Exploring Physics-Informed Machine Learning for System Matrix Formulation in X-ray Imaging Forward Models

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INTRODUCTION

- **Limitations of Traditional ML:** Requires large datasets, lacks explainability in X-ray imaging.
- **PIML Integration:** Combines physical laws with ML for more accurate models.
- **Improved Image Reconstruction:** Enhances accuracy and flexibility in X-ray imaging.
- **Key Applications:** Boosts precision in electronics, medical imaging, and material inspection.

There exists a challenge in accurately constructing a system matrix for X-ray imaging forward models, due to *limited datasets, lack of interpretability*, and *insufficient integration of fundamental X-ray physics*.

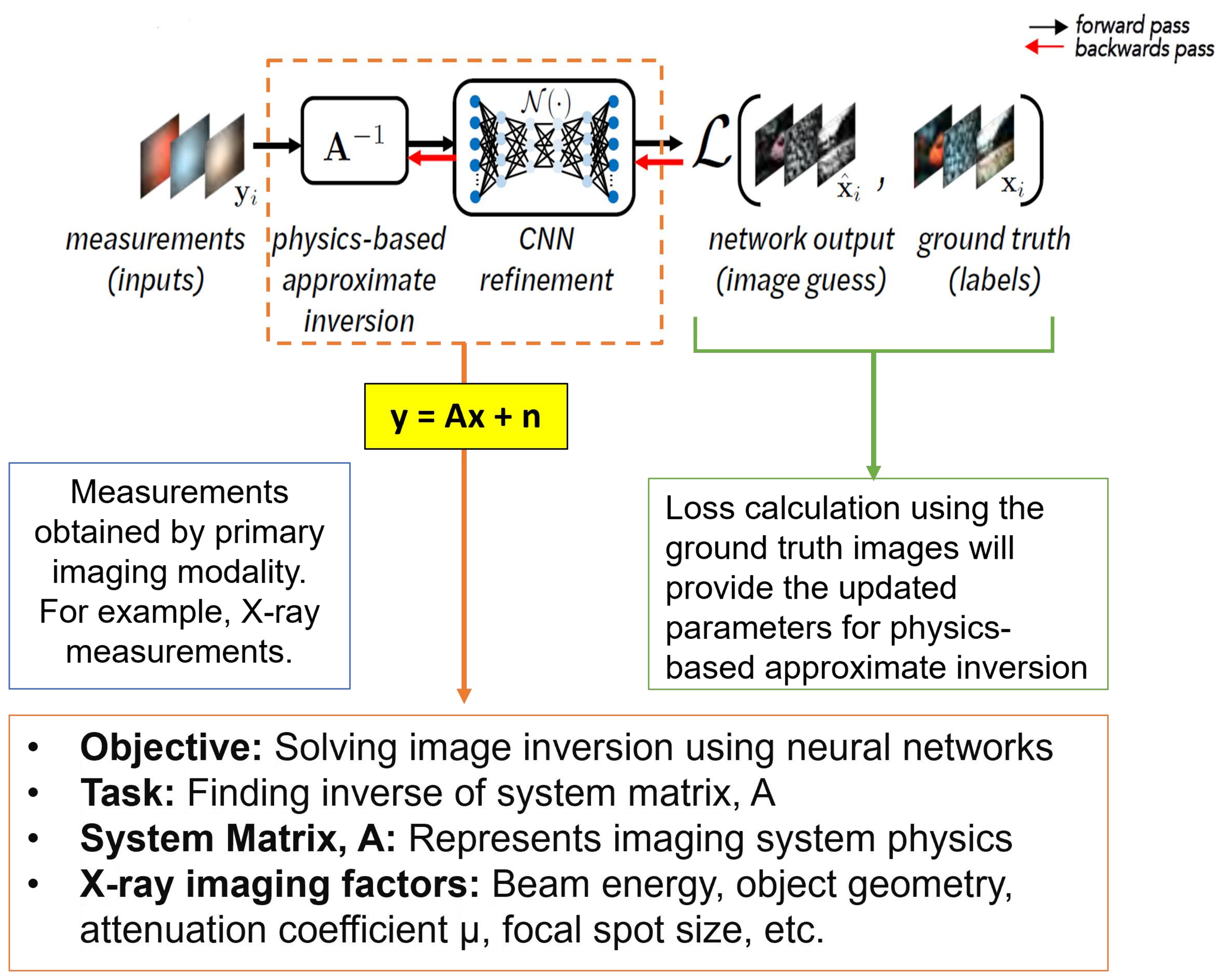

Fig. 1 Applications of Physics-Informed Neural Networks (PINNs) in computational imaging[1]

Proposed Solution

- Using Physics-Informed Neural Networks (PINNs) for system matrix construction in X-ray imaging models.
- Embedding X-ray physics, like attenuation and scattering, into the machine learning process.
- Minimizing a loss function that balances data fidelity with physical law compliance.
- Achieving accurate and interpretable results with limited training data.

