Spectral imaging and tomographic reconstruction methods for industrial applications

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6 Conclusions and outlook

6.1 Conclusions

6.1.1 Overview

Quality control is a challenging but essential procedure in industrial imaging. With X-ray imaging, the inner structure of an object can be visualized and hence, unwanted and potentially hazardous elements can be identified by detection systems. Since single X-ray radiography results in superimposed images, extracting and analyzing features from these images may lead to suboptimal decision-making. Recent years have seen a significant increase in tomographic imaging quality, especially resulting from spectral imaging and machine learning technologies. These techniques have the potential to significantly increase the effectiveness of industrial imaging without sacrificing too much on processing speeds.

As one of the most important branches of industry, food processing is the recurring theme in this dissertation. In particular, foreign object detection is an essential component that should attain both high accuracy and high throughput. In order to improve this trade-off, X-ray imaging can be used in conjunction with machine learning. **Chapter 2** addresses a common issue with machine learning regarding the need for large volumes of suitable training data. By incorporating computed tomography into a workflow, high-quality pairings of X-ray projections and ground truth locations of foreign objects can be generated with minimal manual labor. The resulting datasets enable the training of neural networks for high-speed foreign object detection.

By enhancing the features for analysis of industrial products, spectral X-ray imaging offers an improvement to standard X-ray inspection. The additional information spectral X-ray imaging offers also results in much larger data volumes, of which a significant fraction may be redundant. In **Chapter 3**, a network architecture named Data Reduction Convolutional Neural Network (DRCNN) is proposed to mitigate this problem. With this architecture, a neural network learns to combine the image features that are needed for a specific task (foreign object detection, for example) and compresses these into a much smaller data volume. This approach increases the quality of feature extraction and reduces data sizes and possibly processing times.

Spectral X-ray imaging also offers improvement in the three-dimensional reconstruction of products of interest. In spectral X-ray CT, reconstructions can be computed with projection data probed at different X-ray photon energies. These different energy levels are treated in a more generalized manner as channels in **Chapter 4**. There, a class of algorithms named Multi-Channel DART (MCDART) is proposed that generalizes the Discrete Algebraic Reconstruction Technique (DART) – for objects consisting of a limited number of materials with known attenuation values – to multi-channel data. From a series of experiments, it can be concluded that this class of algorithms can improve reconstructions using multi-channel data.

When an industrial spectral X-ray setup is available, attenuation values of a material can be obtained by directly measuring these with the spectral detector. By doing this for many common materials, a spectral dictionary can be constructed, which can be used as prior information to steer the often ill-posed spectral reconstruction problem to a desirable solution. **Chapter 5** proposes a spectral reconstruction and material decomposition framework, named ADJUST, by posing the problem in such a way that the spectral matrix is a multiplication of an indicator matrix and a spectral dictionary. Contrary to most other spectral material decomposition methods, ADJUST is a method that performs the reconstruction and material decomposition in one step. Moreover, ADJUST can take on objects with more materials and produce more accurate reconstructions than other methods.

6.2 Contributions

The methods presented in this dissertation utilize spectral imaging and deep learning to improve aspects such as the workload, practicality, accuracies, ill-posedness and compression possibilities in problems found in X-ray imaging and CT reconstruction applications. The earlier two sections are concerned with machine learning methods, which are shown to yield improved results for industrial foreign object detection. The latter two sections are concerned with improving the accuracy of CT reconstructions by utilizing spectral X-ray imaging, both with respect to single-channel CT reconstruction as well as to other spectral CT reconstruction methods.

