Journal of Food Engineering 142 (2014) 146–152

Contents lists available at ScienceDirect

Journal of Food Engineering

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

Partial scanning using computed tomography for fat weight prediction in green hams: Scanning protocols and modelling

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ARTICLE INFO

Article history:
Received 8 January 2014
Received in revised form 4 June 2014
Accepted 8 June 2014
Available online 18 June 2014

Keywords:
Computed tomography
Non-destructive
X-ray
Fat
Ham
Models for hams

ABSTRACT

The objective of this work was to study the feasibility of computed tomography (CT) for predicting fat weight using a complete or partial scanning of green hams. Sixty-eight hams covering a wide range of fat weight were divided into calibration (total weight 11.46 ± 0.97 kg) and validation (total weight 11.35 ± 1.13 kg) sets, fully scanned by CT and dissected. Virtual slices were constructed to standardise the number of slices for hams of different length and their fat weight was estimated. Different predictive models were established with partial least square regression (PLS) and ordinary linear regression (OLR) using all the tomograms and with OLR and multi-linear regression (MLR) using a reduced number of virtual slices. The MLR model with 3 virtual slices gave a better accuracy (RMSEV = 145 g) than the PLS model which used all the tomograms (RMSE = 156 g). MLR model using two virtual slice could be accurate enough (RMSEV = 205 g) for industrial monitoring applications.

1. Introduction

The fat weight of whole pork carcasses or cuts such as hams is of interest for the meat industry because of its influence on price, quality parameters and the way in which the meat is to be processed (Blasco et al., 1994; Oliver et al., 1994). Reference methods for quantifying soft tissues are chemical content determination or physical dissection, a tedious and costly method (Monziols et al., 2006). Therefore, the implementation of non-destructive equipment is an interesting alternative for meat industries.

Ultrasonique techniques have proven to be effective in assessing backfat composition in ham (Niñoles et al., 2007). Electromagnetic induction (Serra et al., 2011) or dual energy X-ray absorptiometry (DXA) (Mercier et al., 2006) have also been proposed for predicting the global fat content in ham. However, these technologies do not give information on the distribution of the intramuscular and intermuscular fat. In contrast, Magnetic resonance imaging (MRI) has been used to quantify subcutaneous and inter-muscular fat in pig carcasses (Monziols et al., 2006) giving good results for research studies although at the present time, this technology is not applicable in the meat industry due to the high capital and maintenance costs.

In the last decade, computed tomography (CT), has also been widely used for carcasses classification. Different studies have been published showing predictive models for lean meat content in pig carcasses (Dobrowolski et al., 2004; Romvàri et al., 2006; Vester-Christensen et al., 2009; Font i Furnols and Gispert, 2009; Picouet et al., 2010; Daumas and Monziols, 2011a, 2011b). Regarding adipose tissues, Kongsro et al. (2008) defined a CT based tool to predict the total fat percentage in lamb carcasses. Prieto et al. (2010) proposed predictive equation to determine the composition of beef cuts by CT. More recently, Font i Furnols et al. (2013) proposed a CT based predictive model to estimate intramuscular fat in raw pork loins. Another approach to non-destructively determine intramuscular fat in dry-cured ham by image analysis of CT tomograms was also described by Santos-Garcés et al. (2014) due to the importance of this parameter to improve salt and water content predictions (Fulladosa et al., 2010).

Nevertheless, CT also has its drawbacks; it is an expensive technology, designed for medical applications and so far cannot be used in industrial environments for several reasons. Firstly, the equipment normally used is not designed to operate in the environments normally found in the meat industry. Secondly, special facilities for protecting workers from X-rays are needed. Thirdly, the scanning of a whole ham requires too much time to be integrated in an industry line where only a few seconds are available for analysis.

Industrial CT equipments are currently being developed which will open the door for the application of CT-like technologies in

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http://dx.doi.org/10.1016/j.jfoodeng.2014.06.012
0260-8774/

industry. In order to evaluate their feasibility for different industrial applications, it is important to know whether a desired parameter, such as fat weight in a ham, can be quantified with a small number of tomograms as each tomogram increases the cost and time of measurement.

Therefore, the objective of this work was to study the feasibility of using CT to predict the fat weight of green hams using a complete or partial scanning of the ham. For this purpose, a methodology to identify the number and positions of the tomograms that best predicted the fat weight was proposed. Different predictive models based on these selected tomograms were developed.

2. Materials and methods

2.1. Green hams

Sixty-eight frozen hams (−18 ± 2 °C for 2–4 weeks) from crosses consisting of Duroc, Large White and Landrace breeds ($n = 29$), consisting of at least 50% Iberian breed ($n = 19$) and from the Mangalitza breed ($n = 20$) were obtained from 3 different commercial slaughterhouses in order to have a wide range of fat weight and a variety of ham conformations. The Iberian and Mangalitza breeds are characterized by a high fat content whereas the Duroc, Large white and Landrace are leaner breeds. The weight of the hams ranged between 8.6 kg and 14.5 kg and the ham length was between 50 and 65 cm. The feet were discarded from all the hams. Before scanning the hams were thawed in a refrigerated chamber to an internal temperature of 3 °C.

