Computers and Electronics in Agriculture 151 (2018) 365–375

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

Evaluation of an automatic lean meat percentage quantification method based on a partial volume model from computed tomography scans

Pau Xiberta[a,*], Anton Bardera[a], Imma Boada[a], Marina Gispert[b], Albert Brun[b], Maria Font-i-Furnols[b]

[a] *Graphics and Imaging Laboratory, Universitat de Girona, 17003 Girona, Catalonia*
[b] *IRTA-Food Industries, Finca Camps i Armet, E-17121 Monells, Girona, Catalonia*

ARTICLE INFO

Keywords:
Lean meat percentage
Computed tomography
Partial volume effect
Segmentation
Pig carcass quantification

ABSTRACT

The quality of a pig carcass is mainly measured by the lean meat percentage (LMP), which can be virtually estimated from computed tomography (CT) scans. Different strategies exist to classify the CT voxels into tissues such as fat, lean and bone, being the thresholding-based methods the most commonly used. However, these methods are usually affected by the partial volume effect, and also by data variability, which is implicit from different CT scanners and protocols, since no standard behaviour has been defined. The aim of this paper is to extend an LMP quantification method which uses a partial volume model by adding a new step to detect the animal skin, and thoroughly evaluate the new approach by analysing each of its steps. The evaluation is performed by comparing the whole pipeline of the proposed approach with a simple thresholding method and a thresholding method with bone filling and skin detection, which is an intermediate step of the new pipeline. Five experiments have been designed to test how accurate are the results of the method regarding the LMP values computed from the manual dissection, as well as the robustness to data variability. Two different manual dissection methodologies have been tested: the partial dissection, which estimates the LMP using the lean of the four main cuts of the carcass plus the tenderloin, and the total dissection, which uses the lean of the twelve main cuts. A total of 146 half carcasses have been used for this study (105 using the partial dissection methodology, and 41 using the total dissection one). To evaluate the experiments, the LMP values virtually obtained from the three methods have been compared mostly with the LMP values from the manual dissection, computing the coefficient of determination R^2 from the correlations, as well as the root mean square error of prediction by means of leave-one-out cross-validation. A statistical analysis is performed to resolve if two correlations are significantly different. The experiments' results confirm the high accuracy of the proposed approach for the LMP estimation, and mainly its high robustness to data variability. The experiments also disclose that the detection of the animal skin and its classification as a new tissue, instead of classifying it as lean, improve the results. The evaluated method has demonstrated to be as effective as the thresholding method with bone filling and skin detection, and more robust to data variability than the other evaluated methods.

1. Introduction

Lean meat percentage (LMP) is a key parameter to measure pig carcass quality, it is compulsory in the Europe Union and it determines the basis for the price of the carcass. To compute the LMP from computed tomography (CT) scans, special methods to classify CT voxels into tissues according to its Hounsfield Unit (HU) values are required. Unfortunately, variability between animals and breeds, and also between scanners and protocols makes the definition of a standard correspondence between HU values and tissues difficult (Olsen et al., 2017), and each country has defined its own model (Romvári et al., 2006; Font-i-Furnols et al., 2009; Daumas and Monziols, 2011). Moreover, the partial volume effect further complicates LMP computation, that is, voxels which are usually placed in the border between two tissue regions may have a big uncertainty, and they cannot be classified because they contain more than one tissue. This difficulty has been studied in other fields such as oncology (see Cysouw et al., 2017 for a review), but mainly in the field of neuroimaging (see Tohka, 2014 for a review), evaluating its impact (Dukart and Bertolino, 2014), compiling different methods to enhance the image visualisation (Salminen et al., 2016), and still proposing novel techniques to reduce the effect (Bural et al., 2015; Şener et al., 2016).

* Corresponding author.
E-mail addresses: pau.xiberta@udg.edu (P. Xiberta), anton.bardera@udg.edu (A. Bardera), imma.boada@udg.edu (I. Boada).

https://doi.org/10.1016/j.compag.2018.06.019
Received 3 May 2018; Received in revised form 5 June 2018; Accepted 9 June 2018

To tackle the partial volume problem, different strategies have been proposed. Assuming a uniform probability for the non-pure tissues over the image, i.e. each partial volume voxel has the same probability for every non-pure tissue, Santago and Gage (1993) propose a model with six Gaussian distributions, three for the pure tissues and three for the two-class partial volume ones, with a set of parameters which have to be minimised to fit the model to the histogram. With the same assumption, Laidlaw et al. (1998) reconstruct a continuous function incorporating neighbouring voxels information into the classification process to improve its accuracy, and Ruan et al. (2000) first use a mixture model to define a Gaussian distribution for each pure and partial volume tissue, and then reclassify the partial volume classes into the pure ones using a Markov random field and multifractal analysis.

Other studies assume little variation in the probability for the non-pure tissues between neighbouring voxels, which can be modelled using a Markov random field. Choi et al. (1991) use a maximum *a posteriori* estimation of partial volume voxels in multichannel images, and a method to iteratively reestimate the mean intensities of each tissue class in each slice, while Pham and Prince (2000) propose a similar method for single-channel images using a Bayesian approach which places a prior probability model on the parameters. Finally, Nocera and Gee (1997) describe a segmentation algorithm which also uses a maximum *a posteriori* estimation with an adaptive Bayesian approach, and takes into account both the partial volume and the shading effect.

