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A semi-automatic and an automatic segmentation algorithm to remove the internal organs from live pig CT images

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

[a] Graphics and Imaging Laboratory, University of Girona, 17003 Girona, Catalonia, Spain
[b] IRTA, Finca Camps i Armet, E-17121 Monells, Girona, Catalonia, Spain

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ABSTRACT

Removal of internal organs such as lungs, liver, and kidneys is a key step required to compute the lean meat percentage from Computed Tomography (CT) scans of live animals. In this paper, we propose two segmentation techniques to remove these organs focusing on pigs. The first method is semi-automatic, and it starts with the first CT slice and a manually defined mask with internal organs. Then, it applies a four-step iterative process that computes the masks of the next CT slices by using the information of the previous one. To find the best boundary it uses a Dynamic Programming-based approach. At each iteration the user can check the correctness of the new computed mask. The second method is fully automatic, and segments each slice individually by using distance maps and morphological operators, such as dilation. It is composed of three main steps which detect the pig's torso, pre-classify the voxels in different tissues, and segment the internal organs using the information of such classification. Although it has some parameters, user interaction is not required to obtain the results. The proposed approaches have been tested on CT data sets from 9 pigs, and compared with a manual segmentation. To evaluate the results, the precision, recall, and F-score measures have been used. From our test, we can observe that the performance of both methods is very high according to their average F-score. We also analyse how the accuracy of the results in the semi-automatic approach increases when more user interaction is applied. For the automatic approach, we evaluate the dependence of the results on the algorithm's parameters. If robustness is enough, and high accuracy is not required, the automatic algorithm can be used to segment a whole pig in less than 50 s. However, if the user wants to control the level of accuracy, the semi-automatic algorithm is preferred. Both methods are useful to reduce the time needed to segment the internal organs of a pig from hours (manual segmentation) to minutes or seconds.

1. Introduction

The evaluation of farm animals and their carcasses in terms of lean and fat content is of great importance for breeding companies and meat industry. It can be used to improve breeding programs, to produce the desired product, and to optimise carcass and cuts processing. Over the last years, imaging technologies have become general tools to estimate and predict the body composition of farmed animals, such as computed tomography (Lambe et al., 2013; Carabús et al., 2015), magnetic resonance imaging (Mitchell et al., 2001; Kusec et al., 2007; Kremer et al., 2013), hyperspectral imaging (Akbari et al., 2008), and visual image analysis (Doeschl-Wilson et al., 2005). For a review see Scholz et al. (2015). These technologies provide non-invasive, objective, and accurate estimates of body composition. In this paper, we focus our interest on computed tomography (CT) slices which provide very accurate and precise information of animal composition, either to analyse sheep (Glasbey and Robinson, 1999), pig carcasses (Font-i-Furnols et al., 2009; Vester-Christensen et al., 2009; Picouet et al., 2010; Bardera et al., 2014), live pigs (Luiting et al., 1995; Kolstad, 2001), or the comparison between live pigs and their carcasses (Lambe et al., 2013; Carabús et al., 2015). However, to extract meaningful information from these slices specialised processing techniques such as image segmentation are required.

Segmentation aims to separate image pixels according to the represented tissues (Banik et al., 2009; Gonzalez and Woods, 2002). To compute the lean meat percentage (LMP), it is necessary to identify lean meat, fat, and bone in the images. Currently, LMP prediction is determined online in carcasses using various types

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

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of equipment based on different technologies (Pomar et al., 2009). Despite the wide variety of segmentation techniques, the choice and adoption of the proper one is challenging and still harder when dealing with CT slices from live animals. In this case, an extra difficulty arises due to internal organs which are perfectly represented in the slices but not required for the LMP computation. The densities of the internal organs, measured in Hounsfield Unit (HU) values, are similar to the HU values associated with fat and muscle of the carcass (except for the lungs, whose values are very low). Thus, if the internal organs are included in images and their HU values are considered for the prediction of body composition, they will affect the results (Font-i-Furnols et al., 2015a). To overcome this problem, we propose two different algorithms to virtually extract the internal organs from the CT slices before the LMP calculation.

The first algorithm (based on Glasbey and Young, 2002; Glasbey, 2013) is semi-automatic. First, it takes two consecutive CT slices and the mask of the internal organs represented in the first slice. Then, it applies a four-step iterative process that computes the masks with the internal organs of the next slices. At each iteration, the user can interact to check the correctness of the computed mask. To create these masks, a Dynamic Programming-based approach is used (Bellman, 1957). Dynamic Programming methods are able to solve a complex problem (usually an optimisation problem) by breaking it down into simpler subproblems. The solutions of these subproblems are computed only once and stored for later reuse, thus saving computation time (Brown, 1979). The proposed method has some parameters related to the resolution and the smoothness of the masks. To support the processing of different animals, the proposed algorithm also integrates an optimisation process which automatically fits these parameters to the animal species.

