Classification of bovine muscles from texture analysis of meat slices images

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Background

The quantification of meat quality is a challenge of major importance to the meat industry. The possibility of an automated quality grading has been investigated by Miller *et al.* [1], and Cross and Whittaker [2]. Included among the multiple muscular tissue characteristics which influence meat quality are connective tissue quantity and spatial distribution, which define the grain of meat, and are of great importance because they are directly related to its tenderness [3,4].

Several approaches have been studied for the characterisation of meat quality. Non destructive methods of marbling characterisation (quantity and distribution of intra-muscular fat) have been investigated for the classification of muscles or parts of muscles using the characteristics of the connective tissue. Among the many methods, ultrasonic techniques used on living animals or on muscles, have been extensively explored [5,6].

The direct analysis of connective tissue in muscle slices should also lead to the determination of morphologic parameters, specific to the various muscles and animal types [3]. 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 is proposed: a global characterisation of photographic images of meat slices, performed under visible or ultraviolet (UV) light.

Objectives

Texture analysis techniques, by image processing, were used to characterise various types of image. Each type of image was assumed to present a specific pixel distribution which can be characterised by textural features. These features contain representative information of visual characteristics (coarseness of the texture, regularity, presence of a privileged direction, size of a representative neighbourhood, etc.), but also of characteristics which can not be visually differentiated. The set of values produced make up a vector which is called a texture signature.

Texture analysis were used to classify photographic images of meat slices. The connective tissue contains two important components, fat and collagen, which are highly variable not only between muscles but also between animals for the same muscle. These components appear clearly on photographic images. Connective tissue is particularly emphasised by ultraviolet light due to its autofluorescence.

Therefore, the approach proposed consisted of a global characterisation of photographic images of meat slices, performed under visible or ultraviolet light. More precisely, the aim was to evaluate the possibility of classification of meat samples from various muscles of entire male or castrated bovines, of various ages.

Methods

The meat slices analysed came from 19 animals (male Montbeliard animals raised at INRA of Theix by the CMH Laboratory). Ten of the animals were castrated at the age of one month. They were slaughtered at the age of 4 months (10 calves), 12 months (5 animals) and 16 months (4 animals). After slaughter at the research centre's abattoir, the carcasses were chilled to 2°C and the selected muscles (*semitendinosus* (ST), *semimembranosus* (SM) and *biceps femoris* (BF)) were excised 2 days post-mortem. One centimetre thick meat slices (5 cm x 5 cm) were cut in the middle of the muscles, perpendicularly to myofibre orientation.

Due to the small number of samples in each class, the digitised images were subdivided into four quadrants of size 256 x 256 pixels. The resulting images were of large enough area to be representative of the texture samples. There were therefore 228 samples available to represent the set of 18 classes (3 different muscles, 3 classes of age and 2 kinds of animal: castrated or not). The number of samples per class varied from 8 to 20.

Before processing, the images underwent a filtering in view to emphasise the texture. Figure 1 shows an example of an original and filtered image of a meat sample acquired under visible light.

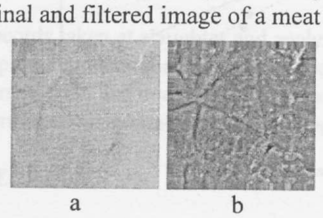
a b

Fig. 1: Original (a) and pre-processed (b) image (acquired under visible light).

Visual observation of the images leads to an appreciation of differences in texture between certain classes; for example the connective tissue pattern can be seen more clearly in images of ST muscle than of other muscles. In general, the 4-month old animals have large inclusions in the connective tissue on images of SM muscle but not on images of BF muscle. The visual variations of texture between the various classes can be described in several ways, such as the possible presence of a pattern in the connective tissue, its size and its regularity, the homogeneity of the images, the amount of fat and collagen and the thickness of the inclusions.

In order to quantify these properties, and if possible to point out non visible specific texture elements, various categories of features were extracted [7]

For each meat sample, 117 features were obtained on both visible images and UV images, which gave a total of 234 features. The 117 features were composed as follows: 12 from first order statistical features (6 calculated before pre-processing and 6 after), 2 from power spectrum, 6 from the Min-Max method, 10 from the Run-Length method, 12 from Neighbourhood Matrices, 8 from Fractal methods, 8 from the Texture Spectrum method, 57 from Cooccurrence Matrices and 2 morphological features.

Classification results

Two classification techniques (KNN: K Nearest Neighbours method [8] and RCE: Reilly, Cooper and Elbaum method [9]) were applied to the series of images. To evaluate the importance of the variation factors, several experiments were conducted with various aims for classification (classification according to age, muscle and castration factors).

The first attempts were conducted with several values of the parameter k in the KNN method (k = 2,3,4). This value is limited by the number of samples in each class. The least represented class in our set of images contained only 8 samples and therefore only four for the training set. Hence, k = 4 was the maximum value. In general, it was observed that the rate of correctly classified samples increased with k (when the number of samples per class was large enough. As the number of samples in each class was relatively small, the classification experiments were conducted several times with various test and training sets. The rate of correctly classified samples remained approximately constant.

Classification using the 18 classes lead to weak results (table1). Only 42 % of the samples were correctly classified. The results were poor mainly for classes containing few samples.

The classifications according castration factor gave 70% of correctly classified samples. This result is surprisingly high since visual inspections showed that the textures of images of castrated and non castrated animals were very similar.

Other experiments were conducted to perform classification according to age (3 classes) or muscle (3 classes) factors. The set of images was subdivided to classify the age of animals for a particular muscle, or to classify muscles when the age of animals was known. The classifications according to age or muscle factors gave scores higher than 94% of correctly classified samples; in some cases the score of 100% was even reached.

All the classifications have been performed using the most relevant texture features identified in each case from the 234 features calculated (117 features calculated on visible images and 117 calculated on UV images). The more frequently used features are those calculated on cooccurrence matrices ("inverse difference moment", "difference entropy", "difference variance" and on grey level run-length matrices ("grey level non-uniformity"). Fractal features seem to be less relevant for the classification of samples.

Conclusion

The classification of meat samples using the texture analysis of images has proven successful particularly according to age for a given muscle or muscle at a given age. Certain classification experiments lead to 100 % of well classified images, and a larger number of samples should improve the classification rate when a large number of classes is considered.

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Classification goals (number of classes)	Type of images used (number of images)	% correctly classified 3-KNN	% correctly classified 4-KNN	% correctly classified RCE
Age, Muscle and Castration(18)	all samples (228)	42.1% (48 out of 114)	-	-
Castration(2)	all samples (228)	-	69.2% (79 out of 114)	70.1% (80 out of 114)
Age (3)	SM (76)	94.7% (36 out of 38)	97.3% (37 out of 38)	97.3% (37 out of 38)
Age (3)	ST (76)	-	94.7% (36 out of 38)	94.7% (36 out of 38)
Age (3)	BF (76)	-	97.3% (37 out of 38)	94.7% (36 out of 38)
Muscle (3)	4 month old animals (120)	-	98.3% (59 out of 60)	95% (57 out of 60)
Muscle (3)	12 month old animals (60)	-	96.6% (29 out of 30)	90% (27 out of 30)
Muscle (3)	16 month old animals (48)	100% (24 out of 24)	100% (24 out of 24)	100% (24 out of 24)

Table 1. Classification results

KNN: K Nearest Neighbours method; RCE: Reilly, Cooper and Elbaum method