Dual Energy X-ray Material Decomposition

Computer Integrated Surgery II
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Introduction

- We proposed a novel learning-based pipeline of doing dual energy X-ray material decomposition, by explicitly combining model-driven approach, physical constraints and learning-based regularization to an integrated optimization objective function.
- The pipeline was trained on synthetic dataset generated using DeepDRR. Performance is evaluated using real X-rays acquired during femur cement injection cadaver study. The cement decomposition result is largely improved compared to traditional model-based methods.
- This research shows preliminary proof-of-concept results to introduce learning-based regularization in solving ill-posed inverse problem in mathematical physics.

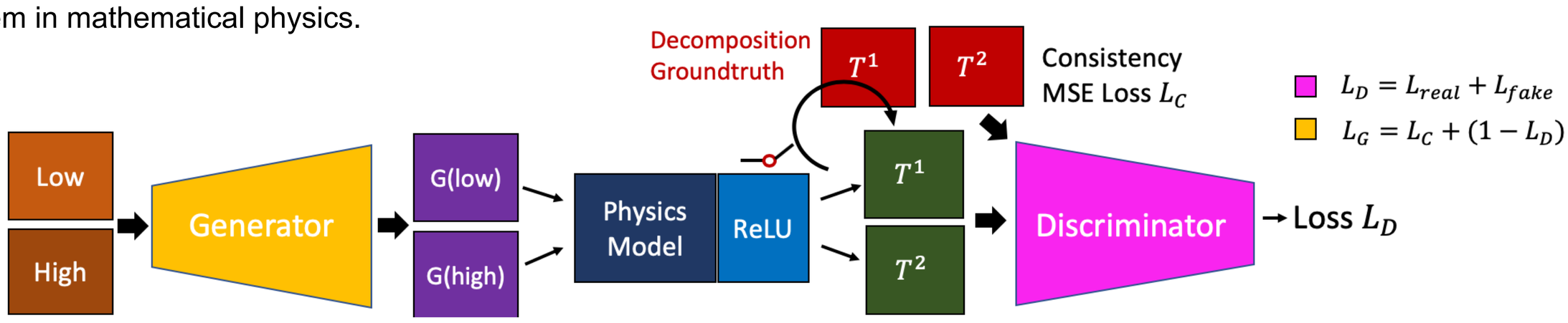

Figure. 1 Proposed pipeline of training material decomposition. The original input is X-ray acquisitions "Low" and "High". The Generator is a U-net based autoencoder, predicting the update of input images. We introduce physics model and ReLU as non-negative constraints to train the pipeline end-to-end.

The Problem

- Standard X-ray imaging brings difficulty for surgeons to identify ROI features from anatomical clutter. Traditional DEXA system was mainly applied to analyze bone density or fat tissue, but lack accuracy on tiny structure, for example, injected femur cement.
- 3D reconstructed femur cement is fuzzy using cluttered X-rays. A better 2D decomposition result will help monitor the shape of reconstructed cement during injection.
- Related studies have presented promising result by using deep learning in solving ill-posed inverse problem. There is opportunity to introduce deep learning to improve dual energy X-ray decomposition.

Our Solution

We formulate the problem as the following optimization objective, where $L(T(\boldsymbol{u}))$ models the non-negative physical constraint of decomposition result. $L_N(T(\boldsymbol{u}))$ is the learned regularization.

$$min_T \boxed{\left(M(\boldsymbol{u}) - WT(\boldsymbol{u})\right)^T \left(M(\boldsymbol{u}) - WT(\boldsymbol{u})\right)} + \boxed{L\left(T(\boldsymbol{u})\right)} + \boxed{L_N(T)}$$

Model-based least square solution — Physical constraint — Regularization

Fig. 2 illustrates the simulation process using femur CT and cement model to generate DRR images. The full pipeline is presented in Fig.1, where we built a fully differentiable framework to train the objective.

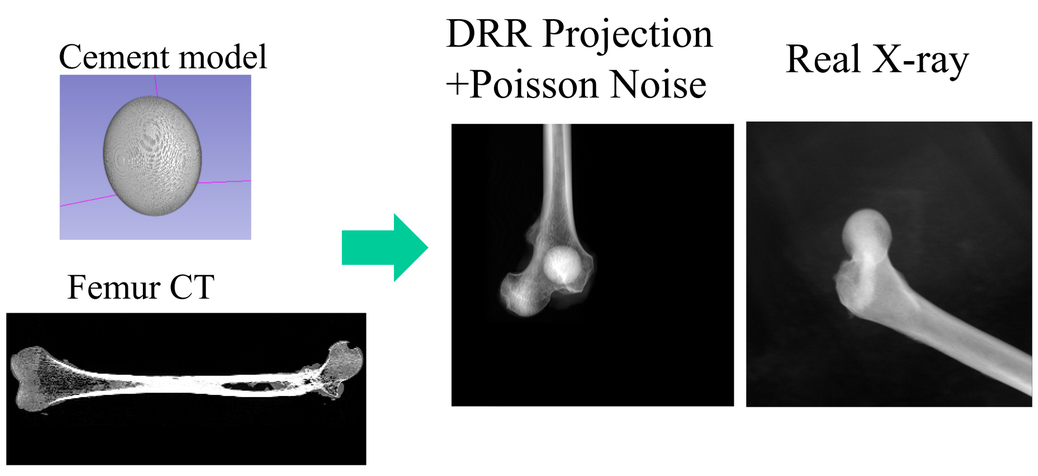

Figure. 2 Simulation DRR using cement model and femur CT

Outcomes and Results

We compare our pipeline with the traditional model-based method in both synthetic and real data set. Fig.3 presents the cement decomposition result. From the real X-ray decomposition, we can see that much more signals appear in the target region.

