Classification Methods for CT-Scanned Carcass Midsections

A Study of Noise Stability

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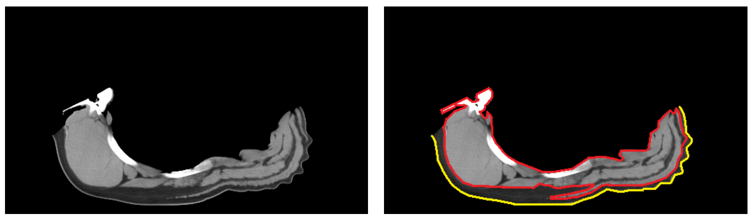
Abstract. Computed tomography (CT) has successfully been applied in medical environments for decades. In recent years CT has also made its entry to the industrial environments, including the slaughterhouses. In this paper we investigate classification methods for an online CT system, in order to assist in the segmentation of the outer fat layer in the mid-section of CT-scanned pig carcasses. Prior information about the carcass composition can potentially be applied for a fully automated solution, in order to optimize the slaughter line. The methods comprise Markov Random Field and contextual Bayesian classification, and are adapted to use neighbourhood information in 2D and 3D. Artificial Poisson noise is added to the provided dataset to determine how well each of the methods handles noise. Good noise handling will allow lower dose scannings. The investigated methods did not perform better than the reference model in terms of classification, but the MRF segmentation showed promising results in a case with extreme simulated noise.

1 Introduction

The Danish slaughterhouses process approximately 20 million pigs every year [1]. This means that even a slight streamlining of the slaughter process might result in huge benefits. One way of streamlining the process, which has been investigated intensively in recent years, is the use of online CT-scanning [2]. Using computed tomography (CT) on a pig carcass (half a pig body), makes it possible to directly extract anatomical information, which otherwise only would be possible to obtain, after the carcass has been cut. This obviously has a huge potential in terms of optimization. There is an anatomical variation between pigs, and CT provides the possibility to determine how well a specific carcass is suited for a certain product before it is cut. Furthermore, prior information can also be used to guide the cutting process to ensure a maximum yield and minimum waste of meat. The use of CT-technology in future slaughter houses has become so well founded, that the long term goal is to scan every pig carcass online before cutting, in order to optimize, organize, and automate the entire slaughter process.

Commercial tolerances provide guidelines and quality measures for products cut from the carcass. If such tolerances can be estimated before the carcass is processed, the initial cuts could be placed optimally. Some of these commercial tolerances can be found from the outer fat layer of the carcass midsection. For the process of segmenting the outer fat layer, a natural step is to partition the voxels into a fat- and a meat class, hereby obtaining the outline of the meat, see Fig. 1.



(a) (b)

Fig. 1. **(a)** shows a slice from the midsection of a CT-scanned carcass. **(b)** shows the same slice with a crude outlining (**red**) of the meat. The outer fat layer is located between the meat outline and the skin (**Yellow**). Note that bone is included in the outline.

We test two methods for creating a binary partition in CT-scanned carcass midsections. Each method utilizes neighbour (contextual) information in both 2D and 3D. However, the voxels of the provided CT-data are anisotropic, which complicates the step from 2D to 3D. Noise is well-known to appear in CT-scans and our motivation for taking neighbour information into consideration is that we expect an increased noise stability. If a classification to some degree can be invariant to noise, it would allow for lower dose CT-scans. In medical applications patients will be exposed less harmful radiation, and in industrial applications it is faster and more cost efficient.

2 Methods

We investigated two different methods in order to classify each voxel of a CT-scan to belong to the two classes denoted π_{fat} or π_{meat}. Both methods were applied utilizing neighbour information in both 2D and 3D.

