Projection-based Material Decomposition by Machine Learning using Image-based Features for Computed Tomography

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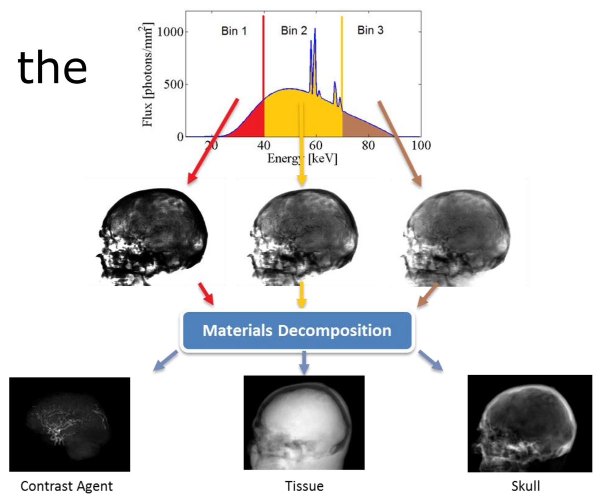
Introduction

Energy-Selective Photon Counting Detectors

- PCDs assign incoming photons to energy bins.
- Spectral CT facilitates the quantitative measurement of material properties.

Material Decomposition

- Decompose acquired object into materials using the polychromatic X-ray data.



Potential Applications

- Single Shot DSA
- Beam-Hardening Artifact Reduction
- Motion Compensation
- Scatter Correction

Why Machine Learning?

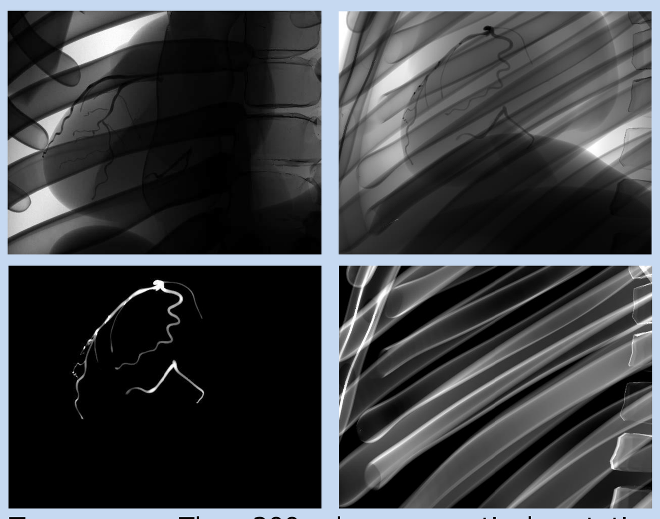
- Machine learning plays an essential role in the medical imaging field:
  - Computer-aided diagnosis
  - Image segmentation, registration and fusion
- Features contain various information and could serve as training features to build a classifier.

Methods

In this paper, we extracted appropriate image-based features from energy-resolved computed tomography images and incorporated these features in a machine learning material decomposition process to separate bone and contrast agent in projection domain.

Data Generation

- Simulation setup
  - Two different scenarios (no motion / motion)
  - 620x480 pixels with pixel size 0.4x0.4 mm
  - 133 projections
  - Noisy and noiseless
- Source and detector setup
  - 3 bins equally spaced from 10 – 100 keV
  - 3 keV bin overlap
  - 2.5 mAs time current product
  - 90 keV tube voltage



Top row: The 200 degree vertical rotation projection (left), the heart cycle and lung motion projection (right).
Bottom row: Two materials that need to be decomposed, Ultravist 370 and bone.

Two Reference Approaches

- Energy Channel[1]
  - Raw projection data of the energy channels.
  - Pixel intensities as features for the BMD method.
- Polynomial Combination[2]
  - Polynomial function for feature calculation: $F = C_0^n + C_1^m + \cdots + C_{N-1}^l$
  - $C_0 \cdots C_{N-1}$ are the N different channels and n, m and l are the power of the channel.

