Material Decomposition using Dual-Energy X-ray of the nView System

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Objectives: Build a learning-based end-to-end multiple material decomposition system using dual-energy X-ray acquisitions by explicitly including the physical constraint in the estimation part.

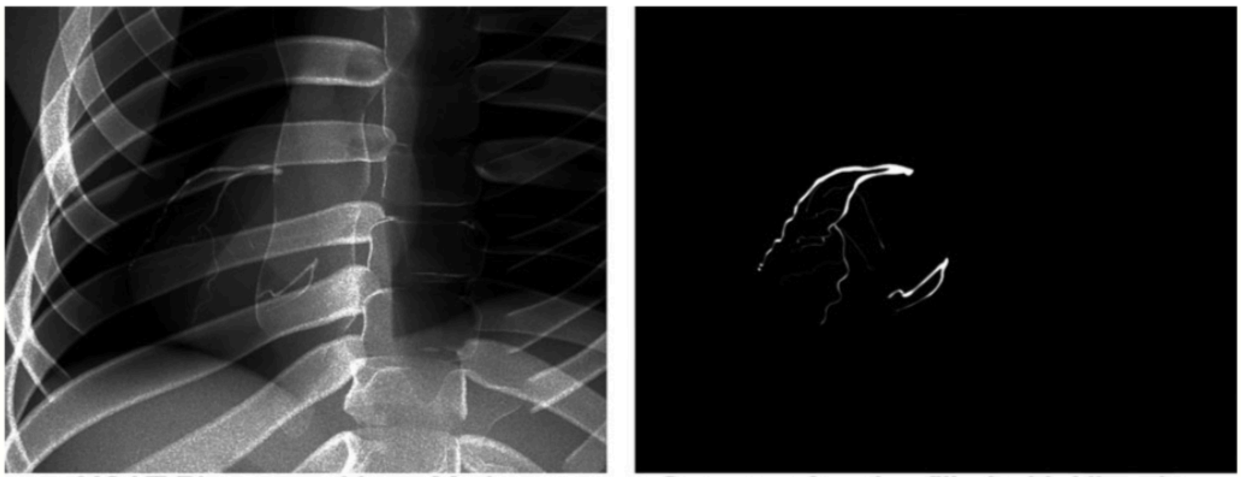


Figure 1 Illustration of material decomposition. Left: Simulated X-ray projection. Right: Decomposed material of interest.

Background and Motivation:

Conventional X-ray imaging is not sufficient to characterize object precisely, especially in the aspect of density, material identity, volume thickness, 3D depth of the object, etc. It is then hard for the surgeons to identify Region of Interest (ROI) using X-rays with multiple material stacked intensities. Also, if the object is small, then it may not be truncated which allows for very good reconstructions. Thus, there is a need to develop a high-quality decomposition system that can separate multiple materials in projection domain.

Taking dual-energy X-ray, which means acquiring two radiographs the same position at two distinct energies, is a popular method to enable the recover of material density and thickness based on the physics of X-ray formulation. According to the Beer-Lambert law, $N = N_0 \cdot exp(-\mu \cdot T)$, where N_0 is the number of photons emitting from the source, N is the number of photons received from the detector, T is the thickness of the material, and μ is the attenuation parameter. After log measurement, $m_E = -Log(N/N_0) = T \cdot \mu$, m_E and μ have formulated a linear relationship weighted by T.

Then, in the case of two materials, we can formulate the following linear system with two energy projections, note as LE and HE,

$$\begin{cases} m_{LE} = \mu_1^{\;LE} \cdot \boxed{T_1} + \mu_2^{\;LE} \cdot \boxed{T_2} \\ m_{HE} = \mu_1^{\;HE} \cdot \boxed{T_1} + \mu_2^{\;HE} \cdot \boxed{T_2} \end{cases}$$

In this scenario, the analytical solution exists, because there are two unknowns for two equations. While in a more realistic situation with multiple materials considering energy-dependent attenuation, the measurement will look like

$$m_{[E_1,E_2]}(r) = -Log(\int_{E_1}^{E_2} N_0(E) \cdot e^{-\sum_i T_i(r) \cdot \mu_i(E)} dE)$$

Then, we have more unknown $T_i(r)$ than our measurements. The problem will become mathematically ill-posed. Even in the above two-material situation, we are not including noise, disturbances, uncertainties and scatter inside the detector, which will make the solution far from ideal state. Including all these factors, the problem is very hard to model and resolve using traditional methods.

