An Intelligent System Approach for Probabilistic Volume Rendering using Hierarchical 3D Convolutional Sparse Coding

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Motivation

- Intensity-based feature model may not work well under certain harsh conditions (e.g. noise and anisotropic shapes)

Method

Method Overview

- Get voxel feature using Hierarchical Convolutional Sparse Coding
- Voxel Classification
- Multi-labeled volume using Probabilistic Transfer Function

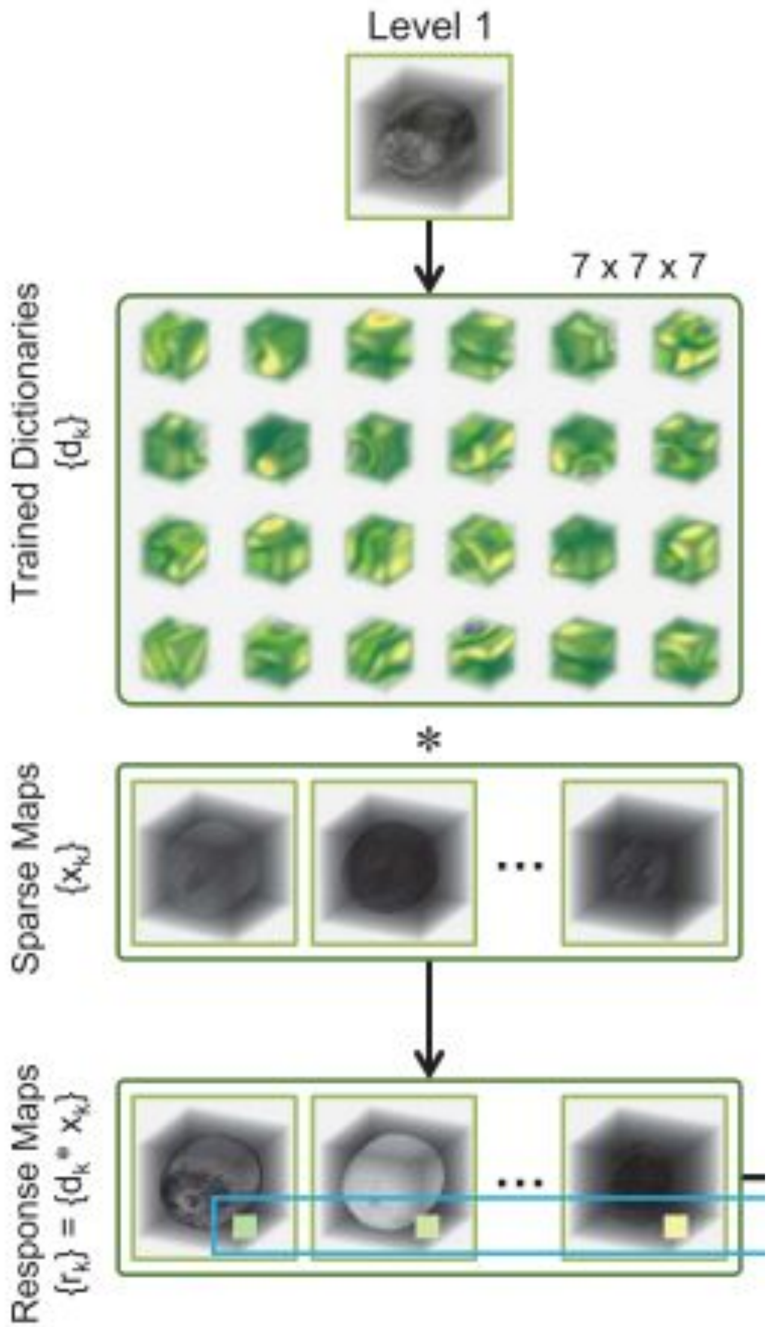
Convolutional Sparse Coding

- For a set of images, find a set of filters (atom) and its associated sparse map to represent it.
- $s = \sum_k d_k * x_k$ (d: filters, x: sparse map)
- Optimization problem:

$$\min_{d,x} \frac{\alpha}{2} \left\| s - \sum_k d_k * x_k \right\|_2^2 + \lambda \sum_k \|x_k\|_1 \quad s.t.: \quad \|d_k\|_2^2 \leqslant 1$$

