Virtual Dissection of CT Scanned Pig Carcasses

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Introduction
Knowledge of the weight of tissue types in pig carcasses is generally only available after manual dissection. The use of computed tomography (CT) has demonstrated to be a promising approach to gain knowledge on the lean meat weight (Romvari, 2005), but less effort has been put into gaining knowledge about the weight of other tissue types from CT. Knowing the weight of individual tissue types will directly give access to other measures such as the weight of the carcass and the Lean Meat Percentage (LMP). Applying contextual methods from the field of image analysis we hope to make a virtual dissection of pig carcasses.

Materials and Methods
25 CT scanned and manually dissected left side carcasses were used. Each CT scan consists of approximately 140 slices (z-direction) of the size 512x512 pixels (xy-direction). The resolution in the x-y-z-directions are 1 mm, 1 mm, 10 mm respectively. The carcass weight was also available. To classify each slice of the CT scans, we used the Owen-Hjort-Mohn algorithm contextual Bayesian classifier (Larsen, 2000). We classified each voxel to belong to one of the classes \(\pi_{\text{fat}}, \pi_{\text{meat}}, \pi_{\text{bone}}\) on basis of its own and the neighbours’ voxel values. For each voxel we denote its value by \(X\) and build a feature vector \(D = (X, X_B, X_C, X_E, X_W)^T\) from it neighbouring values. Given this feature vector \(D\) we want to make a classification, that is we want to find the \(\pi_{\text{fat,meat,bone}}\) that maximizes \(P(C = \pi | D = d)\). Using Bayes Theorem and the law of total probability we have:

\[
(1) \quad P(C = \pi | D = d) = \frac{P(D = d | C = \pi_{\nu})P(C = \pi_{\nu})}{P(D = d)} = \frac{\sum_{a,b,c,d} P(D = d | C = \{\pi_{\nu}, \pi_{\alpha}, \pi_{\beta}, \pi_{\gamma}, \pi_{\delta}\})g(\pi_{\alpha}, \pi_{\beta}, \pi_{\gamma}, \pi_{\delta}|\pi_{\nu})}{h(d)}
\]

where the prior \(P(C = \pi_{\nu})\) can be estimated from the Hounsfield spectra, \(h(d)\) is the unconditional density for \(d\) and the index \(a, b, c, d\) is one of the 34 different class configurations of the neighbors. \(g(.)\) is especially interesting in the sense that we only allow 2 different classes within the neighbourhood and only in the spatial pattern shown in figure 1.

Materials and Methods

![Allowed spatial connectivities for the class configurations.](image)

When postprocessing the result from the Bayesian classifier using mathematical morphology it is possible to correct some of the marrow misclassified as meat or fat. The final result of this virtual dissection is a class label on each of the voxels in the CT scan, i.e. when knowing the voxel volume, the volume of each tissue type can be estimated. Using this result we can model the weight of the carcass as a weighted sum of the tissues volumes:

\[
(2) \quad W = \beta_1 V_{\text{meat}} + \beta_2 V_{\text{fat}} + \beta_3 V_{\text{bone}}
\]

The \(\beta\)'s in this model can be interpreted as tissue densities, so estimating the \(\beta\)'s from known examples makes it possible to predict carcass weight from a CT scan.

Results

Using the method described above, the 25 CT scanned left side carcasses were virtual dissected. An example of the virtual dissection of two different slices is seen in figure 2. The method is demonstrated to be robust to noise and artifacts but this also means that finer structures disappear in the virtual dissected image. The post-processing step works well and the marrow inside the bone is not found to be fat nor meat.

![Figure 2. Result of the virtual dissection of a slice.](image)

Estimating \(\beta\)'s in equation (2) from the 25 pig carcasses we obtain the correlation between measured and predicted weight (figure 3, left). We find \(R=0.9996\) and a standard deviation of the residuals of \(\hat{\sigma} = 0.1209\) kg. Performing leave-one-out cross validation (figure 3, right) we find \(R=0.9994\) and a standard deviation of the residuals of \(\hat{\sigma} = 0.1357\) kg.

![Figure 3. Left: Correlation between measured and predicted weight. Right: Correlation between measured and predicted weight using cross validation.](image)

Conclusion

A contextual analysis approach, the Owen-Hjort-Mohn algorithm, combined with a postprocessing step using mathematical morphology was developed for performing a virtual dissection of pig carcasses from CT scans. The virtual dissection was performed on 25 CT scanned left side carcasses and a model of the carcass weight based on virtual dissections was suggested and evaluated against known weight.

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References