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Application of texture image analysis for the classification of bovine meat

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Abstract

Texture analysis has been used to classify photographic images of meat slices. Among the multiple muscular tissue characteristics that influence meat quality, the connective tissue content and spatial distribution, which define the grain of meat, are of great importance because they are directly related to its tenderness. Connective tissue contains two important components, fat and collagen, which are variable with muscles, breed and also with age. These components are clearly visible on photographic images. Fat and collagen are particularly emphasised by ultraviolet light. The meat slices analysed came from 26 animals raised at INRA of Theix by the LCMH Laboratory. Three different muscles were selected and cut off from carcasses of animals of different breeds and of different ages. The biological factors (muscle type, age and breed) directly influence the structure and composition of the muscle samples. The image analysis led to a representation of each meat sample with a 58 features vector. Classification experiments were performed to identify the samples according to the three variation factors. This study shows the potential of image analysis for meat sample recognition. The correlation of the textural features with chemical and mechanical parameters measured on the meat samples was also examined. Regression experiments showed that textural features have potential to indicate meat characteristics.

1. Introduction

Artificial vision is a technique largely used in the field of food product. This technique consists of associating a video camera, devoted to image acquisition, with a computer used for image analysis. The automatic analysis of images requires a first step of digitisation which transforms the video signal into a two-dimensional matrix of numbers. Each matrix entry is a pixel (picture element) with an entire value called "grey level". Usually the grey level values are coded with an eight bits number, allowing to distinguish 256 grey levels from 0 (black) to 255 (white). The image analysis is implemented to characterise an object or a surface on the visualised image, in particular by analysing the texture. The image texture can be defined as the spatial organisation of grey levels of pixels of digitised images. Thus, the meaning of the term texture, when image processing is concerned, is completely different from the usual meaning in the field of food product.

In general, the process of texture analysis requires the calculation of various features for each texture. These features contain information representative of visual characteristics (coarseness of the texture, regularity, presence of a privileged direction, size of a representative neighbourhood), but also of characteristics which can not be visually differentiated. A wide range of applications of image texture analysis to characterise food products have been proposed. For example, statistical methods have been used to describe the porosity of extruded biscuits from photographic digitised images (Maloigne, Fernandez, Smolarz & Bouvier, 1989). The "angle measure technique" was implemented by Esbensen, Hjelmen and Kvaal (1996) as a texture features extractor on bread images. These authors proposed the method as an alternative to human sensory analysis. In an other domain, the structure of myofibrillar protein gel has been analysed by applying on images, obtained by transmission electron microscopy, a granulometry method based on morphology mathematics (Bastien, Joandel-Monier & Culioli, 1997).

In the field of meat science, several authors have proposed image analysis approaches to characterise meat

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sample images. The quantification of meat quality is a challenge of major importance in the meat industry. Among the multiple muscular tissue characteristics that influence the meat quality, connective tissue quantity and spatial distribution, which define the grain of meat, are of great importance because they are directly related to its tenderness (Dumont, 1986; Lepetit & Culioli, 1994).

Several approaches have been studied for the characterisation of meat quality. Non destructive methods of marbling determination (quantity and distribution of intra-muscular fat) have been investigated for the classification of muscles or parts of muscles. Among these methods, ultrasonic techniques used on living animals or on muscles, have been largely explored (Abouelkaram, Berge & Culioli, 1997; Whittaker, Park, Thane, Miller & Savell, 1992). These techniques investigate the texture analysis of ultrasonic images (Amin, Wilson, Roberts & Rouse, 1993; Brethour, 1990), in particular to correlate textural features with the intramuscular fat content (Kim, Amin, Wilson, Rouse & Udpa, 1998) or the texture analysis of elastograms (Miller et al., 1996).

The direct analysis of the connective tissue on muscle slices should also lead to the determination of morphologic parameters, specific to the various muscles and animal types. However, the implementation of such an analysis is difficult because the connective network is a complex structure, exhibiting different levels of organisation. Therefore, a different approach consisting of a global characterisation of photographic images of meat slices was proposed. Gerrard, Gao and Tan (1996) used histogram description and morphologic features calculated on colour images to accurately predict the colour and marbling score of beef steaks. The analysis of meat images, performed under visible or ultraviolet (UV) light, has also emphasised the potential of texture analysis to identify meat samples according to various variation factors (Basset, Dupont, Hernandez, Odet, Abouelkaram & Culioli, 1999). To further explore the possibilities of this approach, other texture analysis techniques have been implemented in this paper and have been tested on another set of images of bovine meat slices. The automatic recognition of meat samples could enable us to objectively identify the meat origin. Then, the correlation of textural features with physical measurements performed on the same samples and related to meat quality is examined.

