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Lamb muscle discrimination using hyperspectral imaging: Comparison of various machine learning algorithms

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ABSTRACT

Lamb muscle discrimination is important for the meat industry due to the different pricing of each type of muscle. In this paper, we combine hyperspectral imaging, operating in the wavelength range 380–1028 nm, with several machine learning algorithms to deal automatically with the classification of lamb muscles. More specifically, we study the discrimination of four different lamb muscles, namely, *Longissimus dorsi*, *Psoas major*, *Semimembranosus* and *Semitendinosus* from thirty lambs of Churra Galega Mirandesa breed. The objective of the paper is to determine the best method for muscle classification.

In the experimental study we report an analysis of the performance of seven classifiers. We study their behavior when they are applied over the original data as well as over the data pre-processed using Principal Component Analysis (PCA) to reduce the dimensionality of the problem. The seven classifiers used to differentiate the muscle types are two Artificial Neural Networks, namely the linear Least Mean Squares (LMS) classifier and the Multilayer Perceptron with Scaled Conjugate Gradient (MLP-SCG), two Support Vector Machines (SVM), namely the ν SVM and the SVM trained with Sequential Minimal Optimization (SMO), the Logistic Regression (LR), the Center Based Nearest Neighbor classifier and the Linear Discriminant Analysis. The best result, determined using a leave-one-animal-out scheme, is provided by the linear LMS classifier using the original data, since it correctly classifies 96.67% of the samples. The LR, the MLP-SCG using original data and the SVM trained with SMO on data preprocessed with PCA are also suitable techniques to tackle the lamb muscle classification problem.

1. Introduction

Spectroscopy, a technique that allows to collect information about how light interacts with matter for hundreds of different wavelengths, has been widely used in food quality control Sun (2010); Wu and Sun (2013). The reason is that spectroscopic analysis is fast, non-destructive, since it can be done without sample preparation, it does not require contact with the sample and it allows one for complete automation, which makes it a good method for online tests in a production line.

Spectroscopy has been used in regression problems such as the determination of several features of beef, pork, lamb and poultry meat such as protein, fat, fatty acids, moisture percentage, pH, drip loss, water holding capacity, Warner-Bratzler shear force, color and sensory attributes like flavor, tenderness and juiciness Prevolnik et al. (2004); Prieto et al. (2009); Elmasry et al. (2012). Spectroscopy has also been applied in classification problems such as discrimination of fresh from frozen-then-thawed meat Prieto et al. (2009), of animal breed and feeding systems Juarez et al. (2008), or separation of muscle types Kamruzzaman et al. (2011). There are

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few proposals in scientific literature to tackle the problem of separating muscle types and this problem will be the focus of the present work. To do so, we will use a type of spectroscopy called hyperspectral imaging.

Hyperspectral imaging has been used in reflectance mode, which means that it measures, for a certain wavelength, the percentage of light intensity that is reflected by the sample relative to the total intensity of light incident on the sample. Spatially, hyperspectral imaging measures simultaneously several hundred points over a sample. Spectroscopic analysis is usually combined with machine learning algorithms, which are capable of learning from examples and whose task is to convert the acquired spectra into the desired sample parameters regardless if they are chemical or physical features. Nowadays, there is a trend to try to use spectroscopic systems operating at wavelengths larger than 900 nm instead of the range 400–1000 nm, as the former range is thought to provide more information Elmasry et al. (2012). We will show that the latter wavelength range is an alternative to the former range as long as the classification algorithms are carefully chosen. For this reason, we carry out a comparison of seven classifiers, which is unusual in meat classification problems based on Prieto et al. (2009); Wu and Sun (2013) reviews.

In this paper, the spectra of four muscle types, namely *Longissimus Dorsi* (LD), *Psoas Major* (PM), *Semimembranosus* (SM) and *Semitendinosus* (ST), of lamb meat (which is highly appreciated throughout the world) are classified using seven machine learning algorithms with the aim of finding the best one. The relevance of this classification for the meat industry is due to the different pricing of the different muscles. Furthermore, Principal Component Analysis (PCA) Wold et al. (1987), which is a well-known dimensional reduction technique, is applied so as to determine whether decreasing the number of variables has a positive effect on the classifiers performance or not.

