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Abstract. X-ray computed tomography is increasingly used as a non-destructive method for studying three dimensional food structures. For meat products, studies have focused mainly on fat and protein content due to limited contrast capabilities of absorption based techniques. Recent advances in X-ray imaging have made novel X-ray image modalities available, where the refraction and scattering of X-rays is obtained simultaneously with the absorption properties, providing enhanced contrast for soft biological tissues. This paper demonstrates how data obtained from grating-based imaging can be segmented by means of multivariate and contextual methods to improve the classification of soft tissues in meat products. The results show that the presented segmentation method provides improved classification over univariate segmentation.

Keywords: X-ray CT, phase contrast, dark field imaging, grating interferometry, image segmentation.

1 Introduction

In meat science a great effort is put in determining quality parameters that affect the consumer acceptability of the end product. These include fat to meat ratios, tenderness, texture and taste. X-ray computed tomography (CT) has been a preferred method for obtaining non-destructive measurements of food structures, giving three dimensional information. However, due to low contrast capabilities between soft tissues, fat and protein distribution of meat products have been a main focus [4, 5, 12]. Recent advances in X-ray imaging have introduced new imaging modalities such as phase contrast and dark-field, obtainable by grating-based interferometry [2, 9, 10]. The modalities measure the absorptive-, refractive- and scattering properties of a sample. A quantitatively higher contrast has been reported both when imaging refractive properties compared to absorptive [7, 11] and also when imaging scattering properties compared to absorptive [1]. In a recent study [8], it was shown how a simple bivariate threshold

method utilizing the absorptive and refractive properties combined gave a better segmentation of meat products over the two univariate segmentations separately.

In this study, we apply established classification and segmentation methods in order to investigate the applicability of a contextual multivariate segmentation method for meat products from grating-based imaging. The aim is obtain a segmentation capable of discriminating between different materials with similar absorption properties such as meat and water, and also plastic and meat marbling. Such a segmentation would allow for a post-quantitative analysis of water loss in meat products due to heat treatment and better detection of plastic foreign objects in a production line. The result is presented by applying the method to tomograms obtained of a pork backfat sample from a laboratory-based grating interferometer set-up. Finally, a comparison of the univariate and multivariate segmentation is made.

2   Materials and Methods

X-ray Modalities In Fig. 1, the three types of physical interactions - absorption, refraction and scattering - used as imaging modalities in grating-based interferometry are illustrated. The effect on an incoming Gaussian shaped beam profile (black) is depicted when elements with different properties are measured. The profiles shown in color represent what is recorded when a material is present. In green, the effect of an absorptive material is shown to attenuate the beam, while in blue, the effect of a refractive material is seen to be a transverse shift in the position of the beam profile. Lastly, the small-angle scattering from a material with ordered micro-structures causes the beam profile, here shown in red, to broaden. By separating the attenuation, transverse shift and broadening of the beam, it is thus possible to measure three complementary imaging modalities. This can by done by grating-based imaging (GBI), which relies on an X-ray interferometer, consisting of periodic gratings for measurements. For further details, the reader is referred to [2, 9].

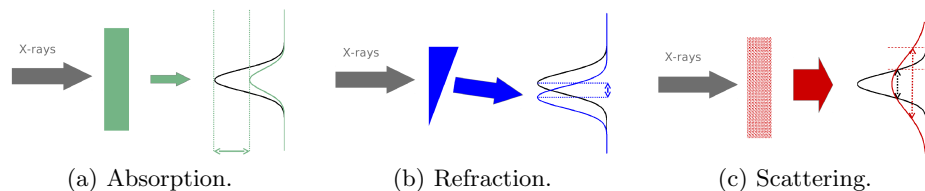(a) Absorption.   (b) Refraction.   (c) Scattering.