METHODS

Table 1. Summary of the physical effects, image acquisition parameters, unknown parameters, and corresponding signal models for X-ray computed tomography (CT) imaging[2]

Physical Effect	Image Acquisition Parameters	Unknown Parameter	Signal Model
X-ray Attenuation	Tube Current (mA)	Attenuation Coefficient	Beer-Lambert Law: $I = I_0 * \exp(-\int\mu(x)dx)$
Scattering	Tube Voltage (kVp)	Scattering Properties	Scattering Model (e.g., Rayleigh, Compton)
Detector Efficiency	Detector Sensitivity	Detector Characteristics	Detector Response Function
Beam Hardening	Filter Material/Thickness	Energy Spectrum	Polyenergetic Attenuation Model
Motion Artifacts	Exposure Time	Patient Motion Parameters	Convolution with Motion Blur Kernel
Detector Noise	Pixel Size	Electronic Noise	Gaussian or Poisson Distribution

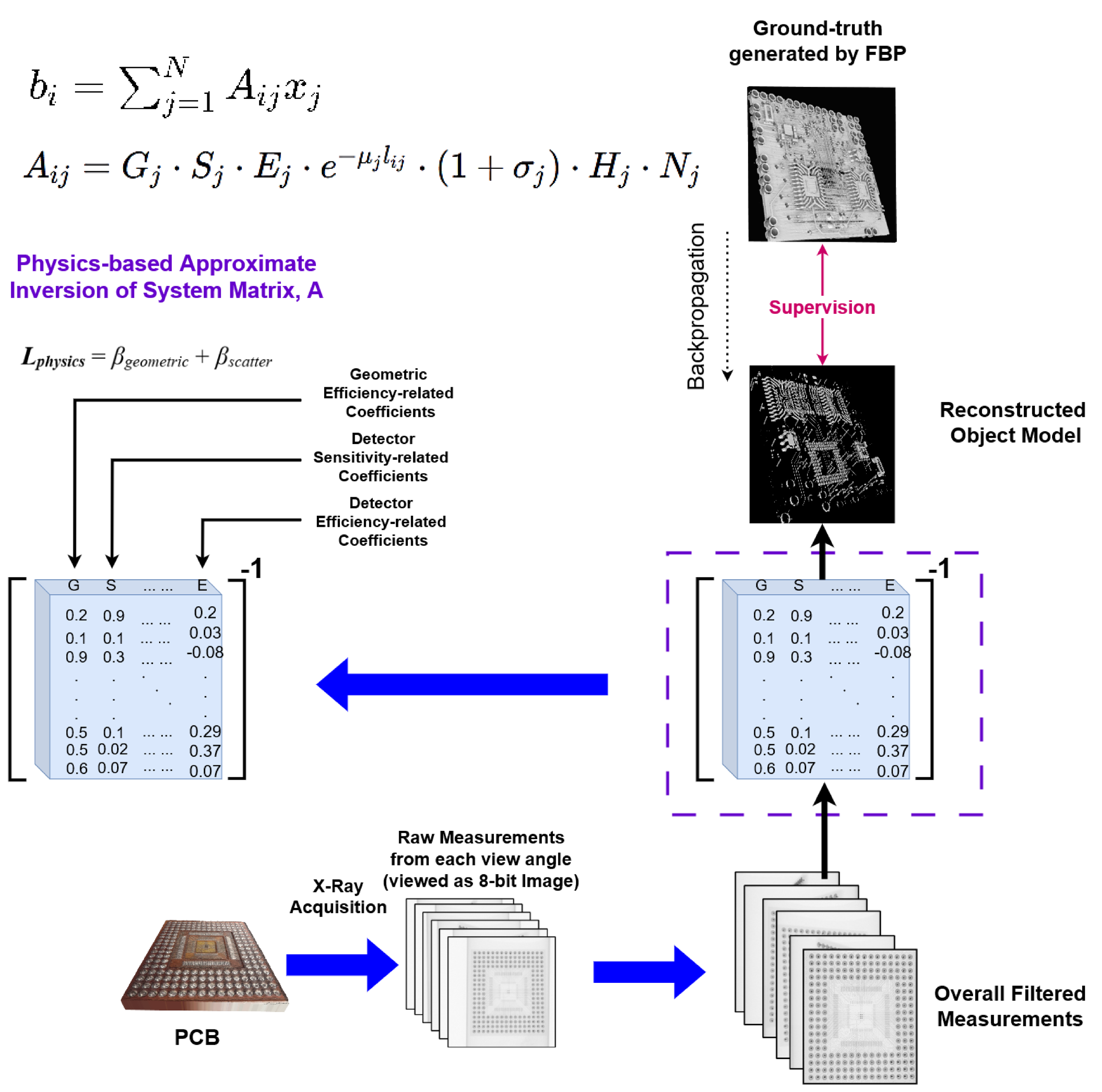

Fig. 2 Physics-Informed Machine Learning (PIML) for system matrix formulation in X-ray imaging forward models: A PCB inspection case study

Influential Factors: Material Properties, Geometric Configuration, Energy Spectrum and Detector Response, Scattering Effects, and Noise Modeling.

DISCUSSIONS

Existing Challenges

- Modeling X-ray interactions with complex materials often leads to errors.
- Scattering in dense materials introduces noise, requiring intensive corrections.
- Minor misalignments in the X-ray system cause significant reconstruction errors.

Future Research Directions

- Advanced modeling of X-ray interactions with complex materials.
- Integration of PIML with real-time feedback for better reconstructions.
- Efficient scatter correction for high-density materials.
- Optimization of geometric setups and noise modeling frameworks..

Advanced modeling of X-ray interactions, PIML integration, efficient scatter correction, and geometric optimization.

CONCLUSIONS

1. **PIML improves precision, resilience, and interpretability in X-ray system matrices by integrating physical laws.**
2. **Tackles challenges in material interaction modeling and noise reduction, even with limited data.**
3. **Sets the foundation for enhanced X-ray imaging across diverse applications.**

Integrating PIML with physical laws has the potential to significantly enhance X-ray imaging accuracy and robustness.

REFERENCES

1. Monakhova, K., Ng, R., and Bloom, J., "Physics-informed machine learning for computational imaging," tech. rep., University of California, Berkeley (2022).
2. X-ray computed tomography. *Nat Rev Methods Primers 1, 17 (2021).* https://doi.org/10.1038/s43586-021-00020-7