Deep learning in conjunction with X-ray imaging methods has rarely been applied in certain industrial areas, such as food processing. The workflow presented in **Chapter 2** for efficiently generating training data for deep learning on radiographs has application potential in an industrial setting, as evidenced by the accuracy results on the real-world dataset. By making use of computed tomography, foreign objects can be represented in a 3D volumetric space rather than a 2D radiograph. This makes separation of foreign objects from the remaining object substantially easier. As a result, the annotation of the X-ray projections becomes radically less time-intensive and less prone to interpretation. On top of this, much more training data can be generated from each scanned product, implying that the number of products that need to be scanned is limited. Regarding improving quality control by object inspection at a production line of a factory, this contributes significantly to the workload of setting up a deep learning driven analysis and decision-making machinery in an industrial context. Additionally, Chapter 2 also provides an open X-ray dataset, which is generally not easy to come by, to test methods for object detection.

The DRCNN architecture covered in **Chapter 3** applies machine learning to spectral data reduction. As suggested by the results in that chapter, when hyperspectral imaging is used for industrial X-ray imaging, training with DRCNN can be used to optimize the compression and throughput speed for a specific task, such as detection tasks. In addition, training with this architecture achieves better understanding of essential features in the data and can possibly speed up the (hyper)spectral X-ray data acquisition. This approach is helpful for all applications where hyperspectral imaging – not necessarily with X-rays – is concerned. For instance, in optical hyperspectral imaging applications such as remote sensing or surface-based hyperspectral inspection, the method contributes to better compression, transmission, speed and accuracy.

Similar to how the workflow in Chapter 2 exposes the advantages of using 3D CT with respect to separating foreign objects, the MC-DART method in **Chapter 4** exploits the improved separability of voxels in a reconstruction through multi-channel imaging. By incorporating a high-dimensional segmentation step, the method presents a framework for reconstruction of multi-channel data in a more effective manner than independent channel reconstructions. The method can be scaled to any number of channels, and therefore allows for a higher number of materials in an object. The usage and properties of the MC-DART method are demonstrated using simulated spectral X-ray imaging mechanisms. However, MC-DART can also be used for other multi-channel modalities, given that the object of reconstruction can be represented in a discrete manner.

When prior information on spectral material signatures is available in the form of a spectral dictionary, the ADJUST method proposed in **Chapter 5** can produce material maps of an object from its spectral X-ray CT data, given that the corresponding materials are sufficiently distinct in terms of their signatures. The method allows for higher accuracies and for reconstructions of more materials than in most existing one- or two-step methods without additional hyperparameters. The results on a laboratory spectral micro-CT dataset imply that applications are possible in both spectral and hyperspectral X-ray imaging.

6.3 Future work and outlook

Spectral imaging and deep learning hold much potential for solving advanced imaging problems. To utilize these advances effectively, algorithms that can adapt to a wide range of problem settings should be developed. A running theme in the research of this dissertation is the modularity of the proposed methods. The DRCNN architecture is designed in such a manner that any CNN architecture can be inserted in the back-end of the network, of which the MSD and U-Net architectures are well-investigated examples in Chapter 3. Similarly, in the class of algorithms that the MC-DART method represents, the algebraic reconstruction method can be chosen at will. Finally, the workflow presented in Chapter 2 has many possibilities for changes and extensions. A number of these are schematically shown in Figure 6.1.

As highly suggested in this dissertation, the workflow from Chapter 2 can be enhanced with spectral X-ray imaging. This can be done in at least two ways: (i) spectral scanning can increase the quality of the CT reconstruction and the subsequent segmentations and virtual projections to obtain better ground truth (Fig. 6.1a), and (ii) spectral input data can be used in the generated training set for better deep learning training and performance (Fig. 6.1d). With spectral CT data, a naive approach of reconstructing each separate channel can be carried out in order to improve the foreign object segmentation. Even better is to incorporate existing algorithms to use the combined information to make a (discrete) reconstruction (Fig. 6.1f), for which integration of the MC-DART (Fig. 6.1g) and the ADJUST (Fig. 6.1h) algorithms are suitable. In the case of hyperspectral or multi-spectral data with a high number of bins, the DRCNN architecture can extract essential features and reduce the spectral dimension of the data to speed up the throughput in the neural network (Fig. 6.1i).