Fig. 1: Illustration of how an incoming X-ray beam is affected when a sample is presented having a) absorptive, b) refractive, and c) scattering properties. *(Reprinted from Torben H. Jensen.)*

Tomography Measurements The simultaneous scan of the absorption, phase-contrast and dark-field CT modalities were performed at the grating interferometer setup at the Technical University of Munich (TUM). The X-ray tube was operated at an acceleration voltage of 30 kV and a filament current of 80 mA. The sample was placed in a polyethylene (PE) container filled with vegetable oil. Included in the container were also two references, a plastic rod and a small container with water. The details of the setup and measurement procedures are described in [8]. The reconstructions were performed as described in [1] and yielded tomograms of $156 \times 291 \times 291$ voxels with an effective voxel size at the sample of 112 μm. A slice each from the absorption and phase-contrast tomograms has previously been published in [8].

Image Analysis A two step segmentation method was implemented, which considers both the spectral and spatial context of the data. First, the voxels are considered as stochastic variables where each voxel represents an observation $x = (x_1, x_2, x_3)^\top$, where (x_1, x_2, x_3) represent the absorptive-, refractive- and scatter intensities, respectively. The data is then modelled as a mixture of multivariate Gaussian distributions using an expectation-maximization (EM) algorithm [6]. From this, the a priori multivariate distributions of the ingredients in the sample are obtained as

$$\phi(x|\mu_i, \Sigma_i) = \frac{1}{2\pi^{3/2}|\Sigma_i|^{1/2}} \exp\left(-\frac{1}{2}(x - \mu_i)^\top \Sigma_i^{-1}(x - \mu_i)\right) \qquad (1)$$

where $\mu_i = (\mu_{i1}, \mu_{i2}, \mu_{i3})^\top$ is the multivariate mean value for each class i and Σ_i is the corresponding full covariance matrix. The data is then modeled as a Markov Random Field (MRF) where the probability of each voxel belonging to the found distributions is estimated. The volume is then segmented by applying a graph cut algorithm as described in [3].
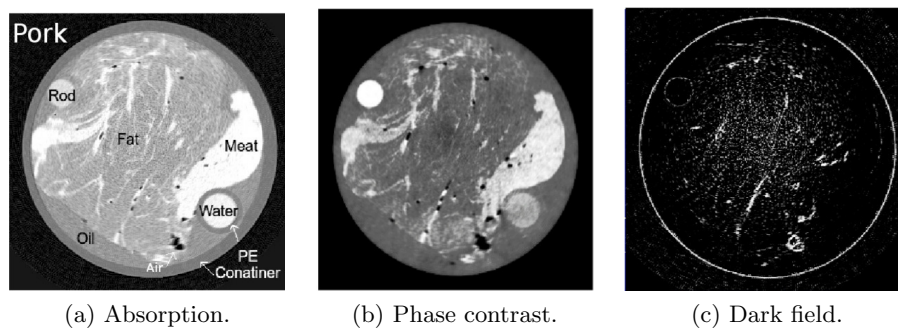

(a) Absorption.   (b) Phase contrast.   (c) Dark field.

Fig. 2: Transverse slices of the X-ray tomograms.

3   Results

Fig. 2 shows transverse slices from each modality. As reference for the multivariate segmentation, a univariate segmentation was first performed, see Fig. 3. Different elements are identified in the three modalities and in total eight elements are classified.

| (a) Absorption. | (b) Phase contrast. | (c) Dark field. |

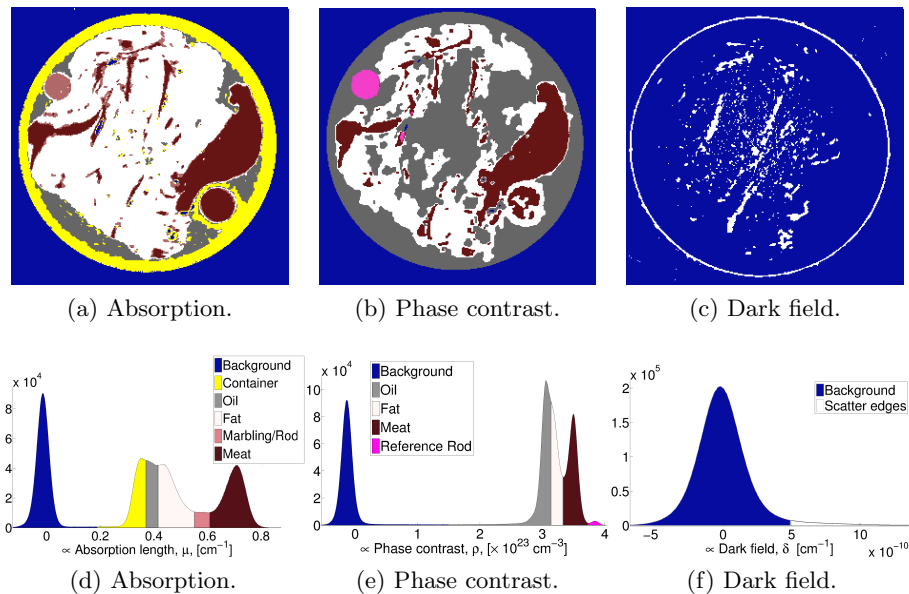| (d) Absorption. | (e) Phase contrast. | (f) Dark field. |

