A Framework for the AI-based visualization and analysis of massive amounts of 4D tomography data for end users of beamlines

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Abstract

This paper reports on the above-mentioned framework and the first results of the BMBF-funded project "An AI-based framework for the visualization and analysis of large amounts of 4D tomography data for end users of beamlines". The aim of the project is to develop a framework for 4D tomography data as a contribution to the digital infrastructure for synchrotron and neutron sources. The imaging artifacts including the compression artifacts of the 4D TB-sized data set are to be compensated by neural networks integrated into the framework. The artifact reduction can be performed in real time at the synchrotron or neutron imaging facility or at the user's home institution. This framework removes the burden from the computing infrastructure of the large synchrotron and neutron facilities, as end users can process the datasets on their own computers at their institution based on the compression of TB data below 128 GB, so that powerful PCs are sufficient to process TB of 4D tomography data. This framework therefore scales with the number of end users using their own PCs as they should be available or purchasable at their institutions.

Keywords: 4D computed tomography, CT, synchrotron imaging, neutron imaging, neural network

1 Introduction

4D tomography at synchrotron sources and neutron sources is extremely data-intensive, as it is based on time series of 3D volume data sets with a storage space of e. g. 50 GB for each time step, so that the entire data set of a 4D tomography scan reaches the one-digit TB range. These data volumes will continue to increase due to increasing temporal and spatial resolution. To date, there is no suitable software (neither open source nor commercial) for handling (visualizing, analyzing and evaluating) such large 4D data sets on normal computers (not computing clusters). As a result, the potential of 4D tomography for science and industry has not yet been fully exploited. Individual users have so far developed individual solutions, often of limited quality or scope, for their specific applications, which are not transferable for use by third parties, e. g. for software quality reasons. The research results in the field of quality improvement of tomography data sets in recent years in the field of artificial intelligence have shown the high potential of neural networks and in particular of deep CNNs (Convolutional Neural Networks) even for large data sets if suitable learning data is available. Image artifacts occur during CT scans, e. g. due to beam variations, and for 4D CT in particular, many types of artifacts occur more frequently due to the shorter exposure times, such as noise and movement or residual phase contrast, which occurs due to longer propagation distances caused by the sample environments used. To date, there are isolated solutions that attempt to reduce these artifacts, but these are generally not made available to the end user. In most cases, the end user returns to his institute after a measurement with reconstructed data and is then dependent on the image quality made available. For this reason, a framework for 4D tomography data will be presented here as a contribution to the digital infrastructure for synchrotron and neutron sources.

2 AI-based imaging methods for integration into the framework for 4D tomography and results

The following the AI-based imaging methods and applications are addressed:

2.1. Compensation of 4D-CT noise and motion artifacts - Compensation of 4D-CT noise and motion artifacts can be effectively achieved using hybrid machine learning techniques that integrate known operators, embedding analytical algorithms within deep networks for image reconstruction. This approach not only enhances the accuracy of image reconstructions by leveraging the strengths of both analytical and data-driven methods but also minimizes error bounds and reduces the required number of training samples, leading to more efficient and precise imaging outcomes. Such hybrid models capitalize on the established efficacy of traditional algorithms while benefiting from the adaptability and learning capabilities of deep neural networks [1].

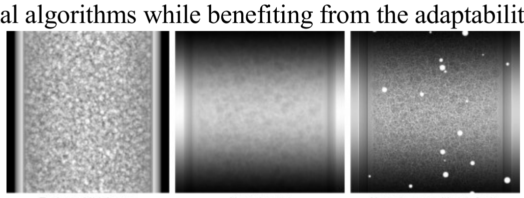

Fig. 1: Simulation of a capillary filled with spheres. Various X-ray imaging artefacts are present.

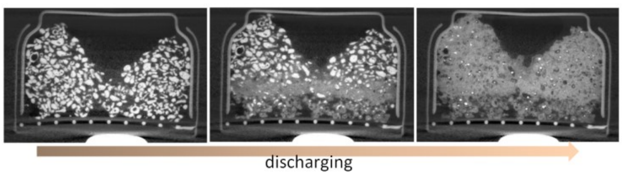

Fig. 2: 4D tomography of a zinc-air battery during discharge; dissolution of the zinc particles [2].

2.2. Generation of 4D CT data sets using simulation - The purpose of the Syris simulator [3] is to provide 4D simulated data sets with various realistic imaging artefacts, e. g. beam fluctuation, motion blur, see Fig. 1 and Fig. 2. These data sets are used to benchmark and train different algorithms in the framework. At first, data sets with individual isolated artifacts are generated in order to disentangle the common 4D imaging problems. Then data sets with all artifacts combined are created which pose a challenge to image processing algorithms.