2. Material

2.1. Selection of muscles

The samples were chosen to exhibit a large variability in terms of composition and structure. Three different muscles were selected and cut off from carcasses of animals of different breeds and of different ages. The biological factors (muscle type, age and breed) directly influenced the structure and composition of the muscle samples.

The meat slices analysed came from 26 animals provided by the CMH Laboratory of INRA (Theix, France). Four different breeds were represented in the set of animals : Limousin (7 animals), Salers (6 animals), Aubrac (7 animals) and Charolais (6 animals). They were slaughtered at the age of 15 months (7 males), 19 months (6 males), 24 months (4 males) and after 3 years old (9 females). After slaughter at the research centre abattoir, the carcasses were chilled down to 2°C and the selected muscles [*semitendinosus* (ST), *longissimus dorsi* (LD) and *triceps brachii* (TB)] were excised 2 days post-mortem. Table 1 summarises the number of samples available for this analysis, in each class. The data set consists of 48 different classes [(4 classes of breeds)×(4 classes of ages)×(3 classes of muscles)]. Each muscle was cut at different locations, perpendicular to the direction of the myofibre, in order to obtain, in most cases, four meat slices.

2.2. Data acquisition

The imaging system was composed of a CCD camera (SONY MACC 77, NOESIS, France) mounted on a photographic bench (Fig. 1). The camera was connected to a PC computer equipped with a digitisation card (Matrox-Meteor). The images were digitised at 256 grey levels. For each meat slice, two images of the exact same size were acquired, one under visible light, the other under UV light (fluorescence). In these conditions, it was possible to increase the contrast between muscle fibre bundles and collagen or fat. The digitised meat surface had to be large enough to be representative of the sample, but not too large, so as to retain a good

Table 1
Number of muscle samples in each class: LD, *Longissimus dorsi*; TB, *Triceps brachii*; ST, *Semitendinosus*

Breed	Age			
	15 months	19 months	24 months	> 3 years
Limousin	LD 1 TB 2 ST 1	LD 1 TB 1 ST 1	LD 1 TB 1 ST 1	LD 2 TB 3 ST 2
Salers	LD 1 TB 1 ST 1	LD 2 TB 2 ST 1	LD 1 TB 1 ST 1	LD 2 TB 2 ST 2
Aubrac	LD 2 TB 1 ST 2	LD 1 TB 1 ST 2	LD 1 TB 1 ST 1	LD 2 TB 2 ST 2
Charolais	LD 1 TB 2 ST 2	LD 1 TB 1 ST 1	LD 1 TB 1 ST 1	LD 2 TB 2 ST 2

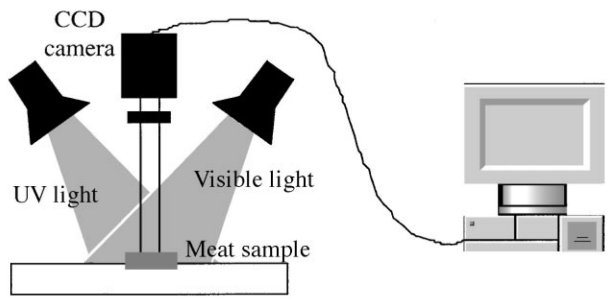

Fig. 1. Image acquisition set up.

resolution of the connective network. A surface of 3×3 cm digitised to 512×512 pixels was considered as a good compromise and was extracted for image processing.

3. Methods

The texture analysis methods used can be classified in two categories. On the one hand, the statistical methods characterise the pixel grey level distribution and organisation. On the other hand, the methods based on morphology mathematics are applied on binary images to characterise larger structures such as lipid and collagen inclusions. The image analysis procedure can be defined as a system in which input is an image and the output is a series of features provided by the analysing techniques implemented. Each image is then characterised by a vector of features. A classification step is then required to define the relevant features, constituting a signature of the studied samples.