Other interesting additional extensions of the workflow include multi-angle data acquisition (often used, for example, for glass container inspection [68]), which, along with multi-energy acquisition, still needs to be fully used in X-ray imaging for detection [8]. Another improvement is to include a separate high-quality scan (Fig. 6.1b) or advanced CT reconstructions for improved segmentation accuracy. For instance, if needed, denoising or inpainting can be applied to the reconstructed CT volumes (Fig. 6.1e). Deep-learning driven noise reduction algorithms [119] and inpainting algorithms are readily available for these purposes. Finally, to further improve the effectivity of the detection by deep learning, more data augmentation

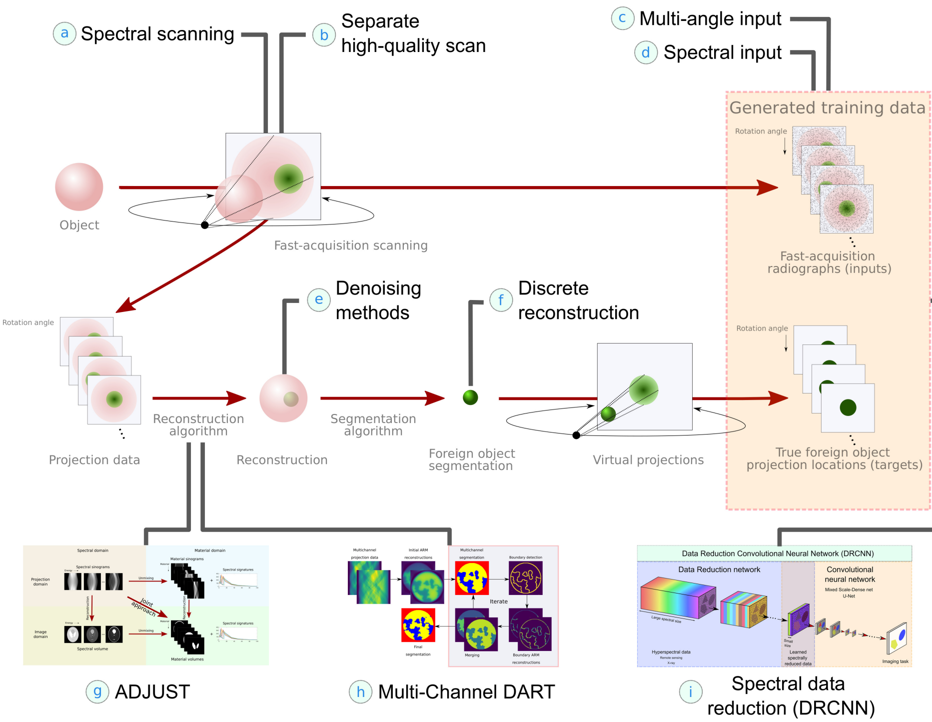

Figure 6.1: The complete workflow of data acquisition from **Chapter 2** with a number of possible extensions and enhancements: (**a**) spectral scanning, (**b**) performing an additional higher-quality scan for improved CT reconstruction, (**c**) multi-angle or (**d**) spectral input for the neural network, (**e**) application of denoising methods to improve the CT reconstruction, (**f**) direct discrete reconstruction resulting in segmented volumes, (**g**) integration of ADJUST for spectral tomography, (**h**) integration of MC-DART for multi-channel data, (**i**) integration of DRCNN in the workflow.

can be carried out in the projection domain [145]. Better still, data augmentation in the reconstruction space [17, 192], combined with realistic forward projections, yields even richer X-ray training datasets.