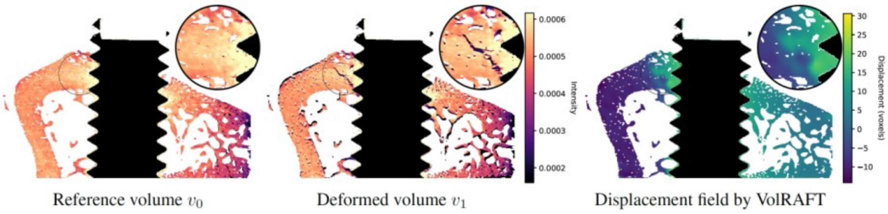

Fig 3: Evaluation of the displacement field based on measured volume pairs. The specimen consists of a titanium screw and surrounding bone. The field component in the direction of the screw's symmetry axis is shown. Adapted from [4].

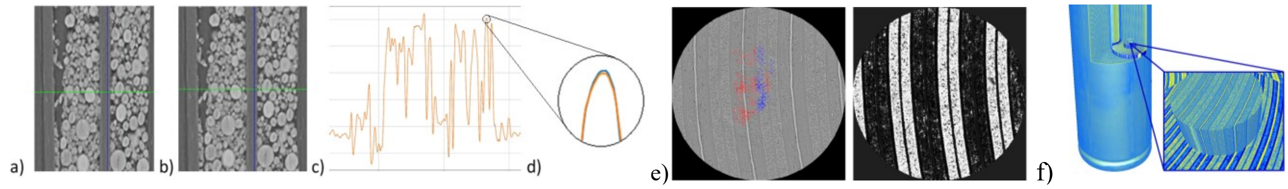

Fig. 4: a) Slice through a volume of a battery scanned on the synchrotron at the Helmholtz-Zentrum Berlin, a) original, b) compressed by a factor of 10, c) profile line through a) and b), d) magnified detail of c). e) Interactive segmentation of a different battery scan (scanned on BM18/ESRF) with user annotations (left) and segmentation result (right). f) Hierarchical imaging of the same battery due to local decompression.

2.3. Micro-CT Digital Volume Correlation - To track deformations and strains in order to elucidate morphology-function relationships of tomography volumetric data, an optical flow neural network is developed for digital volume correlation (DVC) analysis. This network, named VolRAFT [4], estimates the dense 3D displacement field between the reference volume and the deformed volume, using a supervised training approach on synthetic and measured datasets, see Fig. 3. Experiments show that VolRAFT performs well in estimating different displacement fields compared to cutting-edge iterative DVC approaches for high-resolution tomography data of bone-implant interfaces measured at synchrotron radiation-based computed tomography beamline.

2.4. Interactive data-driven segmentation - Due to the large variability of samples at synchrotron facilities, it is difficult to obtain robust deep learning segmentation methods. Therefore, we propose the extension of an interactive segmentation procedure which uses user annotations to train a segmentation model [5]. Thus, reliable results can be obtained in short time without fully annotated training data, cf. Fig. 4e).

2.5. Compression for archiving of 4D tomography data - At high resolution, a medium sample size already results in very large datasets, necessitating efficient compression methods. Based on wavelets [6], data-adaptive and error-bound schemes with better generalizability and control of compression quality can be realized. In addition to archiving, applications include local decompression for visualization, cf. Fig. 4f).

2.6. Framework extension for handling online and real time decompression of the 4D tomography data set - To visualize 4D tomography data of TB size on a user PC, a lossy compression by a factor of 10 is applied to the synchrotron volume data stored in the RAM [7]. In Fig. 4, it is shown that the impact of compression of a factor of 10 has only a negligible effect on the data quality. In the profile line of Fig. 4d), a deviation of the lossy compressed data is only visible in rare cases and is not greater than the width of the profile line. The speed for decompressing the required processing blocks of the compressed 4D tomography data is fast enough for powerful multi-core CPUs to visualize the slices when the user scrolls through the datasets.

2.7. Processed 4D synchrotron data for NN training - The quality of the segmentation/classification of the 4D data is highly dependent on the accuracy of the available training data from real samples. A multimodal, multidimensional characterization approach using a wider range of additional complementary imaging tools, such as electron microscopy or FIB/SEM tomography [8], is used for detailed quantification/identification of the material compositions in the samples or devices (e. g. batteries) analyzed by 4D synchrotron tomography by means of complex, time-consuming hand-made segmentation and "human-in-the-loop" techniques. This allows us to obtain reliable ground truth and training data for improved quantification accuracy and training of NNs. This concept is also applied to 4D neutron tomography data, too.

2.8. Application of the Framework for material characterization: dynamic water content analysis - Froning et al. [9] developed a CNN to predict the permeability of porous material from 3D images. Trained with artificial data, the predictions on real data were more accurate for data from the BESSY synchrotron than for data from a nano-CT device.

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