3.1. Features extraction

The images acquired under visible light exhibited the fine structure of the muscle fibre bundles. Therefore, the texture analysis was performed on these images. The ultraviolet lighting (fluorescence) of meat samples highlighted the marbling pattern. Intramuscular fat and/or collagen appeared more contrasted than on images acquired under visible light and the fine structures were hardly distinguishable. Therefore, these images were not used for texture analysis, but for the characterisation of the amount and distribution of fat and collagen. Visible and ultraviolet images underwent a specific processing before the extraction of features.

3.2. Pre-processing of the images

The meat slices placed under the camera were not perfectly flat. Therefore, the lighting was not homogeneous on the whole surface of the sample and a preprocessing step was required to reduce the effect of this artefact on the digitised images acquired under visible light.

The processing consisted of subtracting from the original image, an image processed with an average mask of 51×51 pixels. This processing reduces the effect of non-homogeneous lighting and emphasises the texture on the image.

After filtering, the images underwent a grey scale remapping using linear scaling. Fig. 2 shows an example of an original and filtered image of a meat sample acquired under visible light.

After a linear grey scale remapping, the ultraviolet images are binarized using a threshold so that the muscle fibres appear in black and fluorescent fat and collagen in white (Fig. 3). The skeleton of the binarised image is also calculated.

3.3. Textural features calculated on images acquired under visible lighting

Fifty different textural features were calculated. They derived from eight texture analysis methods. The relationship between the features calculated and the visual aspect of the images was in most cases difficult to establish. The implemented methods are briefly described hereafter.

3.3.1. First-order statistical features

In fact, features calculated using an image first-order statistics are not textural features because they consider the intensity of individual pixels, independently of their neighbouring pixels. In other words these features merely describe the grey level histogram of an image. However, the mean and variance of grey levels and the moment of higher degrees were calculated (six features) to represent the grey level distribution and the degree of homogeneity of each image.

3.3.2. Co-occurrence matrices

The co-occurrence matrices method describes the second order statistics of the images. This technique is commonly used in texture analysis because it provides for each sample a large set of features, and it can be assumed that at least one of these features reflects the small variation of texture between classes.

This method is based on the estimation of the second-order joint conditional probability density functions $P_{d,\theta}(i,j)$. Each $P_{d,\theta}(i,j)$ is the probability of going from a grey level i to a grey level j in a given direction θ at a given intersample spacing d. The co-occurrence matrix $P_{d,\theta}$ is a representation of the estimated values. It is a square matrix of dimension N_g (N_g is the number of grey levels in the image).

To summarise the content of a co-occurrence matrix, a number of texture features can be defined. A set of 16 features, defined by Haralick, Shanmugam and Dinstein (1973) were calculated. These were the Angular second moment, Contrast, Correlation, Variance, Inverse

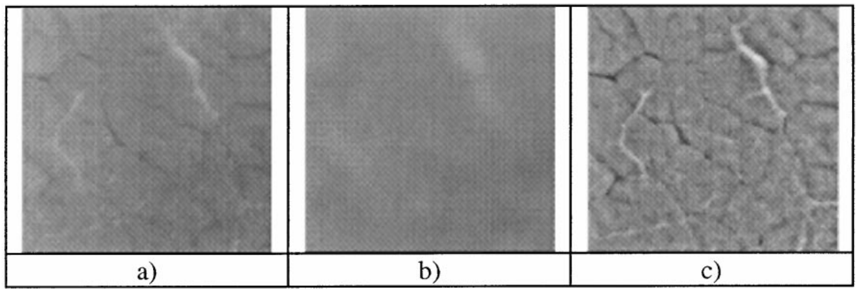

Fig. 2. Example of a meat image (muscle ST, animal Salers, 15 month old). (a) original image; (b) smoothed image of (a); (c) is the result of the grey scale remapping of (a) and (b).

