# Advancing learned algorithms for 2D X-ray computed tomography

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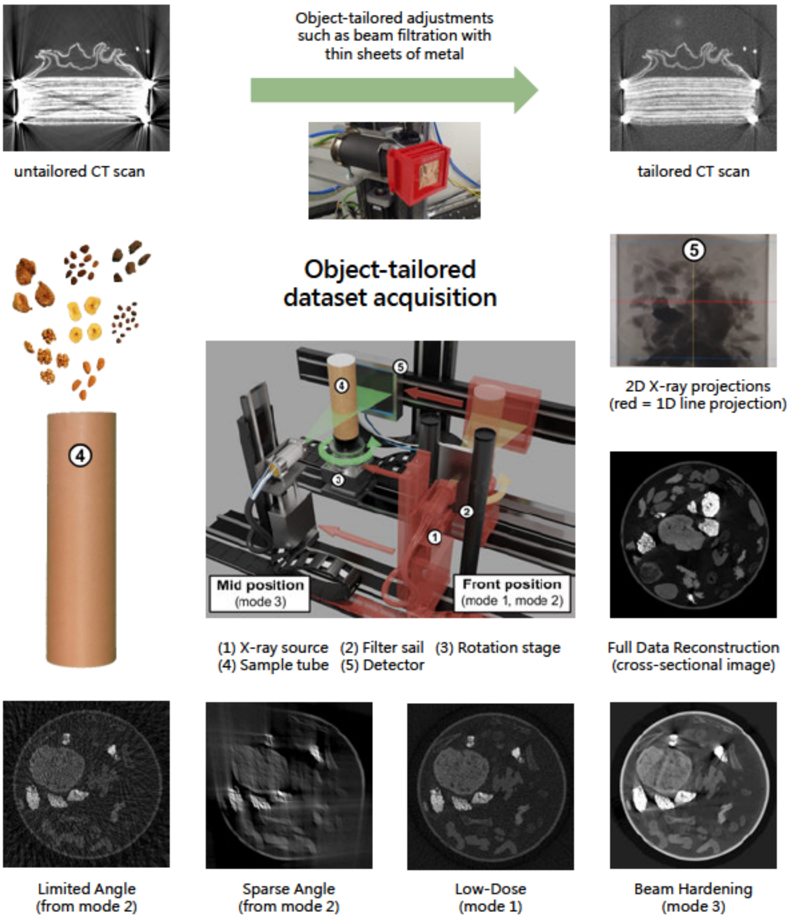
# Summary in English: Advancing learned algorithms for 2D X-ray computed tomography

This doctoral thesis deals with the advancement of learned algorithms for two-dimensional computed tomography (CT). This is an imaging process that calculates digital cross-sectional images from a large number of X-ray projections. The difference to simple X-ray images or radiographs, is that it is not only possible to see through objects or bodies, but also to view their internal structure in cross-sections. Computer-aided image reconstruction is often based on the filtered back projection algorithm and calculates the degree of absorption for each volume element (voxel) of the object. The quality of these image reconstructions depends heavily on the quality of the individual X-ray projections from which the cross-sections are calculated.

In Chapter 2, we look at the acquisition of CT scans tailored to cultural heritage objects. The imaging of cultural heritage objects is usually particularly challenging, as these objects often consist of many different materials with different densities, thicknesses and sizes. In particular, metal structures in cultural heritage objects can lead to a poor visualisation of the objects in CT scans. The continuous spectrum of the radiation source/X-ray tube plays an important role in this. The high-energy photons - the X-rays - that are sent through the scanning object for the CT scan have a statistical energy distribution. Low-energy photons are preferentially absorbed by the scanning object (especially by metallic structures within) and cannot be measured on the other side. This leads to problems in the pre-processing of the X-ray projections and the calculated image reconstructions show heavy visual errors known as image artifacts. One solution to this problem lies in filtering the low-energy part of the X-ray spectrum - the low-energy photons - so that mostly higher-energy radiation penetrates the object. This filtration is carried out using thin sheets of metal made of aluminium, copper, or tin of different thicknesses, which can also be combined with each other. Although this beam filtration leads to a higher average energy spectrum, this process also reduces the intensity of the radiation. Similar to a photograph taken in low light