The second algorithm (an improved version of Bardera et al. (2013)) is fully automatic and specifically designed for pig CT slices. To process a single CT slice, it detects the pig's torso, preclassifies it in several tissues, and segments the internal organs by using the knowledge of these tissues and performing different morphological operations. To obtain the whole segmentation this method is applied to each slice individually.

The aim of this paper is to present these algorithms and the experiments that have been carried out to evaluate their performance. Both approaches have been tested on pig CT slices and compared to a manual segmentation carried out by trained personnel.

2. Materials and methods

2.1. Animals and the CT scan

The set of pigs is composed of 9 female live pigs about 120 kg, and from 3 different genotypes (3 pigs of each one); namely, Duroc × (Landrace × LargeWhite), Pietrain × (Landrace × LargeWhite), and Landrace × LargeWhite. These animals have been CT scanned for previous studies (Font-i-Furnols et al., 2015b; Carabús et al., 2014), where additional information such as breeding, feeding, the CT scanning device and the instrumental settings can be found.

2.2. The semi-automatic algorithm

A key step of the semi-automatic algorithm is the contour detection of the internal organs represented in multiple CT slices, i.e. a 3D image. To carry out this process, we were inspired by the method presented by Glasbey and Young (2002), where an appropriate optimisation problem for 2D images is defined. To solve such problems, a cost function is needed to measure the quality of a solution, and an algorithm has to be used to optimise this function. The cost function can either measure the goodness or badness of a solution; when it measures the badness, it is often called *energy function*, and the optimisation algorithm is used to minimise it (Felzenszwalb and Zabih, 2011). In this approach, an energy function is used, and the optimisation algorithm is based on Dynamic Programming. Below, we describe how Dynamic Programming is applied to segment regions in an image, including the definition of the energy function equations, and we analyse the four steps of the semi-automatic algorithm.

2.2.1. Dynamic programming to segment image regions

Dynamic Programming is a powerful general technique for developing efficient discrete optimisation problems, such as finding the shortest path in a graph. In computer vision, it has been extensively used (Glasbey, 2009; Geiger et al., 1995; Ohta and Kanade, 1985; Amit and Kong, 1996). In our case, we are going to consider the image as a graph where pixels are nodes and the connections between pixels from adjacent columns are edges. The weight of each edge is given by an energy function, and the aim of the algorithm is to find the path that minimises it, which will correspond to the internal organs boundary. The first step, hence, is to define the energy function.

Assuming we have a template of the boundary, i.e. the average of some validated boundaries from other sets of slices, we can compare this template with each possible boundary in the slice to be segmented. For each column, as shown in Fig. 1, a range of consecutive pixels (rows) is selected and compared with the template by computing the root-mean-square difference (RMSD). By moving this range of pixels up and down we obtain a new possible location for that boundary point, and the best fit is considered to be the one with the lowest differences. If y is the slice to be segmented, and μ is the boundary template, and assuming that K is the number of pixels of the range, I is the number of columns, $y_{k,i}$ is the kth pixel of the ith column (the same for $\mu_{k,i}$), the boundary shifts range from $-B$ to B, β is the set of selected boundaries (rows) for all the columns, and row β_i is the selected boundary (shift of the range) for the ith column, we can define the energy function of the boundary as

$$E_B(y,\beta) = \sum_{i=1}^{I} f_i(y,\beta_i), \tag{1}$$

where

$$f_i(y,\beta_i) = \sum_{k=1}^{K} \left(y_{k+\beta_i,i} - \mu_{k,i}\right)^2, \quad \beta_i \in \mathcal{B} = \{-B,\ldots,0,\ldots,B\}. \tag{2}$$

Nevertheless, this formula does not take into account the roughness of the boundary, i.e. two consecutive points of the boundary can be very distant. To get a smooth boundary an extra energy term must be added to the function in order to penalise the gap between rows in consecutive columns. We can define this extra energy term (roughness penalty), E_{RP}, as

$$E_{RP}(\beta) = \sum_{i=1}^{I-1} (\beta_i - \beta_{i+1})^2. \tag{3}$$

If λ is the roughness penalty coefficient ranging from a value of 0 up to ∞, then we just need to apply Dynamic Programming to find the boundary with the minimum energy:

$$\begin{aligned} \hat{\beta} &= \arg\min_{\beta \in \mathcal{B}^I} \{E_B(y,\beta) + \lambda E_{RP}(\beta)\} \\ &= \arg\min_{\beta \in \mathcal{B}^I} \left\{ \sum_{i=1}^{I} f_i(y,\beta_i) + \lambda \sum_{i=1}^{I-1} (\beta_i - \beta_{i+1})^2 \right\}. \end{aligned} \tag{4}$$