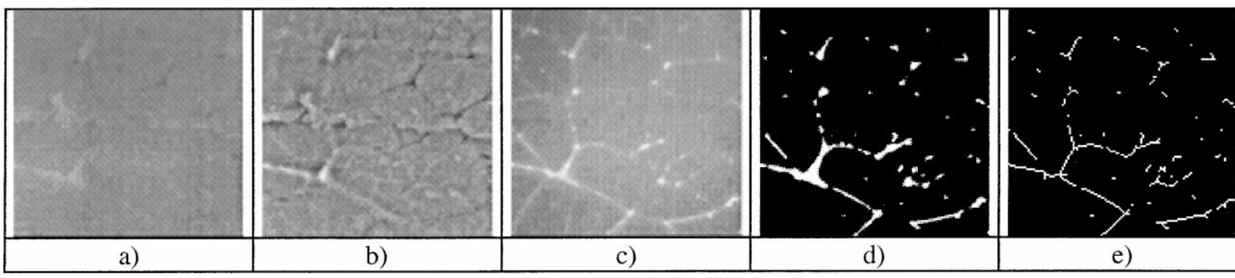

Fig. 3. (a) Original image of a meat sample (muscle ST, Limousin, 15 month old) acquired under visible lighting; (b) results from the pre-processing of (a); (c) is the same sample acquired under UV lighting; (d) binarization of (c); (e) skeleton of (d).

difference moment, Sum average, Sum variance, Difference variance, Sum entropy, Entropy, Difference entropy, Information measures of correlation (4), Maximum probability.

3.3.3. Neighbouring grey level dependence matrix

To avoid angular dependence of the co-occurrence matrix, the neighbouring grey level dependence matrix has been proposed. In this approach, the matrix entries $P_d(i,j)$ represent the number of occurrences where a pixel of grey level i has j neighbours of grey level i in a $d{\times}d$ neighbourhood. From this matrix, features describing texture can be defined analogously to those defined for the co-occurrence matrix. Twelve features were calculated. They were essentially invariant under spatial rotation and linear grey level transformation (Lee, Lee & Kim, 1992).

3.3.4. Grey level run lengths matrix

The grey level run lengths method is based on computing the number of grey level runs of various lengths. A grey level run is a set of linearly adjacent picture points having the same grey level value. The length of the run is the number of picture points within the run. The element $r(i,j,\theta)$ of the grey level run length matrix specifies the number of times a picture contains a run of length j for grey level i in the θ direction. Five features were calculated from these matrices (Galloway, 1975).

3.3.5. Fourier power spectrum analysis

This method requires first computation of the image power spectrum from the bi-dimensionnal discrete Fourier transform. The features commonly used with the power spectrum method are the summation of the frequential components included either in an annular-ring geometry, which gives a measure of the texture coarseness or included in a wedge geometry, which contains directionality information. Because the meat samples were placed under the CCD camera regardless of a particular muscle orientation, directionality information is not useful in our application. One feature representing the texture coarseness was calculated.

3.3.6. Relative extrema measures

The density of local extrema of various sizes in intensity has been proposed for a texture measure. The algorithm looks for relative extrema within a line in a given direction. The scan line is smoothed with a variable threshold T. The number of extrema versus T can be used as a characteristic of the texture (Mitchell, Myers & Boyne, 1977).

3.3.7. Fractal method

The theory of fractals has led to several multi-resolution methods of texture analysis. They assume that images exhibit identical grey level statistics at different scales of examination. A measure of this behaviour is the fractal dimension which is an indication of the coarseness of the texture. The implemented method has been described by Pentland (1984).

3.3.8. Texture spectrum

He and Wang (1991) have introduced a model of texture analysis based on the concept of texture unit, in which an image can be characterised by its texture spectrum. Local texture information can be extracted for each pixel from a neighbourhood of 3×3 pixels which represents the texture unit. The intensity of the central pixel is compared to the intensity of its eight ordered neighbours and the resulting configuration is coded. There are 3^8 possible texture units in total. The spectrum counts the occurrence of each unit in the images. Eight features are then calculated to describe the spectrum.

3.4. Morphological features calculated on images acquired under ultraviolet lighting

As the texture of meat images is created by the connective network, eight features, specifically representative of the distribution and amount of intramuscular fat and collagen, have been calculated. Four were derived from the binarized UV images and four characterised the skeleton of the binarized images. These features measured the number of white pixels, the average size of white areas, the number of objects and the size of the largest object in both images. On the binarized image, the number of white pixels represents the total surface of fat and collagen and on the second image, the length of the skeleton.

3.5. Classification

3.5.1. Selection of features

The classification was performed in view to evaluate the relevance of a selection of textural features to recognise the different meat samples. The implemented classification methods used an iterative selection method. At first, an initial selection of features was made. The selected features were the most relevant according to the Fisher criterion. Then the test data set was classified and the recognition rate was computed. At each iteration, one feature was added, the test data set was re-classified and the new recognition rate was computed. The feature that gave the maximal recognition rate was added to the list of selected features. The algorithm iterates until all the features were used.