Load Image-based Features for Machine Learning

- Gray Level Co-occurrence Matrix (GLCM)
  - Describing texture by considering the spatial distribution and location of certain gray levels.
- Histogram
- Vesselness
  - Used for identification of vascular structures.
- The Trainable Weka Segmentation
  - Compatible to ImageJ
  - Contained a lot of features

Classification Methods

- Linear regression
- Reduced Error Pruning Tree (REPTree)
- Bootstrap Aggregating (Bagging) using REPTree

Evaluation Methods

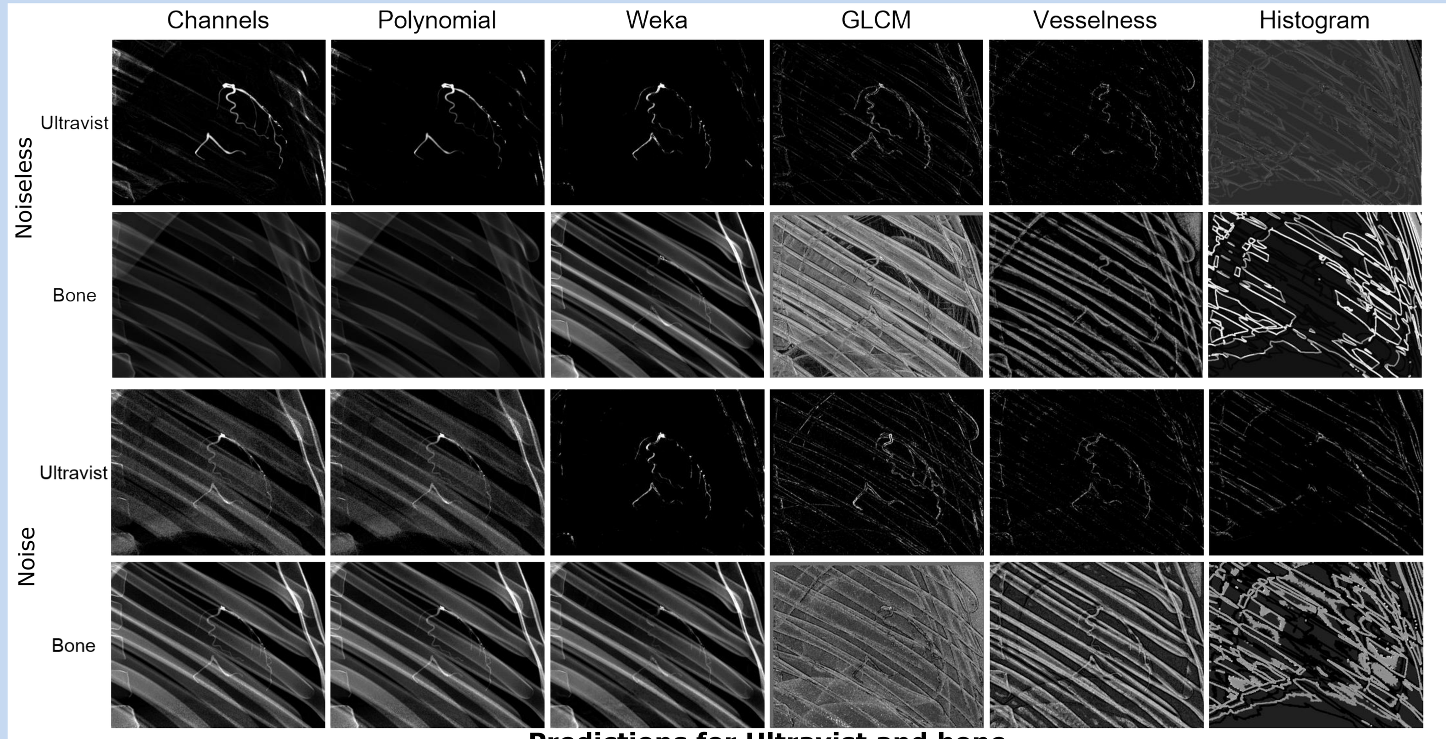
- Linear correlation
- Structural similarity

The studies are carried out in order to examine the feasibility of doing material decomposition using imaged-based features incorporated in machine learning approaches. All methods are implemented in Java-based framework CONRAD[3] and will be made available as open source software.