Fig. 3: The results from the univariate segmentation. Different elements are classified in each of the imaging modalities.

When modeling the data as a mixture of multivariate Gaussians, two additional classes were identified resulting in a classification of ten classes in total. The results are illustrated in Fig. 4a. The graph cut segmentation result can be seen in Fig. 4b. The meat marbling seems to be segmented quite well along with the reference rod, water, container and meat. By considering the dark field modality in the multivariate dataset, the segmentation of scattering edges is obtained, enhancing the segmentation of the marbling. Worth noting is that the separation of water and meat is only obtained by the multivariate segmentation. The results from both the univariate and multivariate segmentations were compared to a manual annotation of a single slice from the data volumes and the rate of correct classification was found, see Table 1. The reason for a lower classification rate of meat in the multivariate case is mainly due to some of the meat voxels being classified as marbling.
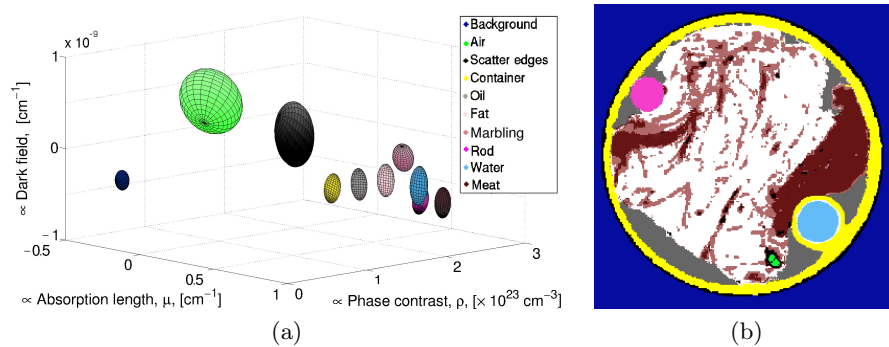
Fig. 4: a) The result from the EM algorithm represented by the covariance matrices of the classes in the pork backfat sample. b) The result from the multivariate contextual segmentation method.

Table 1: Correct classification rate of the segmentation methods given in percentages.

	Meat	Marbling	Plastic Rod	Fat	Water	Oil	Container	Total
Absorption	94.8	24.1	0	72.2	0	57.7	82.6	85.5
Phase Contrast	94.4	0	80.3	47.8	0	89.1	0	74.7
Multivariate	91.0	47.9	97.2	85.0	92.6	73.4	98.1	91.3

4   Conclusions

This paper has presented a segmentation method for X-ray tomography obtained from grating-based imaging. By applying multivariate and contextual segmentation methods a superior classification was obtained. Additionally, the segmentation successfully classified water from the rest of the sample. Such a segmentation allows for a meaningful quantitative post-analysis, for instance when investigating how connective tissues are affected and water loss of meat products due to heat treatment. The results are promising for scenarios where sample elements may only be visible through one of the three contrast mechanisms, as is the case with the plastic rod. This could prove useful for automatic detection of foreign bodies in food products such as plastic and paper which are difficult to detect with absorption alone. A further analysis of the contrast mechanisms is important to fully understand to which measurement conditions multivariate segmentation methods can apply. The influence of partial volume voxels on the Gaussian mixture model should also be investigated, along with methods to estimate the mixture without a priori knowledge of the number of classes.

Acknowledgements

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