3.5.2. Classification methods

The features selection method was tested on our data base with the K nearest neighbours method (Fukunaga, 1972) (KNN). With the KNN method each pattern of the training set is stored as a prototype. The class of a new pattern is directly obtained from the computation of the distance between this pattern and each prototype in the data base. Among the K nearest neighbours, the majority class is assigned to the unknown pattern. This supervised method requires the feature vectors and the true class of each pattern for the learning database.

4. Results

4.1. Classification experiments

For each meat sample, 58 features were calculated: 50 for the visible light images and 8 features for the UV light images as described above. To evaluate the importance of the variation factors, several experiments were conducted with various aims for classification (i.e. classification according to the age of animals, the breed or the muscle). The features selection algorithm was initialised with one feature: the most relevant according to the Fisher criterion. The classification experiments were conducted using randomly-selected 60% of the data in the training set and the testing was performed with the remaining 40% of the data. This process was repeated several times, each time with different randomly-selected training and testing set. The various experiments led, in most cases to similar results. The variability of the classification rate obtained for the various experiments was small when the number of samples per class was large. As the number of meat samples was relatively small, some experiments involved a small number of images and a larger variability was observed. Moreover, the various images were not completely independent because four images were acquired on the same meat sample. However it was verified that the intra-sample variability of the calculated features was comparable to the variability obtained with different samples of the same class. The classification rates obtained are reported in Table 2. In particular, the correct classification rates obtained with a small number of features, have been reported, in order to identify the most relevant features characterising the particularities of the various samples.

Classification using the 48 classes defined in Table 1 did not led to satisfying results. Only 25.4% of the samples were correctly classified. The small number of samples can explain these poor results (several classes include only one animal).

One can remark that the variability between muscles is higher than the variability between breeds or ages. They can be classify more easily. Sixty percent of the muscles (LD and TB) were correctly classified with only two features.

Other experiments were conducted to perform classification from a selected part of the data set in view to avoid one variation factor. The set of images was subdivided for the classification of the muscles or of the breeds according to a particular age, for the classification of muscles or ages when the breed was known and for the classification of breeds or ages from images of one kind of muscle. As expected, higher classification rates were obtained than when all the samples were involved.

The classification of the muscles from animals selected in one age category, regardless of the muscles, led to high identification rates: larger than 72% with two features and larger than 82% with four features. In general, LD muscles presents numerous spread out white flecks. This is more pronounced on Salers images. TB muscles present large and linear fat or collagen inclusions. ST muscles exhibit a more homogeneous background, corresponding to the lean, than other muscles (Fig. 4). These visual particularities are expressed by some textural features as shown on Fig. 5. Because of the large clear areas on muscle TB images, the histogram is not symmetrical according to the mean value of grey levels and the feature describing the dissymmetry of the image histogram is higher than on other images. The homogeneity of muscles ST is characterised by the feature ''non-uniformity of the neighbours number'' calculated from the neighbouring grey level dependence matrix.

The classification of the breeds from the oldest animal category, regardless of the muscles, was a more difficult task: 63.4% of correctly classified samples with two features. Fig. 6 shows examples of images acquired on the same muscles of two different breed animals. Some particularities of each kind of images can be remarked. One concerns the histogram of the images. After a grey scale remapping, the Limousin images appear clearer than the Salers one. A second remark can be made