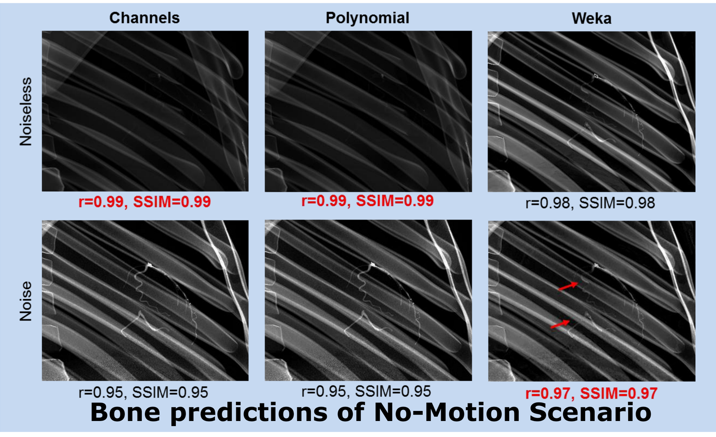
Results

Due to the superior performance, therefore we only present the results with the 90 percent bagging classifier .

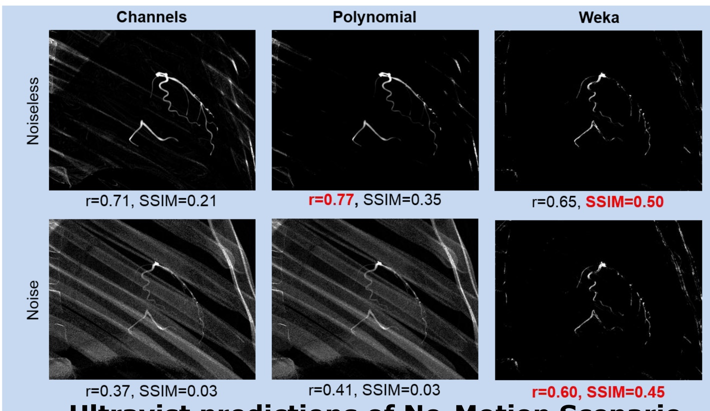
No-Motion Scenario (Short Scan)