Technical Approach:

Thus, we propose to introduce deep learning to build end-to-end prediction framework, by explicitly including the physical constraint in the estimation part.

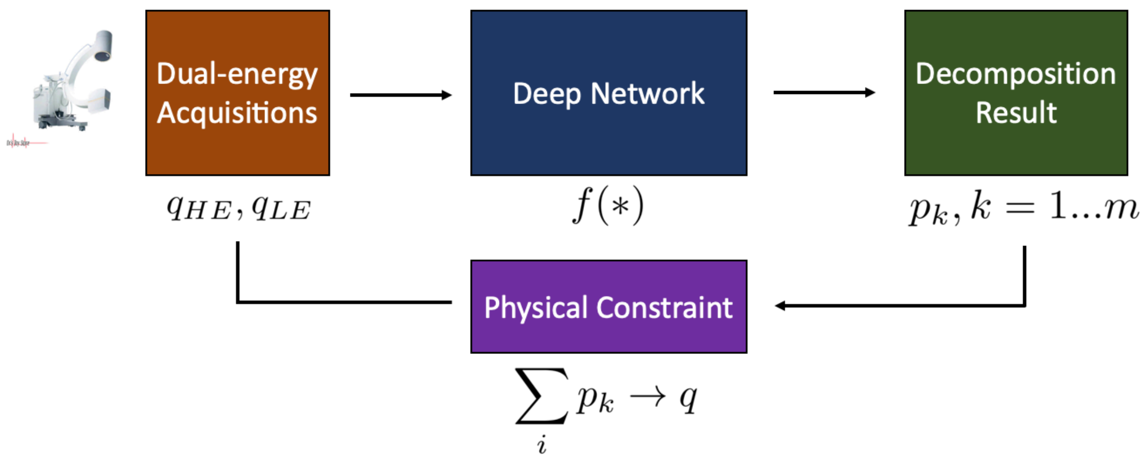


Figure 2. workflow

Figure.2 presents the overall workflow of the proposed pipeline. The input is the dual-energy acquisitions (q_{HE} for high energy and q_{LE} for low energy X-rays). The output is the decomposed projection result $p_k, k = 1 \dots m$, for m materials. One of physical constraints we want to introduce is that the reconstruction from the decomposition result should be close to the original input, which means $\sum_k p_k \rightarrow q$. We expect that the network can model the complex mapping function by training on large data samples.

Simulation Study

In order to conduct simulation study, we plan to use the recently proposed X-ray simulation framework – DeepDRR (Figure. 3), which is designed for fast and realistic simulation of fluoroscopy and digital radiography from CT scans. We can also simulate X-ray projections with different energy levels. Another benefit by introducing DeepDRR is that it enables segmentation in 3D domain, including bone, soft tissue and air, which can be used to generate target decomposition projections as groundtruth images for training.

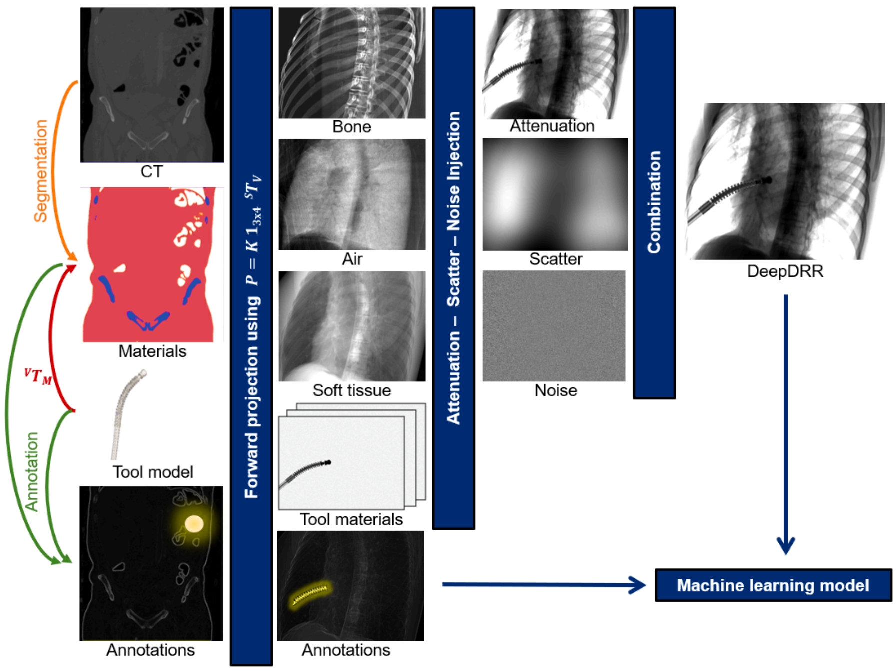


Figure 3 DeepDRR Framework

Simulation study will start from testing on two materials. Iodine is our first target, because it has an obvious K-edge jump in its photon attenuation at around 70keV (shown in Figure. 4), which is a very good feature to do dual-energy decomposition. We plan to first simulate bone injection cement inside the femur, which has iodine, and try to decompose it from the other background materials. If it works well, we then plan to test on more complicated situations.

