BRIDGE TO REAL DATA: EMPIRICAL MULTIPLE MATERIAL CALIBRATION FOR LEARNING-BASED MATERIAL DECOMPOSITION

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Introduction

Spectral computed tomography (CT) started around 1975 as an improvement in CT technology, which enables to gain information on the energy-dependent attenuation properties of the object for material decomposition.

In order to bring our learning-based material decomposition approaches closer to clinical applications, we applied an empirical multi-material calibration as well as performed several experiments to investigate the feasibility of the calibration.

Methods

The proposed empirical multiple material calibration relies on image registration. We used short scan CT data from CRIS's Electron Density Phantom Model 062 (CIRS, Norfolk, Virginia, USA) using a Siemens C-arm CT system. Additionally we built the corresponding numeric phantom data in a software framework. After that we applied registration approaches for matching the simulated data to the acquired data, which generates not only prior knowledge but also ground truth for the following material decomposition process, as well as the ground truth for quantitative evaluations. All methods are implemented in Java-based framework CONRAD[1].

Data Generation

- Real Scan
  - Scanner: Siemens kVp prototype Phantom: CRIS's Electron Density Phantom Model 062 (ED phantom)
  - Source and detector setup:
    - Various kVp setups range at 50kV, 90kV and 125kV
    - 1240×960 pixels, 10s DSA
    - Primary Angle 197.54 (Short scan)
- The numeric ED phantom
  - Building Numeric CrisEDPhantomM062
  - Implement by CONRAD
  - Only inner disk was built
  - Could define same configuration with real scanner.

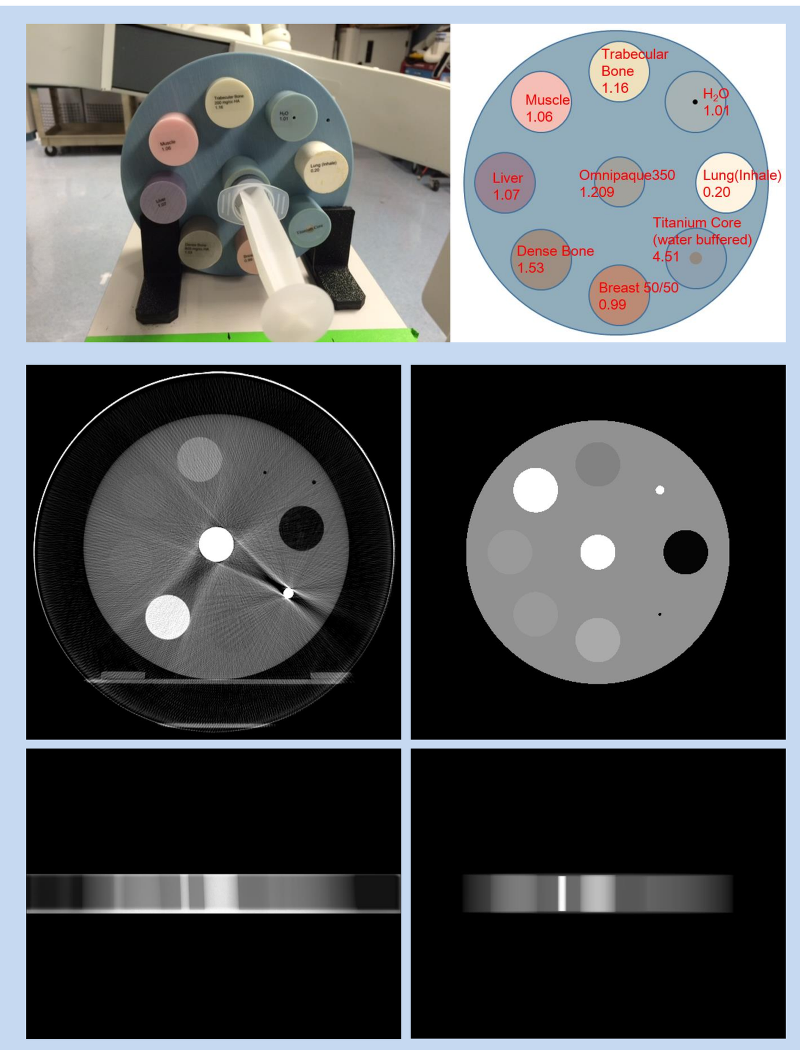

Figure 1: The CRIS's ED Phantom and the corresponding analytic description, as well as the data generation

Data Calibration

- 3D-3D registration[2]
- Yield the ground truth data for the individual material.