Predictions for Ultravist and bone

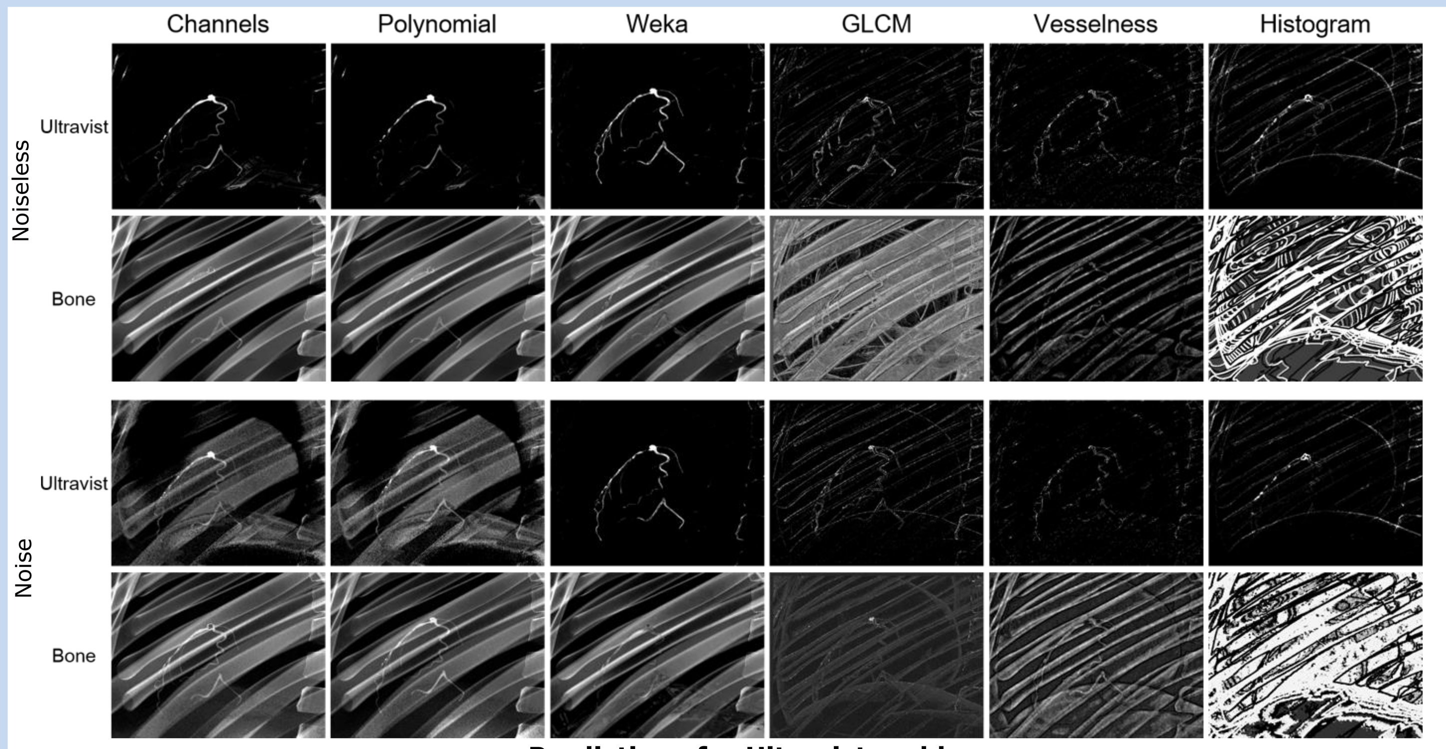


Bone predictions of No-Motion Scenario

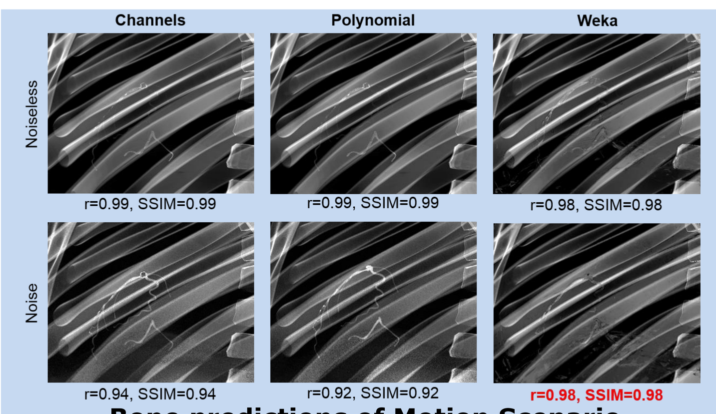


Ultravist predictions of No-Motion Scenario

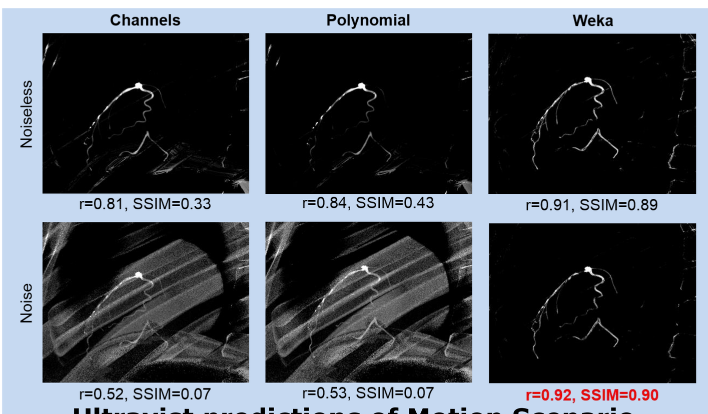
Motion Scenario (Heart and Breathing Motion)