Table 2
Classification results

Classification goals (number of classes)	Type of images used (number of images)	% correctly classified: 2 features	% correctly classified: 4 features	Maximum % of correctly classified
Ages, muscles and breeds (48)	All samples (272)	11.9	17.2	25.4 (18 features)
Muscles (3)	All samples (272)	60	66.4	76.4 (13 features)
Breeds (4)	All samples (272)	33.3	37.8	49.6 (19 features)
Ages (4)	All samples (272)	46.8	53.4	58.9 (10 features)
Muscles (3)	15 month old animals (66)	74.1	88.9	96.3 (17 features)
Breeds (4)	15 month old animals (66)	59.3	74.1	77.8 (8 features)
Muscles (3)	19 month old animals (60)	75	87.5	95.8 (17 features)
Breeds (4)	19 month old animals (60)	48	60	64 (9 features)
Muscles (3)	24 month old animals (48)	85	95	95 (4 features)
Breeds (4)	24 month old animals (48)	45	50	55 (7 features)
Muscles (3)	> 3 years old animals (98)	72.5	82.5	87.5 (13 features)
Breeds (4)	> 3 years old animals (98)	63.4	63.4	63.4 (2 features)
Muscles (3)	Limousin (68)	64.3	78.6	82.1 (6 features)
Ages (4)	Limousin (68)	67.9	67.9	75 (5 features)
Muscles (3)	Salers (67)	71.4	82.1	92.9 (16 features)
Ages (4)	Salers (67)	54.8	67.7	80.7 (7 features)
Muscles (3)	Aubrac (69)	82.8	79.3	89.7 (8 features)
Ages (4)	Aubrac (69)	55.2	65.5	79.5 (19 features)
Muscles (3)	Clarolais (68)	75	70.8	87.5 (8 features)
Ages (4)	Charolais (68)	60	68	80 (7 features)
Breeds (4)	Muscle st (88)	38.9	41.67	50 (15 features)
Ages (4)	Muscle st (88)	67.3	75	80.8 (6 features)
Breeds (4)	Muscle ld (89)	41.7	50	66.7 (11 features)
Ages (4)	Muscle ld (89)	43.2	59.5	62.16 (6 features)
Breeds (4)	Muscle tb (95)	52.63	55.26	63.16 (7 features)
Ages (4)	Muscle tb (95)	52.5	60	67.5 (8 features)

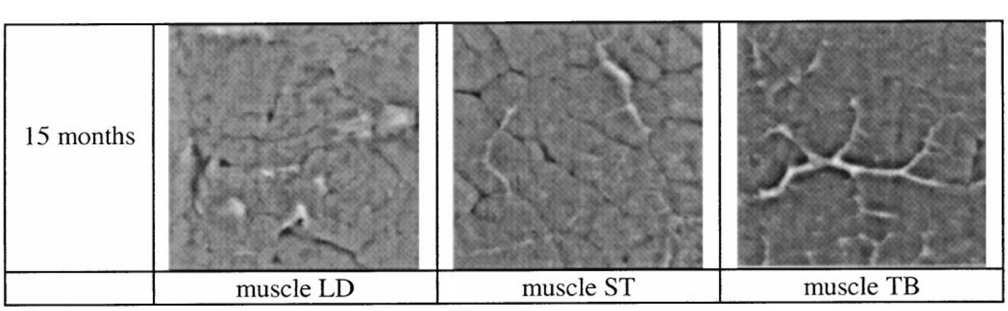

Fig. 4. Examples of images of the three muscles of a 15 month old animal (breed: Salers).

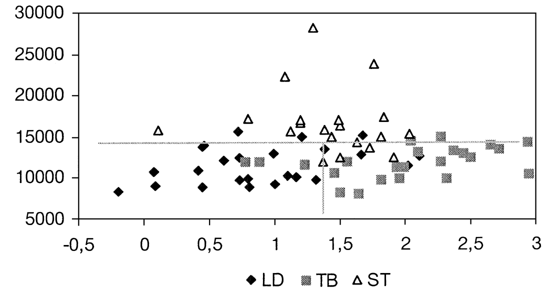

Fig. 5. Representation of the meat samples of Salers animals from two textural features discriminating the three muscles (horizontal axis: histogram dissymmetry; vertical axis: non-uniformity of the neighbourhood number calculated from the "neighbouring grey level dependence matrix" method.

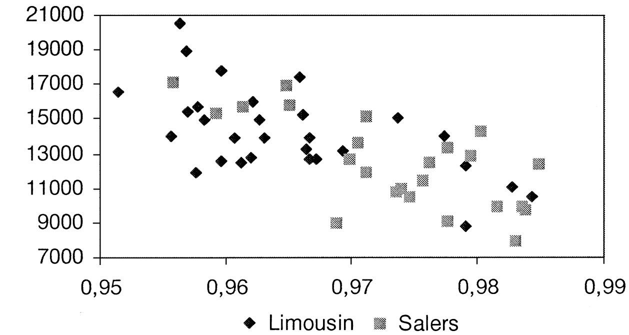

Fig. 7. Representation of the meat samples of two different breeds (age higher than 3 years) according to 2 textural features calculated from the cooccurrence matrix method (x-axis) and from the grey level dependence matrix method (y-axis).

