# DISCRIMINATION OF BEEF MUSCLES BY MULTISPECTRAL IMAGING

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**Abstract – The potential of multispectral VIS-NIR imaging to identified beef muscles in relation with their type and breed origin was examined in the present study. Samples (120 *Longissimus thoracis, Biceps femoris and Semimembranosus* muscles of three breeds of young bulls (Limousin, Blond d'Aquitaine, Aberdeen Angus*)* were investigated by a multispectral device. A total of 10,279 images (*i.d.* 541 cube images) were collected with the nineteen emitting LEDs (405 to 1050 nm). The muscle image cubes were analyzed by considering mean spectral data and image shape features from co-occurrence and difference of histogram matrices. The results of the PLSDA performed on image texture features and spectral data showed good classification depending on the muscle classes considered (*i.e.* muscles types and animal breed). This study demonstrated the promising potential of the VIS-NIR images to authenticate beef muscles.**

**Key Words – Beef meat, discrimination, GLCM, GLHD, multispectral**

## I. INTRODUCTION

Beef manufacturers have particular need in analytical techniques allowing food authenticity [1]. As a matter of fact, with meat questions that arise about the identification of pieces it is therefore necessary to provide a tool to achieve rapid and precise discrimination of raw pieces. Such a tool may be also very useful to discriminate breeds, mainly if they are source of high-grade beef.

Common spectroscopic techniques (fluorescence and infrared) are known to be generally quick and inexpensive to implement. There are used in line as they do not require direct contact with the product to make a measurement. These methods can therefore be a remarkably effective alternative to traditional analyzes. The fluorescence and infrared spectroscopies have demonstrated their ability to be used to monitor food industry processes [2]. However, these methods provide information on a small region of a sample at a time. Therefore, the product analyzed should be homogeneous in order to extract features representative of the whole product properties. This disadvantage can be overcome by the use of hyperspectral (HYS) and multispectral (MIS) imaging techniques. Despite the undeniable benefits of HYS for food control, it is actually difficult to use it on an industrial line due to its price, fragility and the time required acquiring images. The MIS has been used recently in different studies to characterize beef muscle types [3] [4] [5] and show the potential of this method to predict tenderness ($0.89 \geq R^2 \geq 0.75$), discriminate samples according to animal age (85 % of good classification in average) and type (91% of good classification in average) and to predict collagen and lipids content ($0.61 \geq R^2 \geq 0.91$). Those excellent studies show some limits due to the restricted number of muscles, animal diets, and muscle type considered.

The aim of this study was to assess, by introducing a higher variability in samples (muscles types, animal breeds) and a high number of LEDs (19 excitation LEDs), the potential of multispectral data to classify muscles based on their type and breed origin. This objective was conducted both by considering spectra and image texture features.

## II. MATERIALS AND METHODS

***Samples*** - The experiment was performed on 40 young bulls of Aberdeen Angus (AA, n = 12), Limousin (LI, n = 14) and Blond d'Aquitaine (BA, n = 14) pure breeds. The conditions of production of animals were previously published [6].

Three muscles were taken for each animal: *Longissimus thoracis* (LT), *Semimembranosus*

(SM) and *Biceps femoris* (BF). For each muscle and each analysis, samples were taken at the same localization. Muscle samples were removed from the 9th rib for LT and from the centre of the muscle for SM and BF. Carcasses were chilled in a cold room (+2 °C) and muscle samples were taken at 24 h post-mortem. Meat samples were also aged in vacuum-packs at +4 °C for 14 days. After these 14 days of ageing at +4 °C, sample muscles were packed under vacuum and stored at −20 °C until analyses.

***Multispectral image of muscles*** were recorded with a VideometerLab2 (Scorpion SCOR-20SOM, 1200x1200 pixels) measuring light intensity from 405 to 1050 nm with 19 LEDs [7]. Before image acquisition, the camera was calibrated by 3 successive plates: one for reflectance, one for background and one for the pixel position. Before image acquisition, the samples were cut (6 x 5 x 1.5 $cm^3$) and placed in the dark by lowering the hollow sphere of the device. Two acquisitions were recorded per muscle.

Figure 1. Region of interest of *Biceps femoris* (A), *Longissimus thoracis* (B) and *Semimembranosus* (C) muscles at 24 h post-mortem obtained after excitation at 405 nm for Limousine breed.

