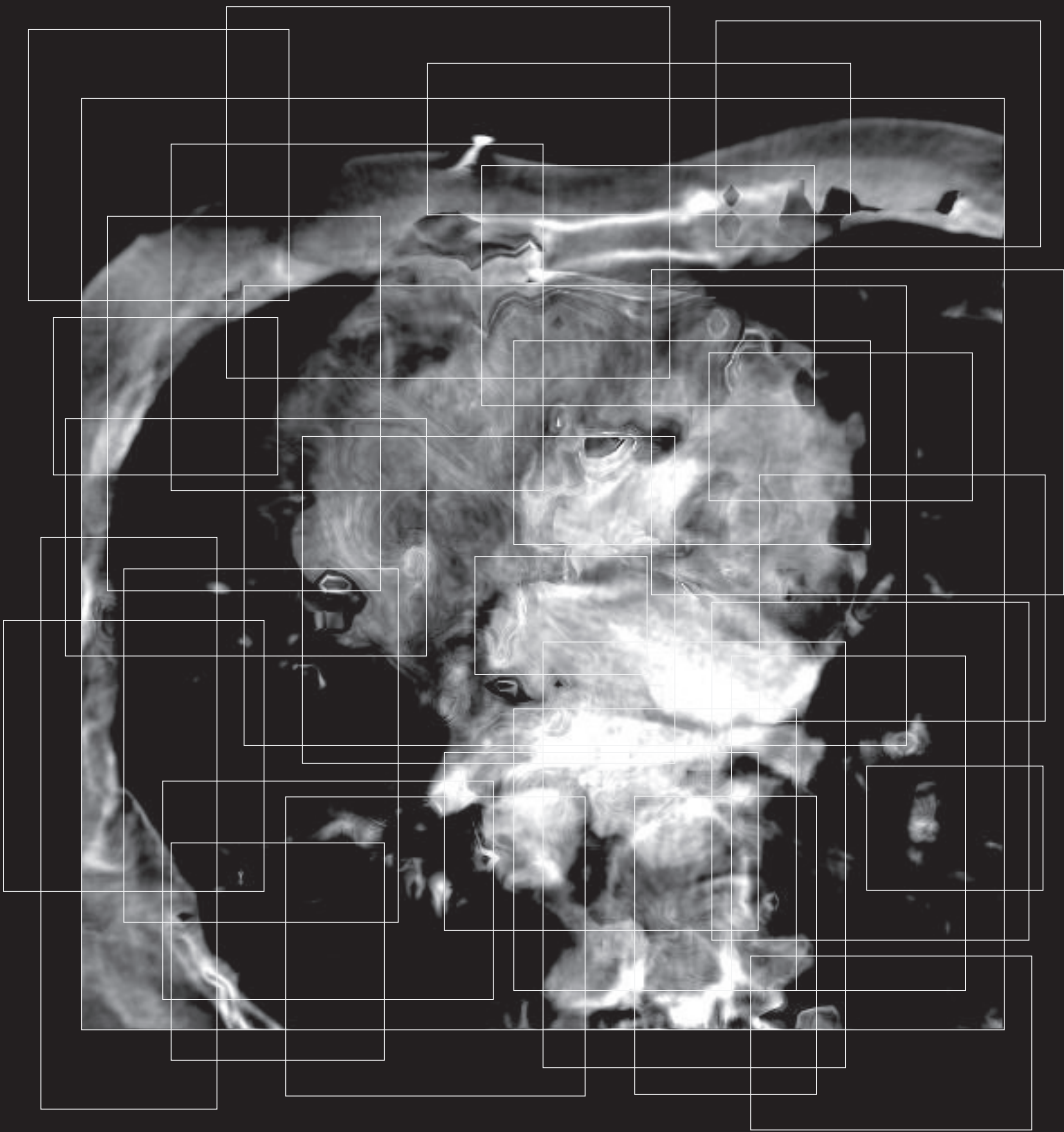
Machine Learning in Cardiac CT Image Reconstruction

Labeled Data Synthesis for the Removal of Motion and Metal Artifacts



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Tanja Loßau

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Promotionskomitee:

Prof. Otto von Estorff	Technische Universität Hamburg, *Vorsitzender des Prüfungsausschusses*
Prof. Michael M. Morlock	Technische Universität Hamburg, *Erster Gutachter*
PD Dr. Michael Graß	Technische Universität Hamburg, Philips Research Hamburg, *Zweiter Gutachter*

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Independent contributors:

Dr. Hannes Nickisch	Philips Research Hamburg
Dr. Tobias Wissel	Philips Research Hamburg
Dr. Rolf Bippus	Philips Research Hamburg
Dr. Holger Schmitt	Philips Research Hamburg
Dr. Frank Bergner	Philips Research Hamburg

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Tanja Loßau

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Shaker Verlag GmbH • Am Langen Graben 15a • 52353 Düren
Phone: 0049/2421/99011-0 • Telefax: 0049/2421/99011-9
Internet: www.shaker.de • e-mail: info@shaker.de

Summary

In the last decade, deep learning techniques have revolutionized the research field of computer vision and reinforced data as the key element for predictive model generation. Also in the medical domain, image processing solutions are increasingly data-driven. However, the required quantity and quality of image and corresponding label data is often a challenge in practice.

This dissertation describes a methodology to leverage the power of state-of-the-art deep learning algorithms bypassing time-consuming, potentially noise-affected and in its complexity limited manual data annotation. The main application focus is the removal of cardiac computed tomography (CT) imaging artifacts. So-called forward models for virtual artifact introduction are developed by incorporating prior knowledge about the cardiac anatomy and CT imaging physics. They form the counterpart of the desired deep-learning-based backward models for image enhancement. Artifact-free clinical data is transformed by the forward models to produce pairs of artifact-perturbed image data and underlying artifact parameters which serve as basis for predictive model training. Estimation of artifact parameters is exclusively performed by convolutional neural networks (CNNs) as these models exploit the low-level statistics of the underlying medical images. The learned networks are used to detect, quantify and remove artifacts.

The proposed methodology is applied to two clinical relevant problems: coronary motion and pacemaker metal artifacts. Due to potential burring and concealing of anatomies and anomalies in reconstructed CT image volumes, artifact reduction is defined as primary goal. In the first application, a forward model is developed to retrospectively simulate motion during the CT acquisition. Pairs of motion-perturbed images and motion parameters are generated. Based on this data, backward models for motion artifact measurement and motion compensation are learned.
In the second application, a forward model inserts synthetic pacemaker leads into clinical data without pacemakers. Based on the resulting pairs of metal-free and metal-affected sinograms, CNNs are trained for metal removal directly in the projection domain. Furthermore, the backward model is extended to localize metal positions inside the image volume. In both applications, generalization capabilities of the learned models are verified on data with real artifacts and with the aid of human observer ratings. In comparison to existing model-based approaches for artifact detection and removal, similar or even higher performances are achieved.

Both applications demonstrate that predictive models trained on synthetic data only can generalize to real-world problems without the need of additional fine-tuning. The dissertation provides a thorough analysis regarding strengths and challenges of labeled data synthesis based on findings made in the addressed applications. The ability of high-level label generation, the data- and the time-efficiency are the main benefits compared to traditional manual annotation. The understanding of the data acquisition physics and the system processing enables efficient and high quality data generation. The proposed general concept of knowledge-driven forward modeling and deep-learning-based predictive backward modeling is extendable to different imaging modalities and clinical applications.

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