2.2. CT scanning and physical dissection

The hams were scanned with a HiSpeedZx/i CT from General Electric Healthcare (General Electric Healthcare España S.a., Barcelona, Spain). Orientation of the ham with respect to the plane of the CT scans was standardized using a laser which goes through the aitch bone and the foot. An axial protocol was performed with settings at 140 kV, 145 mA, a field of view of 460 × 460 mm^2, a tomogram thickness (Z_w) of 10 mm and a rotation time of 1s. For each ham, a set of tomograms of 512 × 512 voxels was obtained. The number of tomograms in each set depended on the length of the ham, the average number being 56, the minimum 50 and the maximum 65. The volume of each voxel (V_v) of the tomogram was 8.07 mm^3. A CT value (CT_v) expressed in Hounsfield units (HU) was obtained for each voxel (Kalender, 2005).

After CT scanning, the hams were boned and the lean, subcutaneous and intermuscular fat tissues were dissected and weight separately. The total fat weight of each ham i ($[F_{Ref}]_i$) was considered to be the sum of the dissected subcutaneous and intermuscular fat (Pietro et al., 2010).

2.3. Calibration and validation sets

In order to develop and validate the predictive models the hams were divided into: a calibration and a validation set. To define both sets the hams were sorted according to fat weight, determined by dissection and subsequently distributed alternatively; one ham for the validation and two hams for the calibration set. Therefore, both sets of samples covered a similar range of fat weight (Table 1). The calibration set contained 45 hams (18 hams from Large white, Landrace and Duroc breed crosses, 14 hams from crosses of Iberian breed and 13 hams from Mangalitza breed) with an average fat weight of 2.52 ± 0.84 kg. The validation set contained the other 23 hams (11 hams from Large White, Landrace and Duroc breed crosses, 5 hams from crosses of Iberian breed and 7 hams from Mangalitza breed) with an average fat weight of 2.50 ± 0.84 kg.

Table 1
Mean, standard deviation (SD), coefficient of variation (CV), minimum (Min) and maximum (Max) values for ham weight and fat weight for the calibration and validation sets.

Dissection	N	Mean (kg)	SD (kg)	CV (%)	Min (kg)	Max (kg)
Ham weight						
Calibration set	45	11.46	0.97	8.4	8.42	13.62
Validation set	23	11.35	1.13	9.9	8.58	12.71
Fat weight						
Calibration set	45	2.52	0.84	33.1	0.86	4.47
Validation set	23	2.50	0.84	33.6	1.17	3.94

2.4. CT data analysis

A special routine was developed in MATLAB (version 7.50-342, R2007.b) to analyse the data from the tomograms. Histograms giving the volumetric distribution of voxels for each for each ham i and tomogram j were calculated. Using a density calibration equation (Eq. (1.0)) defined by Picouet et al. (2010), histograms of attenuation values were converted to histograms of mass in order to establish the mass distribution $MD_{ij}(CT_v)$ for each tomogram j and the mass distribution $SMD_i(CT_v)$ of each ham i.

$$d(CT_v) = 0.997649 + CT_v \times 0.001413\ (\mathrm{g} \times \mathrm{cm}^{-3}) \quad (1.0)$$

2.5. Prediction models

2.5.1. Determination of fat weight using all the tomograms

Prediction models using all the tomograms were developed using two different statistical analyses; ordinary linear regression (ORL) and partial least square regression (PLS).

The OLR model was run with the linear regression procedure from XLSTAT software (Version2010, Addinsoft, France). The integral of the mass distribution SMD_i (CT_v) histogram within the CT_v limits representing the fat region was used as the input variable.

The PLS model was run with the module PLSPro from XLSTAT software (Version2010, Addinsoft, France). The difference in the coefficient of determination ${R^2}_{r+1} - {R^2}_r < 0.025$ was used as the test criteria to stop the iteration of the PLS factors. The mass distribution SMD_i (CT_v) histograms of each ham along the HU scale, within the limits representing the fat region, were used to develop the PLS model.

2.5.2. Determination of fat weight using selected tomograms

2.5.2.1. Development of virtual slices. The number of tomograms needed to scan a ham (T_i) ranged from 50 to 65. The first challenge to solve when reducing the number of tomograms used to develop the model is to standardise the number of slices per ham for hams of different length, so that slices selected for the models would refer to the same anatomical region of the ham, regardless of the actual length.

To do so, the tomograms were numbered starting with number one at the proximal end (butt). All the hams were then divided into 65 virtual slices ($VS = 65$) being the number of tomograms of the longest ham used in the experiment. Therefore, the thickness of the virtual slices was equal (for hams with 65 tomograms) or smaller (for hams with less than 65 tomograms) than the thickness of a tomogram. The term "virtual slice" is used here to avoid confusion with the term tomogram, as "tomograms" are real CT data whereas virtual slices are estimations from these data (Fig. 1). With this correction, hams from different breeds (different in conformations and lengths) could be anatomically compared more easily since the number of virtual slices was the same for all the hams. The use of hams with different lengths for the development of the models can make these models more robust to this variation and