Learning-based Material Decomposition[3]

- Feature extractor:
  - The spectral information (namely "Channel")[4]
  - The polynomial spectral information (namely "Polynomial")[5]
  - the Trainable Weka segmentation feature (namely "WEKA")[6]
- Classification Methods: Bootstrap Aggregating (Bagging) using REPTrees

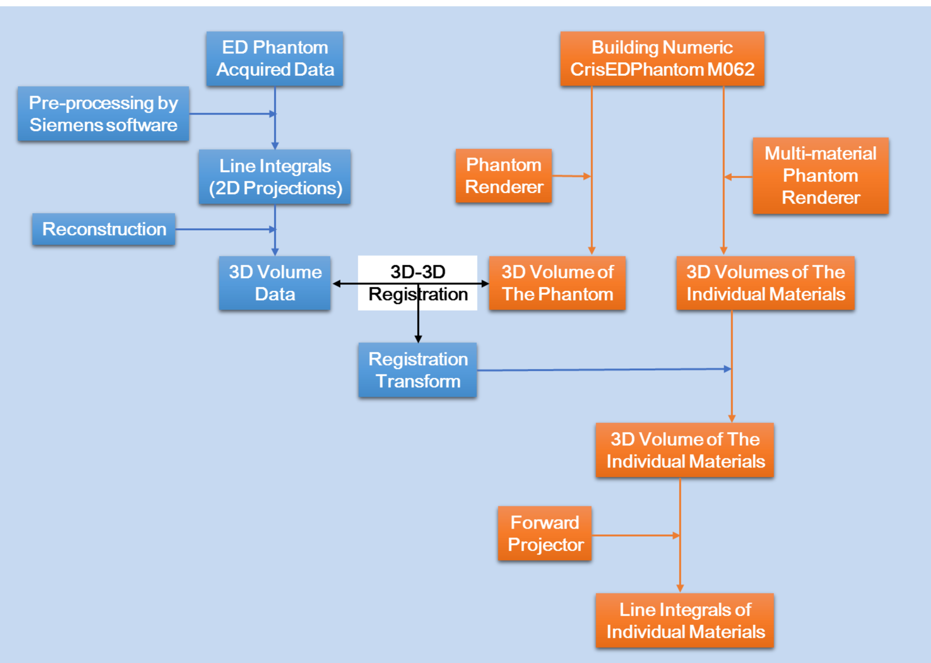

Figure 2: The calibration procedure flow chart

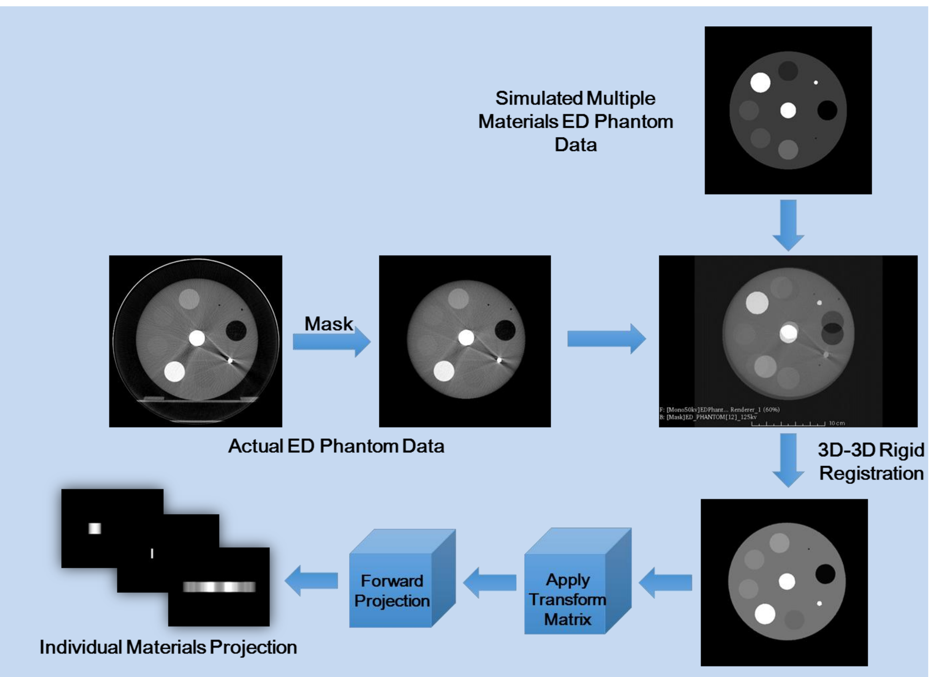

Figure 3: The 3D-3D registration procedure

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Results

Figure 4 and Figure 5 show the material decomposition results of titanium rod, dense bone and water, and the respective reconstructions of the material decomposition results, along with the quantitative results.