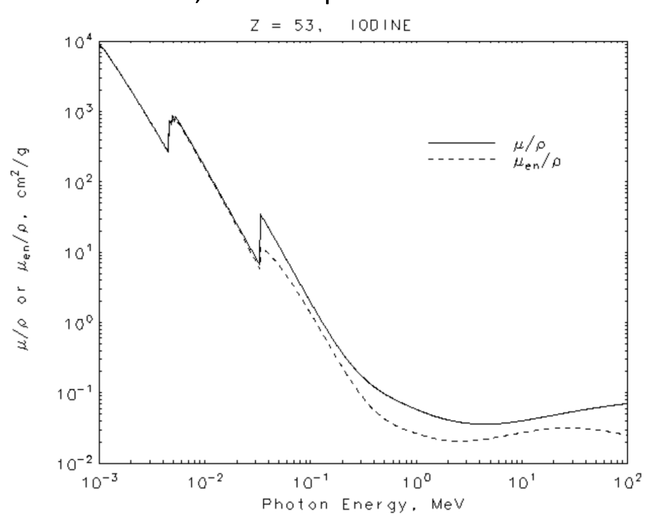


Figure 4 Iodine attenuation coefficient.

Real X-ray Validation

For Real X-ray validation, we plan to use the nView system, which is a fast 3D reconstruction system using low dose X-ray projections. Because the X-ray projections and reconstruction have correspondence with this system, its 3D reconstruction data can be used to label material groundtruth for validation.

Figure 5 Image captured from the nView system

We plan to use this nView system to conduct femoroplasty injection experiment and collect dual-energy dataset during cement injection process for validation of the proposed algorithm.

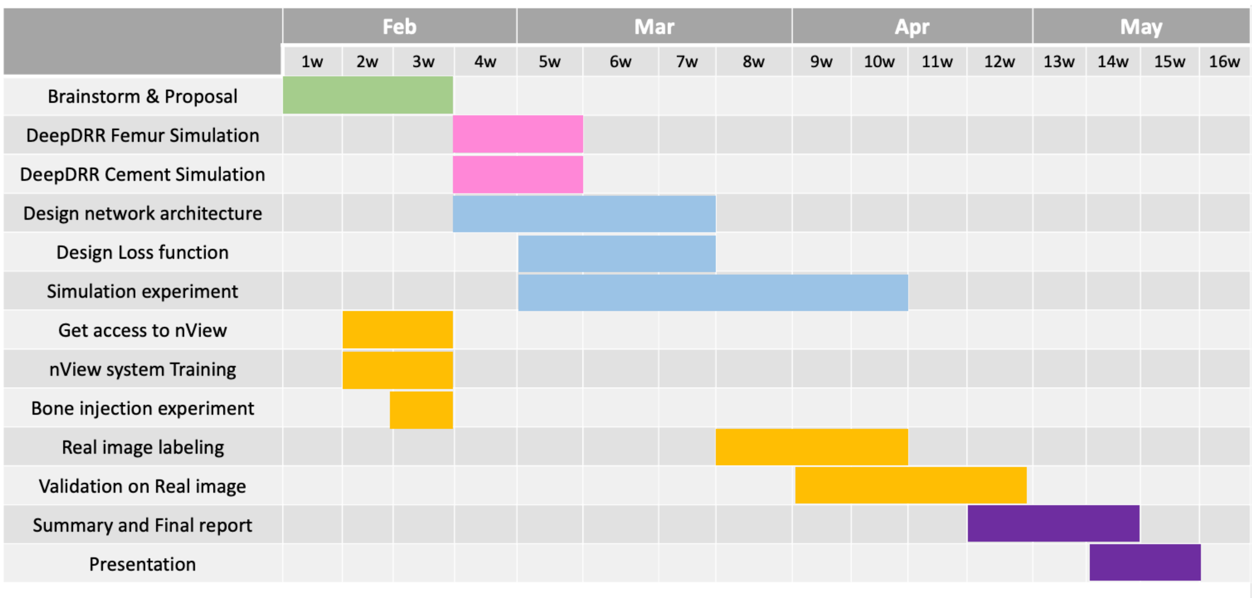
Deliverables:

