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

**Member:** Cong Gao

**Mentor:** Mathias Unberath, Mehran Armand, Russell Taylor

**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.](image)

**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 \( \mu \) is the attenuation parameter. After log measurement, \( m_E = -\log(N/N_0) = T \cdot \mu \), \( m_E \) and \( \mu \) 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 \( HE \),
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

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

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 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 $p_k, k = 1 \ldots m$, 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](image)

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](image)
**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.

![Image](image.png)

*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:

<table>
<thead>
<tr>
<th>Minimum</th>
<th>Expected</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>simulation</td>
<td>X-ray simulation software using DeepDRR framework from femur CT data</td>
<td>X-ray simulation software with cement/metal simulation, improvement of noise, scattering modeling, well fit nView system effect</td>
</tr>
<tr>
<td>algorithm</td>
<td>Deep Network software</td>
<td>Deep Network software with well-performed architecture and generalization ability</td>
</tr>
<tr>
<td>Validation</td>
<td>Processed data &amp; Validation result from real bone injection experiment</td>
<td>Real time cement monitoring using the nView system</td>
</tr>
</tbody>
</table>
Dual-energy X-ray material decomposition

Cong Gao, 2nd year Computer Science PhD

Dependencies:

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

Schedule:

<table>
<thead>
<tr>
<th></th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1w</td>
<td>2w</td>
<td>3w</td>
<td>4w</td>
</tr>
<tr>
<td></td>
<td>5w</td>
<td>6w</td>
<td>7w</td>
<td>8w</td>
</tr>
<tr>
<td></td>
<td>9w</td>
<td>10w</td>
<td>11w</td>
<td>12w</td>
</tr>
<tr>
<td></td>
<td>13w</td>
<td>14w</td>
<td>15w</td>
<td>16w</td>
</tr>
</tbody>
</table>

- Brainstorm & Proposal
- DeepDRR Femur Simulation
- DeepDRR Cement Simulation
- Design network architecture
- Design Loss function
- Simulation experiment
- Get access to nView
- nView system Training
- Bone injection experiment
- Real image labeling
- Validation on Real image
- Summary and Final report
- Presentation

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:


