CONTEXTUAL ANALYSIS 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).

Until now, most analyses of CT scans have been based on the Hounsfield spectra that does not consider the spatial context in CT scan. Applying contextual methods from the field of image analysis we hope to make a virtual dissection of pig carcasses.

Materials and Methods

57 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 *xyz*-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 c_{fat}, c_{meat} and c_{bone} on basis of its own and the neighbours' voxel values. For each voxel we denote its value by X and the value of its neighbours to the north, south, east and west by X_N,X_S,X_E,X_W which leads to the feature vector $\mathbf{D}=(X, X_N, X_S, X_E, X_W)^T$. Given this feature vector we want to make a classification, that is we want to find the $v \in \{\text{fat, meat, bone}\}$ that maximizes $P(C=c_v|\mathbf{D}=\mathbf{d})$. Using Bayes Theorem and the law of total probability we have:

$$\begin{aligned} P(C=c_v \mid \mathbf{D}=\mathbf{d}) &= \frac{P(\mathbf{D}=\mathbf{d} \mid C=c_v)P(C=c_v)}{P(\mathbf{D}=\mathbf{d})} \\ &= \frac{P(C=c_v)\sum_{a,b,c,d} P(\mathbf{D}=\mathbf{d} \mid \mathbf{C}=(c_v,c_a,c_b,c_c,c_d))g(c_a,c_b,c_c,c_d \mid c_v)}{h(\mathbf{d})} \end{aligned} \qquad (1)$$

where the prior $P(C=c_v)$ can be estimated from the Hounsfield spectra, $h(\mathbf{d})$ is the unconditional density for $\mathbf{d}$ and the index a,b,c,d is one of the 3^4 different class configurations of the neighbours. 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. 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.

Figure 1: Only these spatial patterns are allowed for the neighbourhood

For the carcass weight we assume it can be modelled as a weighted sum of the tissues volumes:

$$W = \beta_{fat}V_{fat} + \beta_{meat}V_{meat} + \beta_{bone}V_{bone} \qquad (2)$$

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

Results & Discussion

Using the method described above, the 57 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 postprocessing step works well and the marrow inside the bone is not found to be fat nor meat.

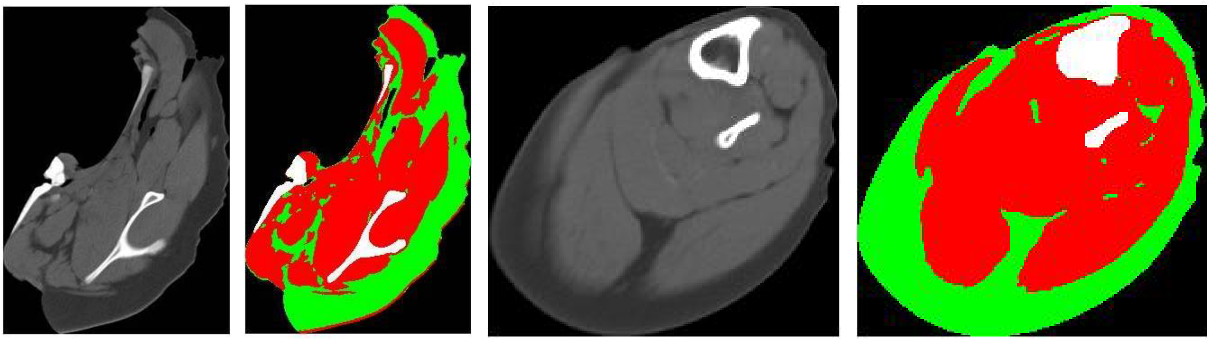

Figure 2: Result of the virtual dissection of two different slices. From left to right: CT slice, virtual dissected slice, CT slice, virtual dissected slice.

Estimating β's in equation (2) from the 57 pig carcasses we obtain the correlation between measured and predicted weight shown in figure 3 (left). We find R=0.9918 and RMSEC=0.5537 kg. The slope of the regression line is 0.9878, and it has an offset of 0.4638. Performing leave-one-out cross validation (figure 3, right) we find R=0.9909 and a residual sum of squares of RMSEP= 0.5840 kg. The regression line has slope 0.9856 and offset 0.5468.

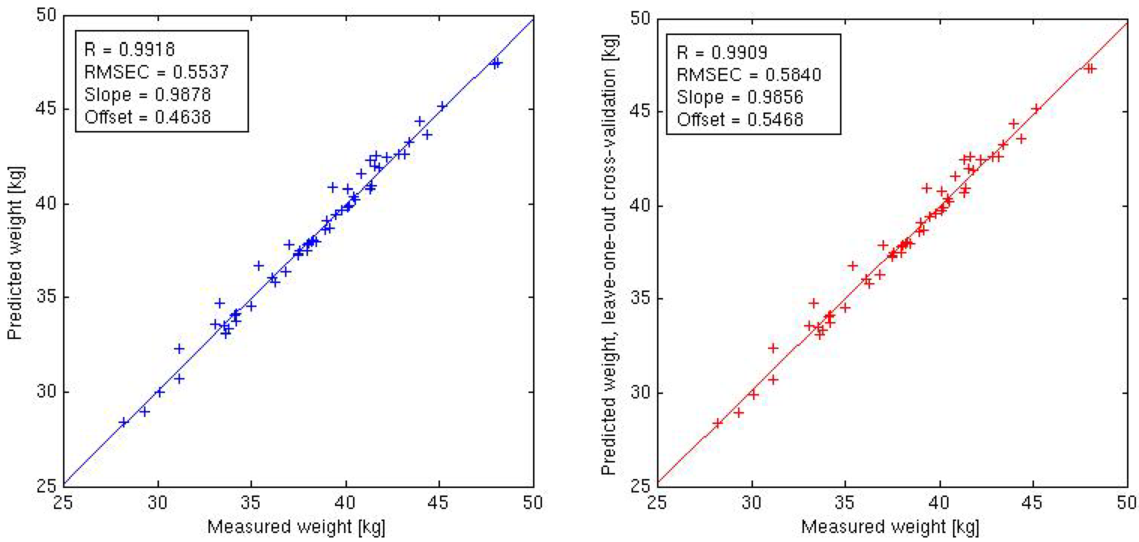

Figure 3: Left shows the correlation between measured and predicted weight. Right shows correlation between measured and predicted weight when performing cross validation.

Conclusions

A contextual analysis method, 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 57 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

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