Minimum	simulation	**X-ray simulation software** using DeepDRR framework from femur CT data
	algorithm	**Deep Network software**
	Validation	**Processed data & Validation result** from real bone injection experiment
	Documentation	**Final Report** of algorithm description, simulation & validation results
Expected	simulation	**X-ray simulation software** with cement/metal simulation
	algorithm	**Deep Network software** with workable architecture
	Validation	**Processed data & Validation result** of cement injection dataset
	Documentation	**Final Report** of algorithm description, simulation & validation results
Maximum	simulation	**X-ray simulation software** with cement/metal simulation, improvement of noise, scattering modeling, well fit nView system effect
	algorithm	**Deep Network software** with well-performed architecture and generalization ability
	Validation	**Real time cement monitoring** using the nView system
	Documentation	**Final Report** of algorithm description, simulation & validation results

Dependencies:

	Dependency	Solution	Alternative	Status
1	Deep DRR software	Contact Dr. Unberath	X	Solved
2	Real Femur CT Data before & after injection	Contact Amir. Farvardin	Contact BIGSS/CAMP lab	Solved
3	Access to the nView system	Contact Dr. Armand	X	Solved
4	nView system useage training	Contact Singchun Lee, watch the nView training video	Contact the nView team	Solved
5	Femur injection experiment	Schedule with Dr. Armand	X	Solved
6	Computation Resource	Desktop from BIGSS lab	MARCC	Solved
7	Feedback from instructors	Attend group/personal meeting	X	Solved

Schedule:



Milestones:

✅ 1. Project Proposal & kick-off

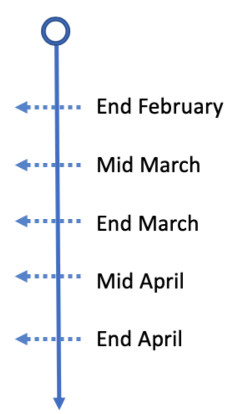
✅ 2. nView system bone injection experiment

❗ 3. Finish simulation software and simulation dataset

❗ 4. Finish network design for 2 materials, get simulation result

❗ 5. Finish network design for multiple materials, get simulation result

❗ 6. Test on real dataset, get validation result



Management Plan:

- Meeting with mentors:
  - Weekly meet with Dr. Armand and Dr. Unberath, Tuesday morning
  - Attend weekly meeting with Dr. Taylor, Friday afternoon
- Data management:
  - Simulation data: save locally on BIGSS desktop
  - Real X-ray data: share across BIGSS shared drive
- Software:
  - Save locally under development, backup through Github on private account
  - Write documents and instructions for software
  - Publish on Github after work is published

Reading List:

1) Mazess, R. B., Barden, H. S., Bisek, J. P., & Hanson, J. (1990). Dual-energy x-ray absorptiometry for total-body and regional bone-mineral and soft-tissue composition. *The American journal of clinical nutrition*, *51*(6), 1106-1112.
2) Rebuffel, V., & Dinten, J. M. (2007). Dual-energy X-ray imaging: benefits and limits. *Insight-non-destructive testing and condition monitoring*, *49*(10), 589-594.
3) Albarqouni, S., Fotouhi, J., & Navab, N. (2017, September). X-ray in-depth decomposition: Revealing the latent structures. In *International Conference on Medical Image Computing and Computer-Assisted Intervention* (pp. 444-452). Springer, Cham.
4) Lu, Y., Kowarschik, M., Huang, X., Xia, Y., Choi, J. H., Chen, S., ... & Maier, A. (2018). A learning-based material decomposition pipeline for multi-energy x-ray imaging. *Medical physics*.
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6) Atria, C., Last, L., Packard, N., & Noo, F. (2018, March). Cone beam tomosynthesis fluoroscopy: a new approach to 3D image guidance. In *Medical Imaging 2018: Image-Guided Procedures, Robotic Interventions, and Modeling* (Vol. 10576, p. 105762V). International Society for Optics and Photonics.
7) Unberath, M., Zaech, J. N., Lee, S. C., Bier, B., Fotouhi, J., Armand, M., & Navab, N. (2018, September). Deepdrr–a catalyst for machine learning in fluoroscopy-guided procedures. In *International Conference on Medical Image Computing and Computer-Assisted Intervention* (pp. 98-106). Springer, Cham.