When analyzing the scientific literature it is possible to find only one work devoted to the discrimination of lamb muscles based on hyperspectral imaging Kamruzzaman et al. (2011). The authors of this work used the wavelength range 900–1700 nm applying PCA to reduce the dimensionality of the problem from 237 variables to 5, which correspond to the 5 principal components. Then, they used the Linear Discriminant Analysis (LDA) Fisher (1936) over six wavelengths chosen from the PCA loadings to classify three different types of muscles, namely, LD, PM and ST. In order to validate their results they used a leave-one-out cross validation process. The present article has the following differences when compared to Kamruzzaman et al.:

1. We use the wavelength range 380–1028 nm to perform the hyperspectral imaging. This is a fundamental difference because such a large difference in the wavelength ranges makes the information gathered and provided to the classification algorithms to be significantly different.
2. We use as cross-validation (CV) method a leave-one-animal-out scheme, which means that the training samples always come from different animals than those of the testing samples. In this manner, we apply a more similar methodology to the real production process usually carried out by the meat industry, which is fundamental to assess the commercial viability of the method.
3. Kamruzzaman et al. point out in the conclusions of their article that: “More research is needed to involve more samples as well as different muscles to improve the accuracy and robustness of the classification maps”. We have taken into account this conclusion by considering four muscle types (the three ones used by them and we include SM) belonging to 30 different animals, while they considered only 10 animals. Consequently, the CV results become more robust and the inclusion of a new muscle makes the problem more complex.

It must be noticed that the full 380–1028 nm wavelength range available from our hyperspectral camera provides relevant spectral information which has been confirmed in a previous work from the authors Fernandes et al. (2011).

The paper is arranged as follows: Section 2 describes the materials and techniques used in the current study. Then, the obtained results along with their corresponding analysis are introduced in Section 3. Finally, the main concluding remarks are drawn in Section 4.

2. Materials and techniques

In this section, in first place, we describe the problem to be solved (Section 2.1). Then, we describe the techniques applied to obtain the images employed to obtain the variables that are used to discriminate the four types of muscles (Sections 2.2, 2.3 and 3.1). Next, we remind both the PCA method (Section 2.4) as well as the basic ideas of the classifiers considered in this paper to tackle the classification problem (Section 2.5).

The sequence of sub-sections shows the work-flow of the applied method because, in the first place, the four muscles are obtained from each animal to be treated. Then, the hyperspectral imaging techniques are applied so that the variables (one for each wavelength measured) characterizing each muscle can be computed. Finally, these variables are used for the classifiers either directly or after being reduced by the PCA method.

2.1. Sample description

The sampling in this work was made on thirty lambs of Churra Galega Mirandesa breed aged between 3 and 4 months old. The animals were slaughtered and dressed according to current EU regulations at a commercial abattoir (Pec Nordeste, Penafiel, Portugal). After slaughtering, carcasses were chilled at 4 °C for 24 h and then were split down by the vertebral column with a band saw and each side weighed. From the left half of the carcass four muscles, the *Longissimus dorsi, Psoas major, Semimembranosus* and *Semitendinosus*, were removed for experimenting, please see Fig. 1. *Longissimus dorsi* is also called *Longissimus thoracis et lumborum*. Each muscle sample was individually vacuum packed and maintained at 4 °C. Then, the muscle samples were bloomed for 30 min and surface moisture was wiped off by paper towels before hyperspectral image acquisition.

2.2. Hyperspectral imaging apparatus

The hyperspectral imaging system, which is depicted in Fig. 2, consists of a spectrograph Imspector V10E (Specim, Oulu, Finland), and a JAI Pulnix (JAI, Yokohama, Japan) black and white camera. It acquires 1392 pixels in the spatial dimensional and 1040 channels in the wavelengths dimension. The 1392 pixels correspond to a line with a length of approximately 110 mm for a distance between the camera and the samples of approximately 420 mm. The 1040 channels correspond to the wavelengths between 380 and 1028 nm with each channel having a spectral width of approximately 0.6 nm. Images are acquired at 8 Hz. The data acquisition software is Coyote (version 2.2.0, JAI, Japan).

A structure with $300 \times 300 \times 175$ mm^3 (length $\times$ width $\times$ height) held the illumination system composed of four 20 W, 12 V halogen lamps (Philips, Eindhoven, Netherlands)) and two 40 W, 220 V blue reflector lamps (Spotline, Philips, Eindhoven, Netherlands). The latter light source is necessary for improving the