Predictions for Ultravist and bone



Bone predictions of Motion Scenario



Ultravist predictions of Motion Scenario

Quantitative Evaluation

Image	Material		Channel r	Channel SSIM	Polynomial r	Polynomial SSIM	Weka r	Weka SSIM
Heart cycle an lung motion	Bone	noiseless	**0.99 (0.00)**	**0.99 (0.00)**	**0.99 (0.00)**	**0.99 (0.00)**	**0.98 (0.00)**	**0.98 (0.00)**
		noise	0.94 (0.00)	0.94 (0.00)	0.92 (0.00)	0.92 (0.00)	**0.98 (0.00)**	**0.98 (0.00)**
	Ultravist	noiseless	0.79 (0.03)	0.32 (0.02)	0.82 (0.02)	0.41 (0.02)	**0.89 (0.02)**	**0.87 (0.03)**
		noise	0.49 (0.05)	0.06 (0.01)	0.49 (0.05)	0.06 (0.01)	**0.89 (0.02)**	**0.88 (0.02)**
Short Scan(no motion)	Bone	noiseless	**0.99 (0.00)**	**0.99 (0.00)**	**0.99 (0.00)**	**0.99 (0.00)**	**0.98 (0.01)**	**0.97 (0.01)**
		noise	**0.95 (0.00)**	**0.95 (0.00)**	**0.95 (0.00)**	**0.95 (0.00)**	**0.95 (0.01)**	**0.95 (0.02)**
	Ultravist	noiseless	0.71 (0.02)	0.21 (0.01)	0.75 (0.03)	0.29 (0.03)	**0.82 (0.11)**	**0.47 (0.12)**
		noise	0.35 (0.02)	0.03 (0.00)	0.35 (0.22)	0.03 (0.00)	**0.55 (0.10)**	**0.40 (0.08)**

Image	Material		GLCM r	GLCM SSIM	Vesselness r	Vesselness SSIM	Histogram r	Histogram SSIM
Heart cycle an lung motion	Bone	noiseless	0.58 (0.00)	0.51 (0.00)	0.52 (0.00)	0.52 (0.00)	0.27 (0.01)	0.19 (0.00)
		noise	0.22 (0.01)	0.01 (0.00)	0.59 (0.00)	0.53 (0.00)	0.14 (0.01)	0.08 (0.00)
	Ultravist	noiseless	0.29 (0.01)	0.21 (0.01)	0.24 (0.02)	0.14 (0.02)	0.34 (0.03)	0.24 (0.02)
		noise	0.25 (0.05)	0.03 (0.01)	0.26 (0.02)	0.18 (0.02)	0.30 (0.03)	0.21 (0.02)
Short Scan(no motion)	Bone	noiseless	0.53 (0.14)	0.45 (0.02)	0.61 (0.02)	0.56 (0.02)	0.07(0.04)	0.07(0.04)
		noise	0.24 (0.03)	0.15 (0.02)	0.62 (0.02)	0.56 (0.02)	0.03(0.03)	0.03(0.03)
	Ultravist	noiseless	0.26 (0.04)	0.17 (0.02)	0.24 (0.01)	0.13 (0.01)	0.03(0.01)	0.00(0.00)
		noise	0.22 (0.03)	0.14 (0.02)	0.26 (0.01)	0.16 (0.01)	0.09(0.01)	0.04(0.00)

The mean and standard deviation of the linear correlation and SSIM between the prediction results from the different material decomposition approaches and the ground truth were calculated and presented in the Table .

Conclusions

- The linear correlation (0.49 to 0.89) and SSIM (0.06 to 0.88) are much improved by using appropriate features in the noise and motion scenario.
- In this study, the bagging classifier always gives the best results.
- The results suggest that it is possible to decompose materials by using appropriate image-based features.

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