Focusing on the LMP computation, several methods have been presented in the literature. Gangsei et al. (2016) and Jansons et al. (2016) use optical probes to collect certain variables, which is an efficient method when working with carcasses, and in Dobrowolski et al. (2004), Judas et al. (2007) and Font-i-Furnols et al. (2009) data from CT images is analysed using partial least squared regression, which does not require the classification of voxels in lean or fat. In this case, volume associated to each HU value is obtained from CT images and used as predictors in the regression. To build their regression equations, Kremer et al. (2013) and Bernau et al. (2015) use linear traits measured by dual energy X-ray absorptiometry (DXA), while Lisiak et al. (2015) proposes a simpler approach using linear measurements over the carcass which do not need the use of expensive classification equipment. Another common method is to use thresholding techniques based on the HU values (Daumas and Monziols, 2011), and even mixing thresholding techniques with some manual interaction in a semi-automatic method (Bernau et al., 2015). Kongsro et al. (2008) have applied a tresholding approach using lamb meat as well, and Lee et al. (2015) have adopted a similar method using beef, the latter also using a chemical analysis to compare the results with the thresholding method. To avoid dealing with the partial volume effect when using the thresholding techniques, some strategies have been proposed. In Vester-Christensen et al. (2009) the partial volume effect has been minimised applying a Bayesian 2D contextual classification scheme to classify voxels into fat, lean and bone. Differently, in Bardera et al. (2014) a five-step process which automatically quantifies fat, lean, and bone tissues from CT scans using a partial volume model based on the one presented by Van Leemput et al. (2003) is described, and a first validation of the method considering 10 carcasses is carried out.

The aim of this paper is to evaluate the quantification method presented in Bardera et al. (2014) considering 146 half carcasses which have been manually dissected after scanning (105 using a partial dissection, and 41 using a total dissection). The introduction to the method's pipeline of a new step which identifies and classifies the animal skin tissue is also analysed. The obtained results are compared in terms of LMP accuracy and robustness to data variability, and the importance and need for each step of the new pipeline is discussed.

2. Materials and methods

2.1. Carcasses and computed tomography scanning

A total of 146 left half carcasses have been used for this study. From these, 133 carcasses come from two commercial abattoirs and have been selected to mimic the Spanish pig carcass population in terms of fat thickness, being all the three sexual types represented. These carcasses also come from several producers and commercial genotypes. Additionally, 13 carcasses from gilts, slaughtered at the pilot abattoir placed at IRTA-Monells, have also been used in this study. These carcasses are from 3 different genotypes as described in Carabús et al. (2014) and Font-i-Furnols et al. (2015). In total, carcasses included in this study have a carcass weight of 86.7 ± 8.7 kg, a fat thickness of 15.7 ± 3.8 mm measured at 6 cm of the midline between the 3rd and the 4th last ribs, and they are from three sexual types (47% females, 41% entire males and 12% castrated males). The Commission Delegated Regulation (EU) 2017/1182 (The European Commission, 2017) established a minimum of 120 carcasses representative of the population to be involved in a dissection trial. For this reason, the number and type of carcasses considered in this work is suitable to be used to evaluate the methodology proposed in this paper to determine carcass lean meat content.

At 24–48 h post mortem carcasses were CT scanned with a General Electric HiSpeed Zx/I device placed at IRTA-Monells. Acquisition parameters were those established by Font-i-Furnols et al. (2009) in carcasses evaluation, that is, 140 kV, 145 mA, Display Field of View (DFOV) between 460 and 500 mm, and matrix size 512 × 512 pixels. Images were acquired helically every 10 mm with pitch 1. Thus, there was not overlapping between images and all the carcasses were scanned completely.

2.2. Manual dissection

After scanning, carcasses were cut following the Walstra and Merkus method (Walstra and Merkus, 1996) and dissected by trained butchers. A total of 105 carcasses were dissected using the partial dissection methodology, i.e. the lean from the four main cuts (ham, shoulder, belly and loin) was manually separated with a knife and weighed. The LMP values were obtained dividing the weight of the lean of the four main cuts plus the tenderloin by the total weight of the four main cuts plus the tenderloin. A correction factor of 0.89 was applied to obtain the LMP values of the carcasses from these cuts, according to the European Regulation definition (The Commission of the European Communities, 2008). The other 41 carcasses were totally dissected, i.e. the lean of all the 12 cuts was manually obtained and weighed, and this weight was divided by the weight of the carcass to obtain the LMP (The Commission of the European Communities, 2008).

2.3. Automatic LMP quantification method based on a partial volume model

The proposed approach to quantify fat, lean and bone from CT carcasses is an improvement of the method presented in Bardera et al. (2014). We propose to extend this automatic five-step method with a new step which detects the animal skin. The six steps are illustrated in Fig. 1 and described below. For more details see Bardera et al. (2014).

1. **Carcass detection.** The pig carcass is detected from the input CT scans, and other structures of the image such as the scanning table and the air are removed. Taking into account that the carcass lies over a cushion which has intensity values similar to those of the air, cropping the bottom part of the image is enough to remove the table and other supporting elements. Then, the carcass is only surrounded by voxels with very low intensities (air and cushion), and it can be detected using a simple thresholding method.