prediction. Similar approach was applied by Ngapo et al. (2012).

Furthermore, for practical use, if it is not necessary to apply the determined marbling score for every individual slice, but the question is the mean Sensory Quality of the whole sample, then the average predicted marbling result of the slices, belonging to the same sample (same carcass) can be compared to the Carcass Classification score. This comparison resulted in correlation of 0.96 for the beef samples.

3.3.4. Pork samples

Altogether 221 rib images were given to the assessment with machine vision systems. During the sensory evaluation of the marbling, according to the expert panel the marbling quality of the given rib slices was found to be in the low to medium range, so the evaluation resulted in Sensory Quality of the samples in the range of 1–3. Furthermore, we faced similar situation, as it was mentioned by T.M. Ngapo (T.M. Ngapo et al. 2012) with remarkable overlap of quality classes comparing the different evaluators. In order to find a more consistent "image processing to marbling score" model, it was necessary to increase the distance between the samples, belonging to different quality classes. A data reduction method (similar to the approach of T.M. Ngapo's group) was applied, omitting the samples in the overlapping areas. Finally, it resulted in 150 samples for further analysis in the distribution, shown in *Table 7.*

Table 7. Cross tabulation of the Carcass Classification vs. the Sensory Quality (PORK)

		Sensory Quality (Marbling)			Total
		1	2	3	
Carcass Classification	1	5	27	0	32
	2	0	37	0	37
	3	0	0	37	37
	4	0	15	8	23
	5	0	12	9	21
Total		5	91	54	150

According to the Carcass Classification (SEUROP score), measured in the slaughterhouse on the carcasses, the classes of S/E/U/R/O (hereafter marked with 1/2/3/4/5, respectively) included 42/44/44/46/45 sample images, respectively.

The results of the processing of the rib images (average values for a given class, and their standard deviation values) are summarized in *Tables 8* and *9,* respectively.

Table 8. Average and standard deviation values of fatness parameters of the Carcass Classification and the Sensory Quality classes (PORK)

Carcass Classification	Fat area (pix)		Meat area (pix)		Fat/Total ratio	
	avg	std	avg	std	avg	std
1	14817	3434	110148	8252	0,1180	0,0226
2	16930	4714	98292	5740	0,1466	0,0388
3	15198	3579	81493	5227	0,1568	0,0351
4	12557	2293	69017	4182	0,1540	0,0274
5	11867	3292	72948	4997	0,1386	0,0300

Sensory Quality	Fat area (pix)		Meat area (pix)		Fat/Total ratio	
	avg	std	avg	std	avg	std
1	12244	4593	103060	3841	0,1055	0,0371
2	14027	3949	87295	18538	0,1397	0,0330
3	15045	3846	80372	7261	0,1565	0,0308

For quality assessment, the same analysis was performed, as in the case of the sirloin samples: Linear Discriminant Analysis for prediction of either the Carcass Classification (slaughterhouse SEUROP-system score of the carcasses), or for the C (marbling score), based on image texture parameters (Entropy, Energy, Homogeneity and Contrast). The results are given in *Table 10* (Carcass Classification) and *Table 11* (Sensory Quality). *Table 12* contains the Classification Function Coefficients (Fisher's linear discriminant functions) for the calculation of the Carcass Classification or the Sensory Quality score for an unknown sample.

Table 9. Average and standard deviation values of image texture parameters of the Carcass Classification and the Sensory Quality classes (PORK)

Carcass Classification	Entropy		Energy		Homogeneity		Contrast	
	avg	std	avg	std	avg	std	avg	std
1	-8,072	0,360	0,1349	0,0228	0,5686	0,0267	242,0	60,1
2	-8,094	0,312	0,1342	0,0197	0,5686	0,0270	233,4	51,1
3	-7,720	0,347	0,1696	0,0210	0,5874	0,0287	261,5	79,1
4	-7,693	0,387	0,1672	0,0251	0,5949	0,0317	269,6	62,6
5	-7,719	0,379	0,1595	0,0236	0,5965	0,0304	247,2	68,7

Sensory Quality	Entropy		Energy		Homogeneity		Contrast	
	avg	std	avg	std	avg	std	avg	std
1	-8,034	0,244	0,1291	0,0166	0,5687	0,0221	210,3	33,6
2	-7,900	0,416	0,1491	0,0274	0,5812	0,0330	254,2	62,5
3	-7,716	0,331	0,1677	0,0214	0,5913	0,0258	247,2	75,3

Table 10. Classification results (predicted Carcass Classification, based on image texture parameters) (PORK)