2.1 Contextual Bayesian Classification

A 2D contextual Bayesian classification scheme has been developed by Hjort *et al.* [8], and extended to the third dimension by Larsen [4]. For these schemes, a feature vector is created for each voxel. This feature vector contains the voxel intensity, X, of the current voxel, along with intensities for the six (for the 3D version) immediate neighbours, i.e. $\mathbf{X} = (X_{\mathrm{C}}, X_{\mathrm{N}}, X_{\mathrm{E}}, X_{\mathrm{S}}, X_{\mathrm{W}}, X_{\mathrm{T}}, X_{\mathrm{B}})^T$ where the subscripts denote current, north, east, south, west, top and bottom respectively. Based on the feature vector we want to make a classification, that is find the $v \in \{\text{fat}, \text{meat}\}$ that maximizes $P(C = \pi_v \mid \mathbf{X} = \mathbf{x})$. Using Bayes theorem and the law of total probability we have

$$P(C = \pi_v \mid \mathbf{X} = \mathbf{x}) = \tag{1}$$

$$\frac{p_v \sum_{a,b,c,d,e,f} P(\mathbf{X} = \mathbf{x} \mid C = (\pi_v, \pi_a, \pi_b, \pi_c, \pi_d, \pi_e, \pi_f)) g(\pi_a, \pi_b, \pi_c, \pi_d, \pi_e, \pi_f | \pi_v)}{h(\mathbf{x})},$$

where p_v is the prior probability of the classes, (a, b, c, d, e, f) is one of the possible 2^6 class configurations of the neighbours, and $h(\mathbf{x})$ is a normalization. $g(\cdot)$ introduces a prior notion of the class configurations, as it only allows the spatial patterns in Fig. 2.

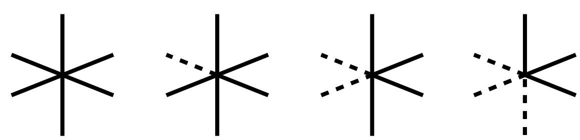


Fig. 2. Four allowed spatial patterns of the class configurations. More patterns are obtained by rotation.

2.2 Markov Random Field Segmentation

The Markov Random Field (MRF) model is well-known from medical image segmentation [3]. It can be used to model the spatial interactions between voxels, and have free parameters to control the amount of allowed interaction in the spatial directins. Following Li [7], an energy function for the MRF can be defined based on a neighbourhood system. The MRF, along with its energy function, can be translated into a flow network, and following Kolmogorov and Zabih [6], the energy can be minimized using graph cuts. This yields an optimal classification of the voxels, into π_{fat} and π_{meat}, for the defined MRF model.

3 Data

Data was provided by Danish Meat Research Institute (DMRI) and consisted of 22 CT pig carcasses scanned at a high dose (80mA), from which the midsections were extracted. Each of the midsections consisted of approximately 70 slices (z-direction) of 512×512 pixels (xy-direction). Each voxel was anisotropic with a physical dimension size of 1×1×10mm in the xyz-directions. Furthermore, the carcasses have been preprocessed by trimming the volumes in the y-direction, in order to remove the scanner table. Fig. 3 shows an entire CT-scanned pig carcass along with the location of the midsection. Additionally, a single midsection, scanned at both high (80mA) and low dose (10mA), was also provided.

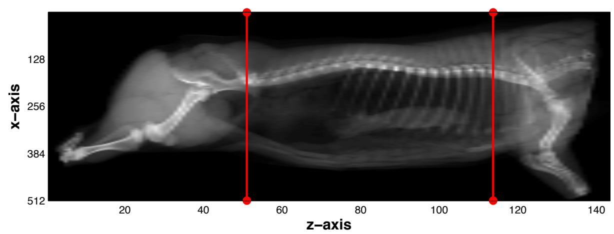


Fig. 3. A pig carcass shown in the xz-plane. The midsection is located between the red vertical lines.

4 Results

DMRI currently uses the 2D variation of the contextual Bayesian classifier along with mathematical morphology. This has shown good results regarding weight estimation of entire pig carcasses [5]. We therefore use this method as reference.

To evaluate the methods, artificial noise was added to the CT-volumes. The noise was modeled by adding Poisson noise, with parameter λ, to the data. An appropriate λ was found by comparing the amount of mis-classified voxels using the reference method on the midsection with true noise data and the same midsection with simulated noise. Additional samples, with increased noise levels, were also created. The noise simulation is illustrated in Fig. 4. More advanced CT-noise modeling was not considered.

The free parameters for the MRF segmentation were estimated for each noise level by looking at the mis-classification rates compared to the reference. It was found that the interaction in the xy-direction should be equal, but the interaction in the z-direction was insignificant.