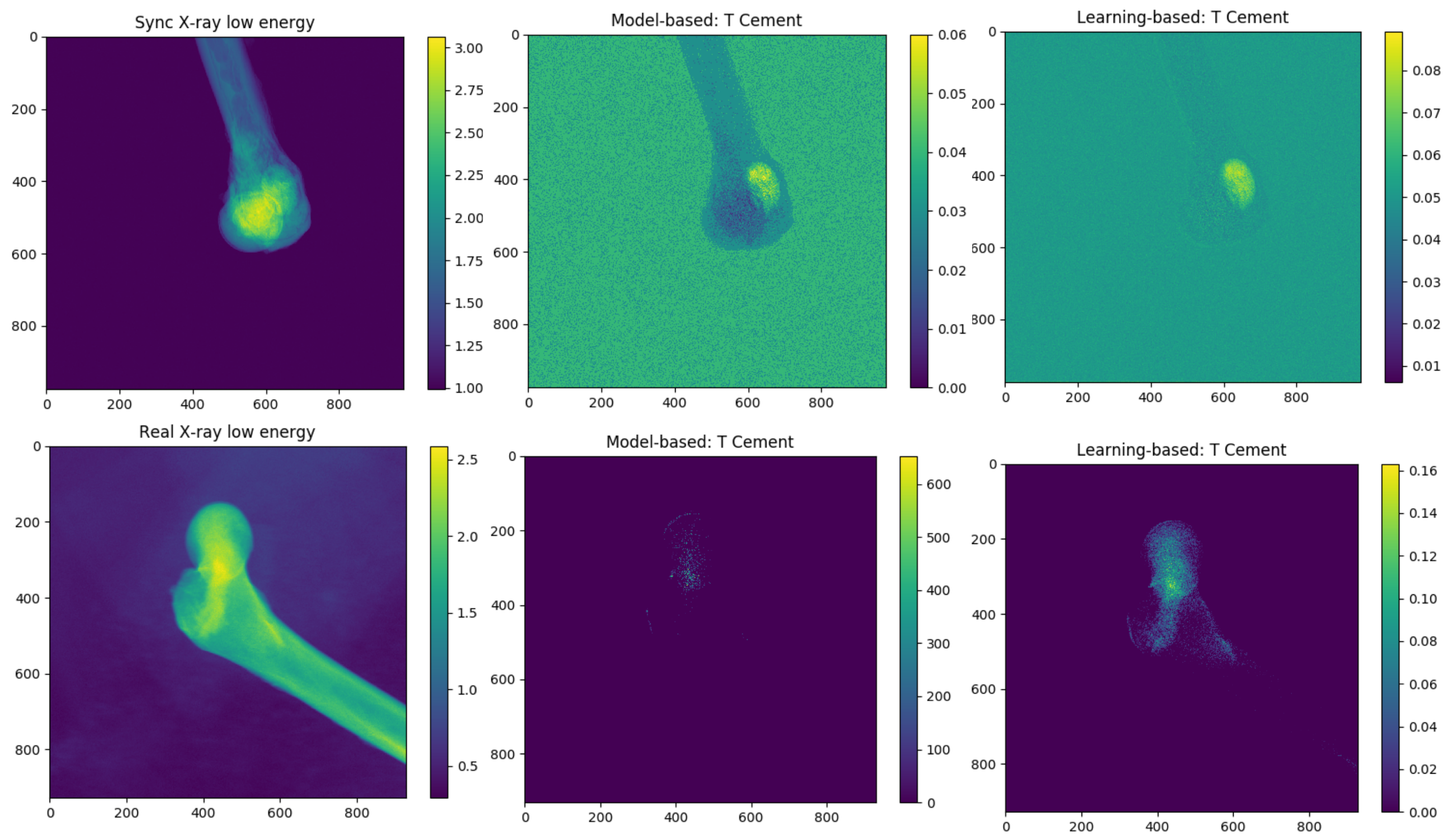

Figure. 3 Decomposition results of cement. Upper row: synthetic data; Lower row: real data.

Future Work

- This frame can be further investigated to include physics parameters into training.
- Introducing deep learning to solve inverse medical physics problem could be used in related applications, like 3D reconstruction.

Lessons Learned

- Understanding math logics is important before running to an end-to-end deep network.

Credits

Cong Gao conducts all the implementation.

Publications

This work could be extended for publication after more validation.

Support by and Acknowledgements

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