The evaluation of the methods presented in this dissertation focuses primarly on accuracy. While the deep learning methods are designed to be fast, the processing times are only briefly touched upon, either in terms of particular time speedups for DRCNN and time complexity classes with MC-DART. A deeper analysis of the processing speedups would be interesting, especially regarding the additional spectral dimension inherent to the data used in most of this dissertation. Nevertheless, this highly depends on the problem setting. For instance, if the X-ray imaging setup is such that the data quality deteriorates, more spectral bins may be needed for successful feature extraction with DRCNN, or more iterations are needed for proper convergence to acceptable solutions with MC-DART and ADJUST. Speed comparisons will become interesting when a practical application and setup are considered. When the speed at a production line is high, motion blurring may become an issue, but we expect that this can be taken care of with machine learning as well. This also applies when many objects are located on the conveyor belt, and the resulting radiographs are composites of single-object radiographs. In this case, either reconstruction methods for overlapping objects [253] or data augmentation will help (although with too many objects, photon starvation could prevent any possible detection at all). Also, in our experiments, perfect (angular) alignment of the foreign object radiograph and the ground truth was not strictly needed. Some erroneous experiments revealed that a slight offset did not significantly reduce the detection rate. This is positive for industrial implementation as it may allow for some accidental misalignment. In general, the generalization of the trained neural networks with approaches in this dissertation to other data from other objects or factory line setups is a topic for further research.

With spectral imaging and spectral CT, there are at least a number of additional challenges. First, spectral detection may not be consistent. Initial laboratory experiments showed that detectors can yield different projection images when experiments are repeated under the same circumstances. Machine learning based object detection methods may overcome this problem to a certain extent, although this again depends on the separability of the materials in the object. Second, the modelling in this dissertation does not include the (not necessarily known) detector response function, which describes the distribution of measured energy for an incident beam of a specific energy. ADJUST still needs to include a detector response matrix in the modelling. In general, incorporation of a detector response function [170] makes the problem more realistic but is often left out to keep the problem convex [6].

The methods presented in this dissertation can be further enhanced. First, the workflow can be extended from segmentation to other sorts of classification, such as binary classification. Secondly, in the spectral simulations used for the workflow, DRCNN and ADJUST results, no densities are taken into account. Including this does not fundamentally change the methods, but they need to be added in the case of practical applications with ADJUST. Thirdly, an evident and straightforward extension to MC-DART is the application to three-dimensional reconstruction problems. Additionally, the requirement for the grey values to be known for MC-DART poses practical challenges. For that reason, a version with automatic grey level estimation is desirable, which can be implemented as a joint optimized problem in which both the reconstruction and the grey levels are optimized (in a similar fashion as TVR-DART [328]). Lastly, task-driven data reduction can be combined with network pruning methods (for example, LEAN [252]) to reduce training time, reduce processing time and improve feature extraction.

While the methods presented in this dissertation aim primarly for industrial imaging, their usage extends beyond this. First of all, the data reduction method and the material decomposition approach of ADJUST can be applied in remote sensing. ADJUST may be used as regularization, like, for instance, directional TV in remote sensing [48]. Data reduction can be applied to all sorts of remote sensing problems, as access to data or equipment is getting less difficult and costly [109, 243]. The biconvex formulation and solution strategy of ADJUST can be used for other CT-related problems, for instance optimal angle selection or automatic grey value estimation in discrete tomography. In addition, ADJUST can be used for general material decomposition, for instance for biological and chemical contamination checks, or in spectroscopy.

The fields of machine learning, spectral X-ray imaging and tomography are rapidly evolving. It is expected that spectral detectors will become the standard for medical imaging in the future, and will be adopted in industrial imaging as well. Depending on the detector possibilities, spectral X-ray imaging may be used for chemical and biological contamination in addition to physical contamination. Deep learning gains momentum in industrial imaging in general and will most surely become a standard in food inspection. The combination of deep learning with spectral X-ray inspection is, therefore, a logical pathway to the future to increase accuracy and throughput. A few key limitations remain that make it how far these developments will push the possibilities. First, imaging and detection are limited to certain imaging resolution (for instance, with micro- and nanoplastics). Secondly, the difficulty of detecting of certain combinations of materials with X-rays will remain a sticking point. Therefore, additional means of noninvasive methods may be needed. For instance, phase-contrast imaging may be more interesting than absorption imaging in certain situations, as this modality yields superior results for the detection of organic materials [80].