Carcass Classification			Predicted Group Membership					Total
			1	2	3	4	5	
Original	Count	1	15	9	4	1	3	32
		2	13	13	1	4	6	37
		3	1	1	24	4	7	37
		4	1	3	3	10	6	23
		5	3	2	2	3	11	21
	%	1	46,9	28,1	12,5	3,1	9,4	100,0
		2	35,1	35,1	2,7	10,8	16,2	100,0
		3	2,7	2,7	64,9	10,8	18,9	100,0
		4	4,3	13,0	13,0	43,5	26,1	100,0
		5	14,3	9,5	9,5	14,3	52,4	100,0

Table 11. Classification results (predicted Sensory Quality (Marbling values), based on image texture parameters) (PORK)

Sensory Quality (Marbling)			Predicted Group Membership			Total
			1	2	3	
Original	Count	1	4	1	0	5
		2	23	43	25	91
		3	0	12	42	54
	%	1	80,0	20,0	0,0	100,0
		2	25,3	47,3	27,5	100,0
		3	0,0	22,2	77,8	100,0

Table 12. Classification Function Coefficients (Fisher's linear Discriminant functions) (PORK)

	Carcass Classification				
	1	2	3	4	5
Entropy	-1177,726	-1177,829	-1180,207	-1182,533	-1179,448
Energy	7127,492	7128,529	7286,768	7250,875	7196,931
Homogeneity	10300,748	10301,290	10269,128	10332,952	10335,832
Contrast	,367	,367	,377	,378	,377
(Constant)	-8204,067	-8205,429	-8231,936	-8281,950	-8250,657

	Sensory Quality (Marbling)		
	1	2	3
Entropy	-1200,344	-1210,559	-1212,585
Energy	7349,993	7491,591	7599,165
Homogeneity	10172,243	10219,648	10198,066
Contrast	,338	,348	,349
(Constant)	-8215,513	-8345,799	-8366,187

The classification results:

– 48.7% of original grouped cases classified correctly in case of prediction of the Carcass Classification;
– 59.3% of original grouped cases classified correctly in case of prediction of the Sensory Quality (Marbling).

In case of the pork tests – having individual samples only low (1) to medium (3) marbling quality – it is not reasonable to apply the measure of the *acceptable classification*, as in the case of the beef samples. However, comparing the results with the outcomes of the working groups dealing with similar topics (e.g. T.M. Ngapo et al. (2012), or P. Jackman et al. (2009)), we have to conclude that the correct classification around 60% (together with the correlation of 0.93 between the average predicted marbling result of the slices, belonging to the same sample (same carcass) and the Carcass Classification score), are encouraging results.

According to the experiences, a special, user friendly program was developed (in Borland C++) for on-site application to manage the images and to calculate the texture parameters. For the purpose of the real-time evaluation, a simplified (histogram-based) algorithm was applied for determination of texture parameters (instead of the time-consuming co-occurrence matrix based approach):

– CV: Coefficient of Variation: $CV = \dfrac{STDEV(I)}{AVERAGE(I)} = \dfrac{\sigma_I}{\overline{I}}$

– C: Contrast: $C = \sum_{i=0}^{255} (I_i - \overline{I}) \cdot p_i$

– E: Entropy: $E = \sum_{i=0}^{255} p_i \cdot \lg(p_i)$

where p_i is the likelihood of the I_i intensity value.