Fig. 5 shows the amount of mis-classifications as a function of the noise level. The methods seems to have approximately equal mis-classification rates for fat

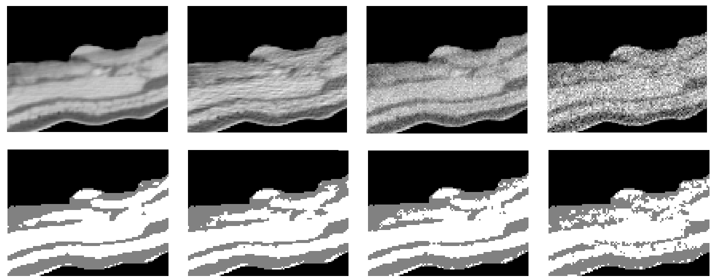
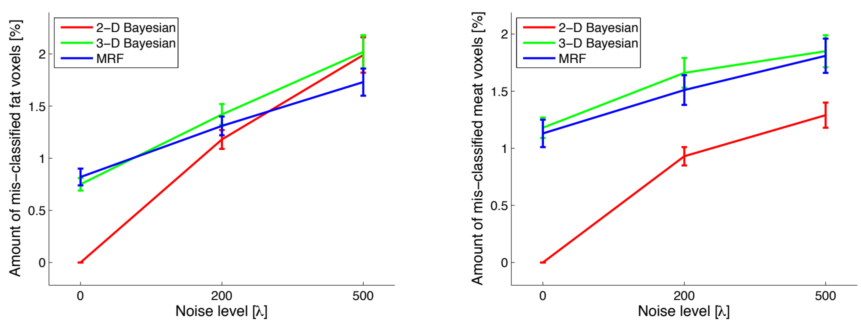


Fig. 4. The first row shows a zoomed view of a slice with, no noise, real noise, simulated noise, and increased simulated noise respectively. Notice that the real noise seems to consist of larger structures, where the simulated noise structures are small. The second row shows the corresponding classifications using the reference method.



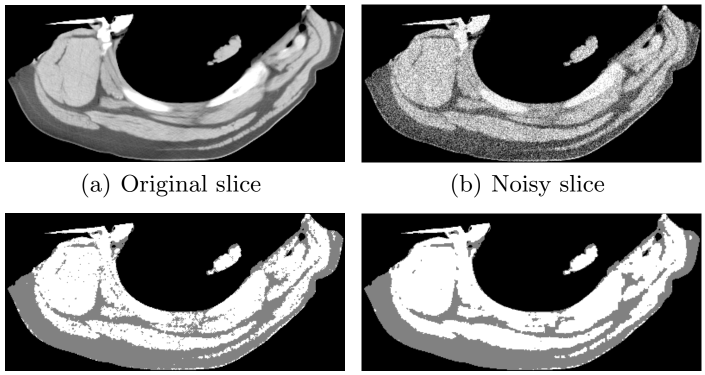
(a) (b)

Fig. 5. The mean of mis-classification rates for fat- and meat voxels for all 22 CT-carcasses. The included interval denotes the standard deviation.

voxels, but not for the meat voxels. This was found to be due to the fat marbling, where a lot of the voxels are a mixture of fat and meat.

As fat marbling lies within larger meat structures and rapidly changing between slices, there was a tendency of overestimating the amount of meat voxels in these areas. It was found that the new methods did not introduce any significant advantages over the reference method in terms of classification.

However, for the case where we wanted to extract an outline of the meat as in Fig. 1, a small scenario with extreme noise was investigated. As seen in Fig. 6, the MRF segmentation was more successful at producing a nice and smooth outline, as the amount of smoothing can easily be controlled contrary to the contextual Bayesian classifiers. This flexibility might be really important for data with real noise, as the noise structures tend to be bigger in these cases.



(a) Original slice (b) Noisy slice

(c) 2-D Bayesian (d) MRF

Fig. 6. Classification results for a case of extreme noise.

5 Conclusion

We have investigated the segmentation of noisy CT-data using MRF and a contextual Bayesian classifier. Extending the methods to the third dimension did not improve the results. However, in a case with extreme noise, the MRF segmentation showed promising results when extracting the outline of the meat, which was the target of the investigation.

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