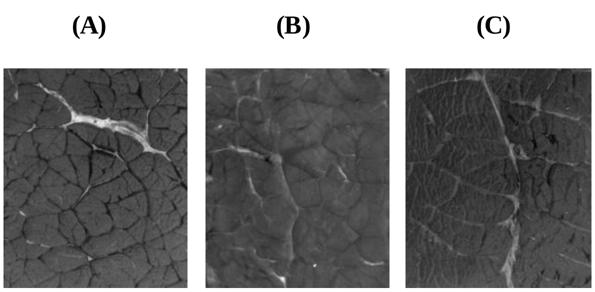
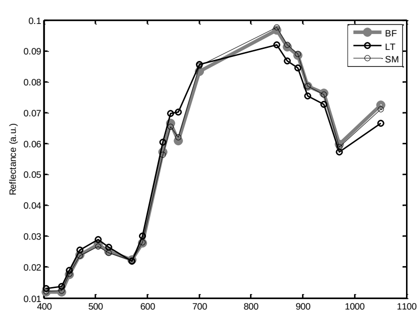



Figure 2 Spectral data of *Biceps femoris* (BF), *Longissimus thoracis* (LT), *Semimembranosus* (SM) muscles for limousine breed.




***Mean spectra (MSPEC) were recorded*** from a Region of Interest (ROI) of 700x575 pixels selected at the center of images (Fig. 1, Fig. 2). These data were treated with or without pre-processing. Three pre-processing (PLS-Toolbox v.7.5 for MATLAB) methods were applied to those data, Standard Normal Variate (SNV), Multiple Scattering Correction (MSC) and Normalization (area under spectrum=1) in order to optimize the discrimination.

***Image texture features extraction*** was achieved by the analysis of the 2nd order statistic of both the difference histogram matrix (GLHD) and gray level co-occurrence matrix (GLCM) calculated on the ROI [8].
For the GLCM, textural features were calculated on 4 GLCM (using a dipole length of 1 and four angles 0°, 45°, 90°, and 135°). A total of 29 textural features were extracted from each GLCM [7].
For the GLHD image texture features were calculated with a dipole length of 1 and 4 angles 0°, 45°, 90°, and 135°. A total of 5 textural features were extracted from each GLHD (mean, variance, entropy, contrast and energy). The different textural features were calculated with a home program (MATLAB) based on *ximage* toolbox.

***Partial Least Square Discriminant Analysis (PLS DA) were calibrated and validated*** with contiguous block cross-validation. The PLSDA were performed on auto-scaled mean spectra (MSPEC) and texture features (PLS-Toolbox v.7.5) in order to evaluate the potential of multispectral data to discriminate muscles. Before performing PLSDA samples were divided in 3 classes for both muscle categories (LT, SM, BF) and animal breeds (AA, BA, LI).

## III. RESULTS AND DISCUSSION

Concerning the discrimination regarding animal breeds (Table 1), best PLSDA models were obtained by considering MSPEC without preprocessing (63% of correct classification on average after cross-validation), than with the GLCM (60% of correct classification in average after cross-validation) and finally with the

GLHD features (53% of correct classification in average after cross-validation). The best classification using textural features were obtained with two excitation wavelengths 505 and 525 nm for GLCM and GLHD respectively. Those bands were previously identified as sensitive to meat color [9] [10]. The 505 nm band was specifically assigned to metmyoglobin [9]. The 525 nm band combined with the 610 nm wavelength was also used as an indicator of the percentage of myoglobin that was in the oxymyoglobin state [11].

Table 1 PLSDA results of beef meat samples for calibration and cross-validation based on the animal breed (BA: *Blonde d'Aquitain*; LI: *Limousin*; AA: *Aberdeen Angus*) (rows observed classification; columns: predicted classification) (RAW: no pre-process)