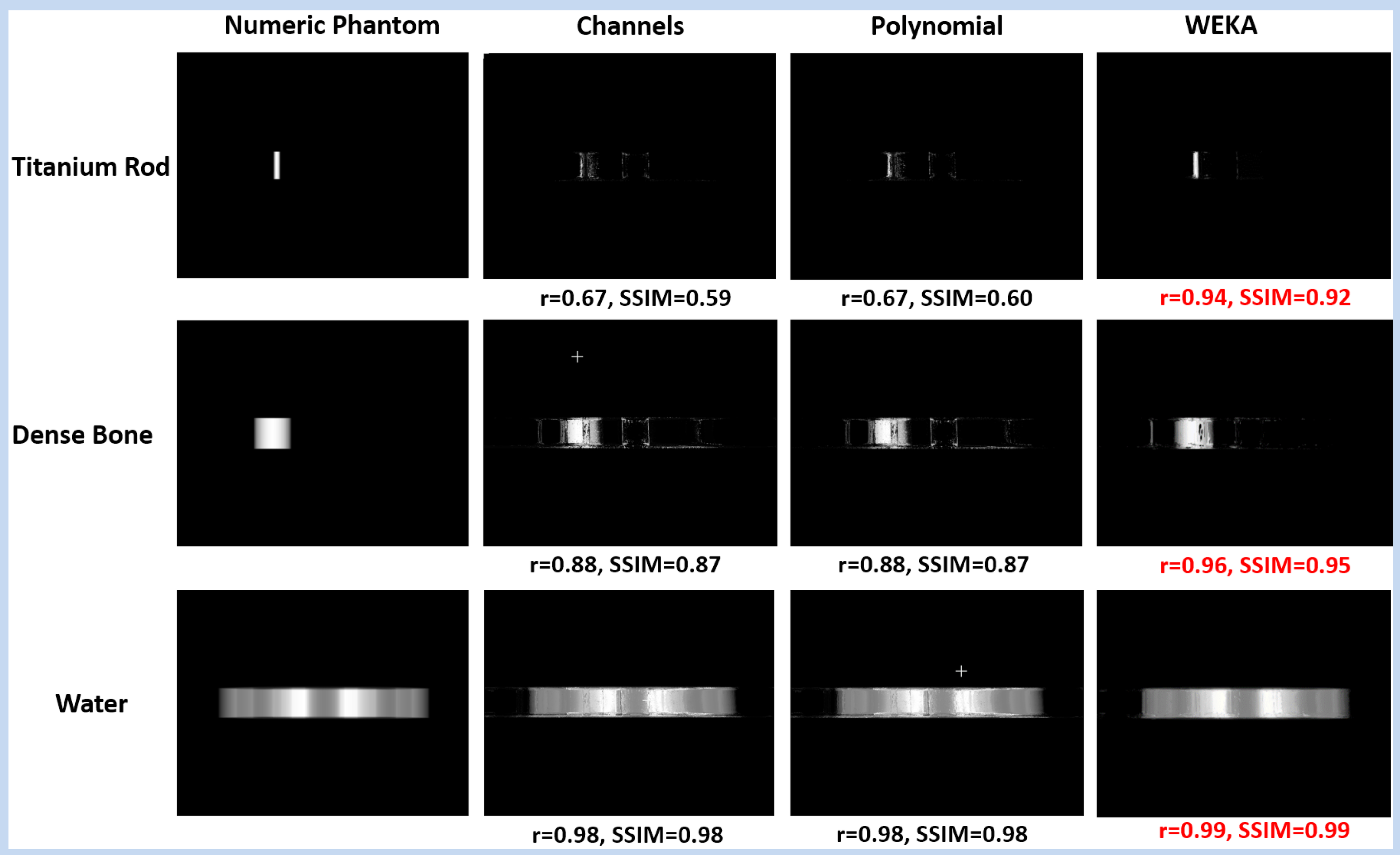

Figure 4: The material decomposition results of titanium rod, dense bone and water, as well as the quantitative evaluation results.