**Figuur S1**: Visual summary.

conditions, the X-ray images can therefore appear noisy, which also has an effect on the image reconstructions. At the same time, lower-energy photons in the imaging process contribute to a higher contrast ratio. The challenge for object-tailored CT scans therefore is to find a balance between sufficiently strong beam filtration and a sufficiently large measurement signal and contrast ratio in the image reconstructions.

In Chapter 3, we use our experience from Chapter 2 on how to perform object-tailored CT scans to acquire a large dataset. The basis of machine learning and the development of learned algorithms lies in meaningful and diverse data from which the algorithms can learn. In the case of two-dimensional CT imaging, this is given by raw measurement data, a large number of X-ray projections, and corresponding image reconstructions. With this combination of data, algorithms can be trained to reconstruct the images in a learned way instead of using classical mathematical iterative reconstruction methods. This is not necessarily an advantage for high-quality measurement data, but becomes increasingly more relevant when the input data is not ideal. For the acquisition of this dataset, we developed a sophisticated measurement setup that would allow us to acquire both high-quality and inadequate data from the same object. For this, we decided to additionally record measurement data with low radiation dose (low-dose) and thus increased image noise as well as measurement data in which we did not filter the X-ray spectrum in advance and thus the images show strong image artefacts due to the spectrally different absorption (beam-hardening). Since we have corresponding optimised as well as inadequate measurement data and their respective image reconstructions, we can train algorithms to convert them into each other.

In Chapter 4, we investigate the question of whether it is sufficient to train learned algorithms for image denoising on artificially noisy measurement data or whether it is necessary to use experimentally noisy measurement data for this purpose. For this purpose, we pair optimised ‘clean’ measurement data from the dataset from chapter 3 with the corresponding noisy ‘low-dose’ measurement data and train two common neural networks (learned algorithms for image processing) to convert them into each other. At the same time, we take the clean measurement data as a basis to simulate and apply artificial noise to it. The simulated noisy data is also paired with the clean measurement data and the neural networks are trained to convert them into each other. We show in our studies that the neural networks trained on the simulated noisy data are better at denoising experimentally noisy measurement data. However, when training them to convert measurement data into image reconstructions, it is better to train the neural networks on experimentally noisy measurement data. The simulation approach for artificial noise does not seem to be complex enough to capture non-linear artifact causes such as beam-hardening mentioned above. Accordingly, the learned algorithms that do not see these artifacts during their training on simulated noisy data cannot remove them afterwards when applied to experimental noisy data.

In Chapter 5, we perform a large comparative study of learned algorithms for CT image reconstruction based on the dataset from Chapter 3. For this purpose, we use the different measurement data of the dataset to define standardized reconstruction experiments. We use the complete 'clean' measurement data for the first CT experiment as a general comparison value. In addition, we use the 'clean' measurement data for six further CT experiments by firstly limiting the used X-ray projections to only 120°, 90° and 60° instead of 360° and secondly reducing the number of X-ray projections to 360, 120 and 60 distributed sparsely over 360°. For the last two CT experiments, we use the noisy 'low-dose' and artifact-inflicted 'beam-hardening' measurement data. A total of three classical mathematical reconstruction methods are compared with twelve learned algorithms. These are divided into four categories: Post-processing networks, unrolled/learned iterative methods, learned regulariser methods and plug-and-play methods. In each category, three algorithms are compared for all CT experiments. The implementation of the experiments and learned algorithms is done in an open-source code collection and can be extended by further CT experiments and algorithms for further comparisons.

With these research studies, we were able to make fundamental contributions to object-tailored CT scans and the future, standardized development and comparability of learned algorithms for CT image reconstruction.