| Method | Preprocess | LED (nm) | Direction | PLSDA factor | Classes | Calibration | | | | Cross-validation | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | AN | LI | BA | GC (%) | AN | LI | BA | GC (%) |
| | RAW | - | - | 10 | BA | 14 | 36 | 153 | **75** | 15 | 48 | 134 | **68** |
| MSPEC | RAW | - | - | 10 | LI | 11 | 106 | 18 | **79** | 30 | 73 | 32 | **54** |
| | RAW | - | - | 10 | AN | 138 | 31 | 5 | **79** | 118 | 52 | 10 | **66** |
| | - | 525 | 135° | 5 | BA | 23 | 49 | 115 | **62** | 24 | 57 | 95 | **54** |
| GLHD | - | 525 | 135° | 5 | LI | 27 | 88 | 51 | **53** | 32 | 76 | 69 | **43** |
| | - | 525 | 135° | 5 | AN | 107 | 37 | 17 | **66** | 101 | 41 | 19 | **63** |
| | - | 505 | 0° | 10 | BA | 19 | 52 | 137 | **66** | 20 | 58 | 120 | **61** |
| GLCM | - | 505 | 0° | 10 | LI | 17 | 86 | 33 | **63** | 21 | 71 | 47 | **51** |
| | - | 505 | 0° | 10 | AN | 123 | 32 | 14 | **73** | 118 | 41 | 17 | **67** |

For classification based on muscle type (Table 2), good classification results are obtained with MSPEC corrected by MSC (83% of correct classification in average after cross-validation), than with the GLCM features (60% of correct classification in average after cross-validation) and finally with the GLHD features (56% of correct classification in average after cross-validation).

Table 2 PLSDA results of beef meat samples for calibration and cross-validation based on muscle types (BF: *Biceps femoris*; LT: *Longissimus thoracis*; SM: *Semimembranosus*) (rows observed classification; columns: predicted classification). (ARE: normalization, area under spectrum=1).

| Method | Preprocess | LED (nm) | Direction | PLSDA factor | Classes | Calibration | | | | Cross-validation | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | BF | LT | SM | GC (%) | BF | LT | SM | GC (%) |
| | ARE | - | | 10 | BF | 127 | 1 | 30 | **80** | 124 | 3 | 313 | **78** |
| MSPEC | ARE | - | | 10 | LT | 16 | 189 | 3 | **91** | 18 | 183 | 5 | **89** |
| | ARE | - | | 10 | SM | 17 | 2 | 123 | **87** | 18 | 6 | 120 | **83** |
| | - | 940 | 45° | 5 | BF | 105 | 1 | 76 | **58** | 58 | 1 | 105 | **35** |
| GLHD | - | 940 | 45° | 5 | LT | 4 | 181 | 1 | **97** | 5 | 181 | 2 | **96** |
| | - | 940 | 45° | 5 | SM | 48 | 0 | 85 | **64** | 94 | 0 | 55 | **37** |
| | - | 940 | 135° | 8 | BF | 112 | 3 | 65 | **62** | 73 | 4 | 91 | **43** |
| GLCM | - | 940 | 135° | 8 | LT | 6 | 181 | 2 | **96** | 7 | 180 | 4 | **94** |
| | - | 940 | 135° | 8 | SM | 42 | 1 | 92 | **68** | 80 | 1 | 64 | **44** |

The best classification considering the textural features were both obtained with the 940 nm excitation LED indicating that discrimination can be assigned to difference in muscle marbling [12].

As far as we know only one study has been investigated on the potential of multispectral image features to discriminate beef muscles (*Longissimus dorsi*, *Gluteus medius*, and *Semitendinosus*) with respect to the muscle type [5]. Those authors reported equivalent results when exciting meat samples with a white-light (91% of correctly discriminated) and UV channel (78% of correct classification). The higher accuracy of muscle classification based on MSPEC compared to textural features may arise from considering texture features of only one LED at a time for discrimination. In order to validate this hypothesis, the GLHD and GLCM texture features, extracted from the 19 LEDs for each direction, were merged in two independent matrices and analyzed by PLSDA. The results obtained for discrimination of animal breeds (61% and 59% of good classifications considering the GLCM and GLHD respectively) gave equivalent results. But this hypothesis was not confirmed when the same calculation was conducted considering the muscle types (69 and 61% of good classifications considering the GLCM and GLHD respectively).

## IV. CONCLUSION

The results reported here lead to conclude that multispectral imaging can be used as helpful tool to discriminate muscles and breeds. However, the robustness of the models for classification has to be improved for several variables. This might be done by increasing the database and testing PLSDA models on this larger set of samples.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