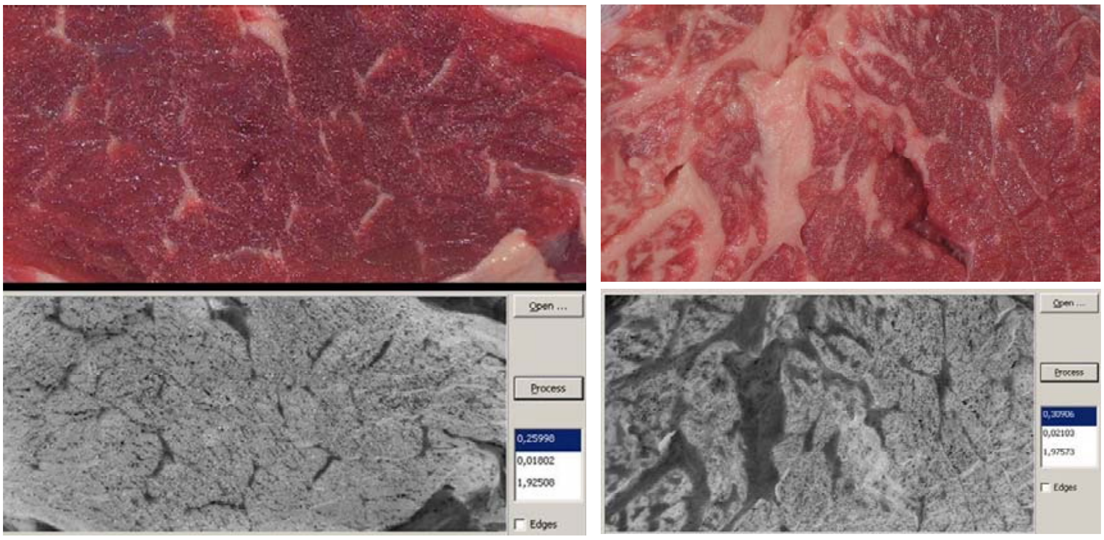


Figure 10. Beef (sirloin) samples, original and processed images with visual and numeric texture information (left: sensory class “1”, right: sensory class “5”)

Program running results are illustrated in *Figures 10* and *11* for beef sirloin and pork rib samples, respectively. This software is presumed to be a useful tool for further data-collection, which can be the base for a more consequent prediction model.

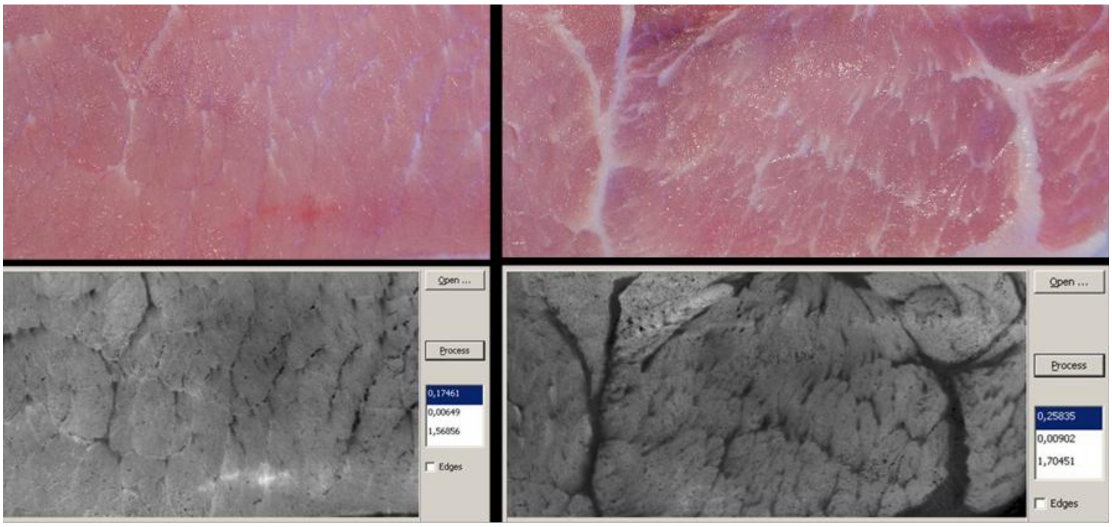


Figure 11. Pork (rib) samples, original and processed images with visual and numeric texture information (left: sensory class "1", right: sensory class "3")

4. Conclusions

Summarizing the results, we can conclude, that

– digital (SLR) camera with fixed recording parameters was proposed to use in industrial environment, if the real-time evaluation of the sample quality is not necessary;

– the DA-based pixel-classification algorithm of RGB images was found to be effective enough for segmentation of fat regions, but the presence of connective tissue can cause overestimation of the fat region, while the presence of reflections can cause underestimation of the fat region. The reflections can be avoided by proper imaging setup, but the distinguishing between the fat and connective tissue regions remains problematic, while measuring only the RGB parameters;

– comparison of image texture properties with the sensory evaluation result gave encouraging results. The relatively high misclassification error can be caused by several factors:

- o uncertainty in "know" categories (e.g. the Sensory Quality, that is the marbling score
- o improper raw material for the model building (in our case the limited marbling quality range of the rib samples)
- o improper imaging circumstances (reflections, camera settings, etc.)
- o overestimation or underestimation of the fat region because of the mentioned disturbing factors.

As there remain a lot of open questions, further work is needed

- – in the field of detailed analysis of the fat regions: connected strings, network, real marbling;
- – extension of the wavelength-range of the investigation, concentrating on the distinguishing of the connective tissue and fat regions;
- – it is necessary to develop user-friendly, interactive software for the meat experts to set up ("teach") a decision supporting system.

Acknowledgements:

This work was supported by TÁMOP –4.2.1.B–09/1 and TÁMOP–4.2.2/B–10 projects.

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