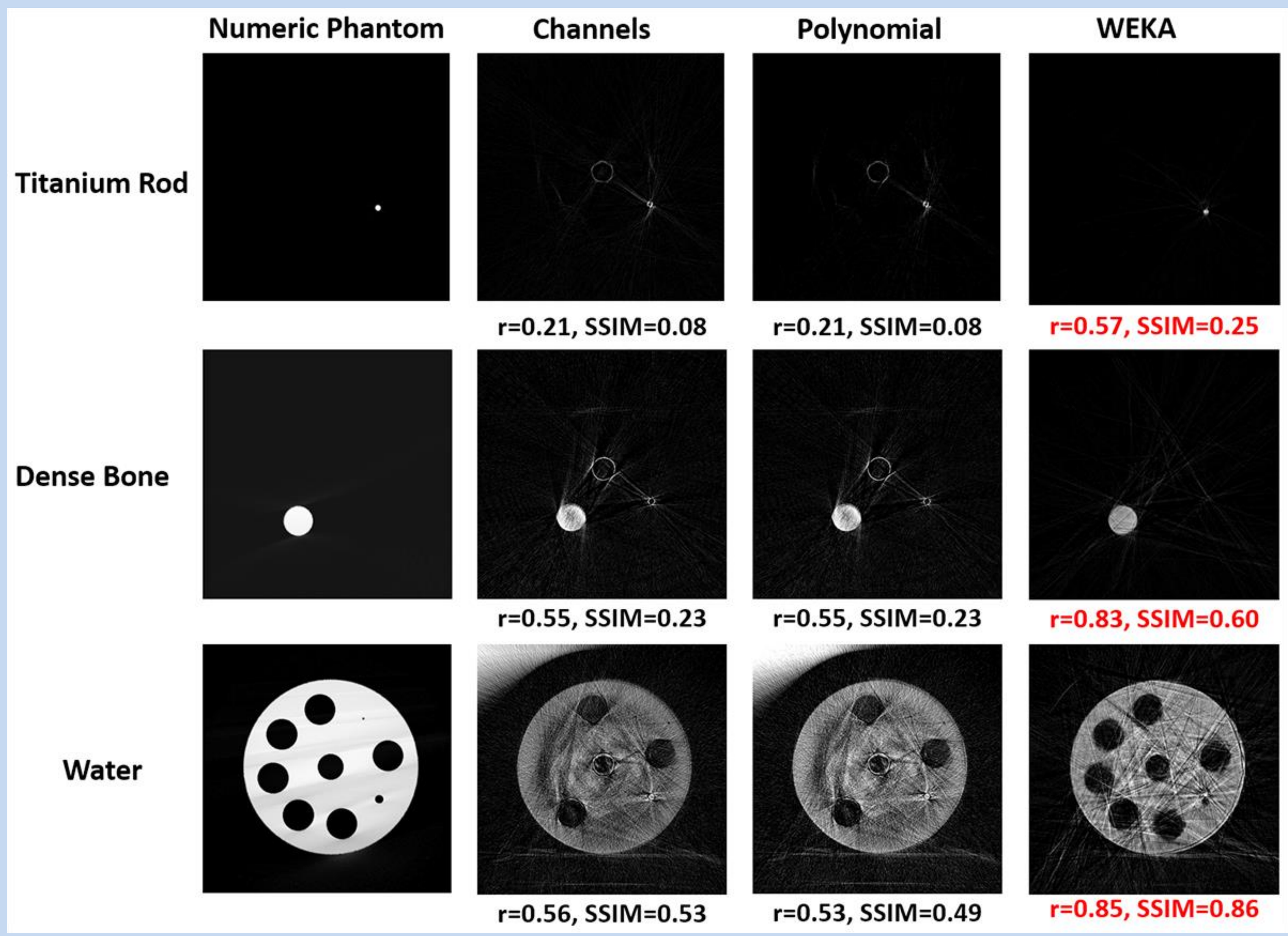

Figure 5: Central slice of the material decomposition reconstruction, and the quantitative evaluation results.

Discussion and Conclusion

In this study, we proved the concept of calibrating multi-material phantom using a registration method. We built the corresponding numeric phantom data using the analytic description of the phantom and the actual scanning setup information. According to the preliminary decomposition results, we successfully decomposed the plugs of different materials using learning-based material decomposition process, which indicates that the empirical multiple materials calibration is valid for learning-based material decomposition.

References

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