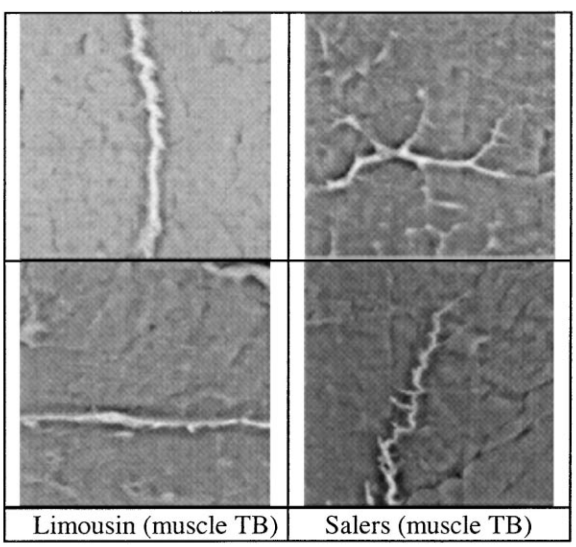

Fig. 6. Examples of TB muscles images of four 15 months old animals of breed Limousin and Salers.

about the shape of fat and collagen inclusions which are more linear and regular on Limousin images than on the Salers images. These trends are expressed by features used in the classification. This is illustrated in Fig. 7: samples of the two different breeds are represented according to two textural features which exhibit a potential to discriminate the two breeds.

The classification of the various samples according to the age of animals requires a large number of features to obtain good classification rates. This seems to indicate that it is difficult to detect some specificities to each age category characterising the connective network. This is illustrated by the images shown in Fig. 8. They represent the muscle LD of Limousin animals of various ages. The connective network appears more clearly on the images of the youngest animals. This is confirmed by the feature expressing the number of elements on the skeleton of the binarized UV images which had much larger value for the youngest animals. But it was not possible to discern an evolution in the other categories of animals with this feature. This is in accordance with the visual examination of the binarized images in Fig. 8.

4.2. Correlation of textural features with meat characteristics

For each of the meat sample used in this study, three chemical parameters were measured : dry matter content, lipid content and collagen content and two mechanical parameters: $k20$, $k80$ ($k20$ is the stress at 20% compression of samples). The chemical values were obtained from the entire muscle samples whereas the mechanical data were measured on each of the four meat slices of each muscle. The efficiency of textural features to indicate the physical parameters was examined. In an initial study, simple correlation coefficients between textural features and physical characteristics were calculated. Table 3 reports the maximal value of correlation coefficients obtained for each physical parameter. It shows that a relationship existed between the meat characteristics and some textural features; however, this relationship was not very strong.

To indicate physical characteristics from textural features, the stepwise linear regression method was used. The textural features were defined as independent variables and physical features as dependent variables. The results are reported in Table 4. The regression was performed by adding textural features until the R-square coefficient R^2 increased significantly.

The experiments had been carried out, on one hand, by taking into account all the available samples and on the other hand with a selected part of the data base. As an example, the regression results obtained for parameters $k20$ and $k80$ with only the textural features provided by the Limousin animals, the 15 month old animals or the TB muscles, are given in Table 4.

The R^2 ranged from 0.3 to 0.59 ($P<10^{-4}$) with a number of parameter k varying from 13 to 21 when all

