



**FACULTY OF ENGINEERING** 

Results

Universitätsklinikum Erlangen

# **Deriving Neural Network Architectures using Precision Learning: Parallel-to-fan beam Conversion**

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### Introduction

- Up to now the concept of *precision learning* [1] was only used to augment networks with prior knowledge
- We want to demonstrate that we can use *precision learning* to formulate different hypothesis on efficient solution schemes that are then found as the point of optimality of a deep learning traning process • We show that on the parallel-to-fan beam conversion problem in the context of Hybrid MR-/X-ray imaging device and compare with an geometrical rebinning method (Fig. 1)



#### Aim:

- Show that neural networks can be used to find efficient solution schemes for unknown operators in a mathematical model
- Find a convolution-based algorithm for the conversion task

# Material and Methods

### Finding a convolution-based algorithm:

parallel-to-fan conversion problem using the discrete reconstruction formulas:

$$\boldsymbol{A}_{f}\boldsymbol{A}_{p}^{ op}(\boldsymbol{A}_{p}\boldsymbol{A}_{p}^{ op})^{-1}\boldsymbol{p}_{p}=\boldsymbol{p}_{f}$$

formulate a hypothesis that the inverse bracket can be approximated by an projection-independent or -dependent filter:

$$oldsymbol{A}_{f}oldsymbol{A}_{p}^{ op}oldsymbol{F}^{oldsymbol{H}}oldsymbol{K}oldsymbol{F}^{oldsymbol{H}}oldsymbol{K}oldsymbol{F}_{p}=\hat{oldsymbol{p}}_{f}$$

• This formula directly gives us the network topology (Fig. 3) to find

Figure 4: Sub-sampling comparison projection-independent filter. The plot colors are red for the reference, blue for the respective line profile and green for the difference. The bottom row shows the respective filters.





the unknown operator as in [2].

### **Training**:

- Additional scaling layer **S** compensates for the normalization between the forward- / back-projector. S gets pre-trained.
- Only numerical phantoms are used (Fig. 2)
- Weights of filter layer **K** are smoothed with a small Gaussian kernel after each epoch to obtain continuous weights

# Results

- Projection-indepented filter can be found but is instable (Fig. 4)
- Projection-depented filter can be found (Fig. 5)
- Sharper results than the interpolation-based method (Fig. 6)

![](_page_0_Figure_32.jpeg)

![](_page_0_Figure_34.jpeg)

Figure 5: Sub-sampling comparison projection-dependent filter. The plot colors are red for the reference, blue for the respective line profile and green for the difference. The bottom row shows the respective filters.

![](_page_0_Figure_36.jpeg)

Figure 6: Comparison of the geometrical and the proposed convolution-based rebinning method with projectiondependent and -independent filter. 121 projections are used for the geometrical method to calculate the difference.

### Conclusion

- An efficient convolution-based algorithm could be found by learning the unknown operator in the mathematical model
- The convolution-based algorithm achieve sharper results that the

#### **Figure 1:** Geometrical rebinning approach [3]. **Figure 2:** Numerical training data.

![](_page_0_Figure_42.jpeg)

Figure 3: Proposed network topology based on mathematical model. Only layer K and S are trained.

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#### interpolation-based pendant

Learning process has to be better understood for a more substantiated regularization

#### References

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### Acknowledgements

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EIT Health is supported by the EIT, a body of the European Union

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