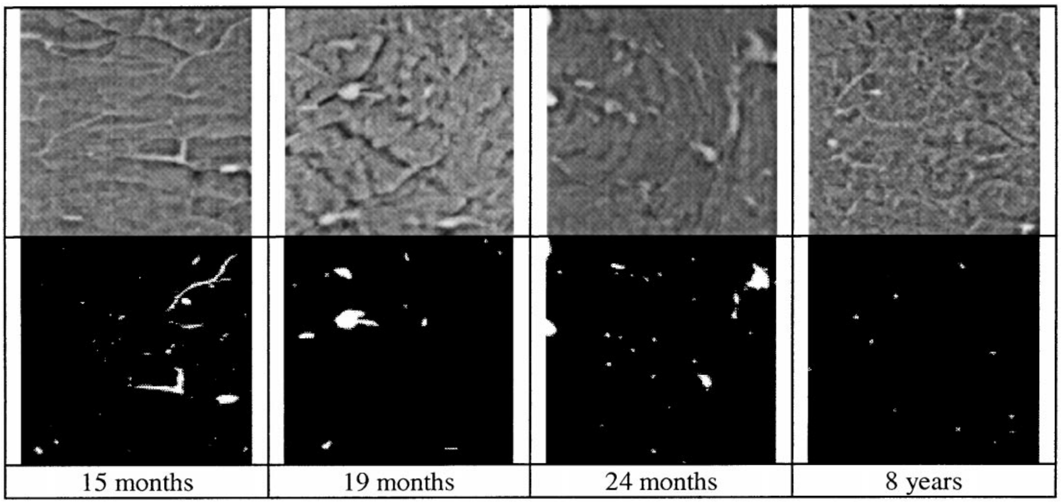

Fig. 8. Images of muscle LD of Limousin animals at various ages acquired under visible lighting (top) and acquired under ultraviolet lighting after binarization (bottom).

Table 3
Correlation coefficients[a]

Physical and chemical parameters	Textural feature	r_{max}
Dry matter	Relative extrema measure	0.41
Lipid	Texture spectrum (diagonal structure)	−0.26
Collagen	Texture specrum (black–white symmetry)	0.49
$k20$	Texture spectrum (degree of direction)	−0.44
$k80$	Texture spectrum (black–white symmetry)	0.41

[a] The most correlated textural feature with each physical and chemical parameters and the corresponding correlation coefficients (r_{max}) are indicated.

Table 4
Stepwise linear regression results for indicating physical parameters from textural features[a]

Dependent variable	All animals					Limousin animals		15 month old animals		TB muscles	
	Dry matter	Lipid	Collagen	$k20$	$k80$	$k20$	$k80$	$k20$	$k80$	$k20$	$k80$
R^2	0.48	0.3	0.59	0.40	0.39	0.63	0.8	0.66	0.73	0.58	0.5
P	$<10^{-4}$	$<10^{-4}$	$<10^{-4}$	$<10^{-4}$	$<10^{-4}$	$<10^{-4}$	$<10^{-4}$	$<10^{-4}$	$<10^{-4}$	$<10^{-4}$	$<10^{-4}$
k	21	17	17	20	13	19	19	20	11	19	20

[a] k is the number of features used in the regression.

the meat samples are considered. When one variation factor was eliminated in the regression, higher R^2 coefficient were obtained and the results were statistically significant ($P<10^{-4}$). The feature $k80$ can be indicated with $R^2=0.8$ ($P<10^{-4}$) from textural features calculated on Limousin images. When only the younger animals are considered, the regression of $k80$, performed with 11 features accounted for a high amount (73%) of the variability in the observations ($R^2=0.73$, $P<10^{-4}$). The textural features calculated from one selected muscle seemed to be less efficient for the indication of the mechanical parameters.

From these results, one can remark that the prediction capability of physical parameters is improved when few variation factors are involved in the data. This indicates that the definition of a global model of prediction for a physical parameter is a difficult problem. It is not convenient to consider simultaneously the effects of age, breed and muscle on the texture of the images to build robust prediction models.

5. Conclusion

In this study, the texture of photographic images was analysed using several feature extraction methods to evaluate the possibility of identifying bovine meat samples.

The classification of the samples showed encouraging results. Certain classification experiments led to a large score of correctly classified images with a few number of features.

Textural features calculated on visible and UV light images have the potential to be used as a method of indicating physical characteristic of meat samples. Hence, texture analysis has a good potential in the elaboration of an objective method for the evaluation of the quality of meat. The possibility of certifying the origin of the meat and the kind of meat proposed to the consumer is of major interest.

The textural features which revealed to be relevant in the classification experiments derived mainly from the "texture spectrum" method, from the "neighbouring grey level dependence matrix" method and from the "first-order statistical measurements". These latter features are not really textural measurements, as they describe the grey levels histogram. However, they are often efficient in a classification because they give a global description of the marbling and of the lean grey level intensity, whereas texture measurements are a description of the local structure of the connective tissue. Even if the muscle structure is emphasised by fluorescence, the features calculated on ultraviolet images and describing the connective tissue are not sufficient to identify the various samples.

The discriminant capacity of some features has been discussed in this paper. However, the various features calculated are not completely uncorrelated and some of them express slight variations in the image texture. Thus, the selection of some features as the more relevant according to a classification goal is not obvious.

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