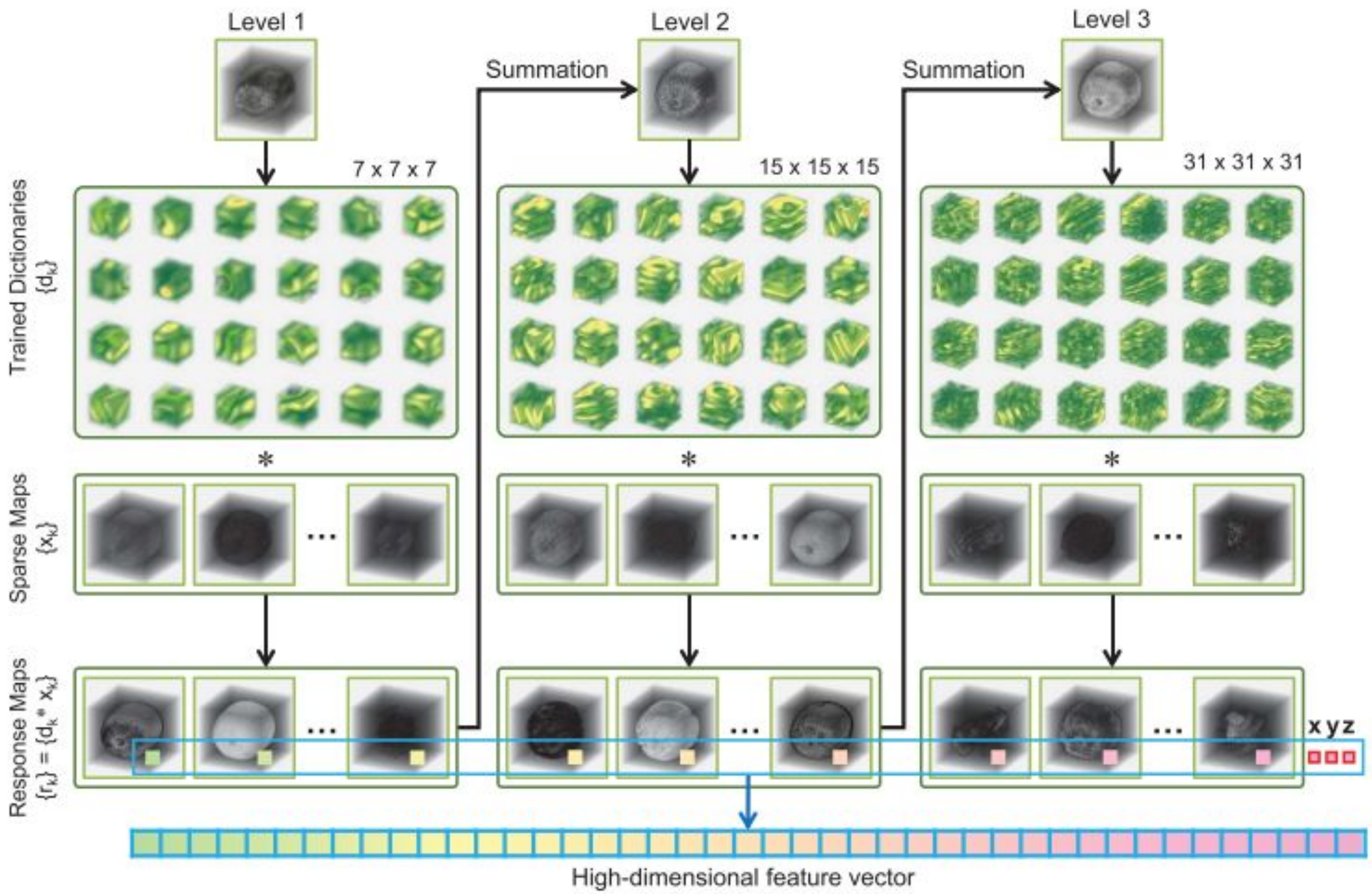
- The second term force the x to be sparse

3D Convolutional Sparse Coding



Hierarchical

- Use different size of filters to gather different level of feature resolution to form the High-dimensional feature vector



Classification

- User define the labels for voxels using a drawing tool.
- On-the-fly regression training (random forest algorithm)
- Random forest algorithm: Ensembled decision trees

Probabilistic Transfer Function

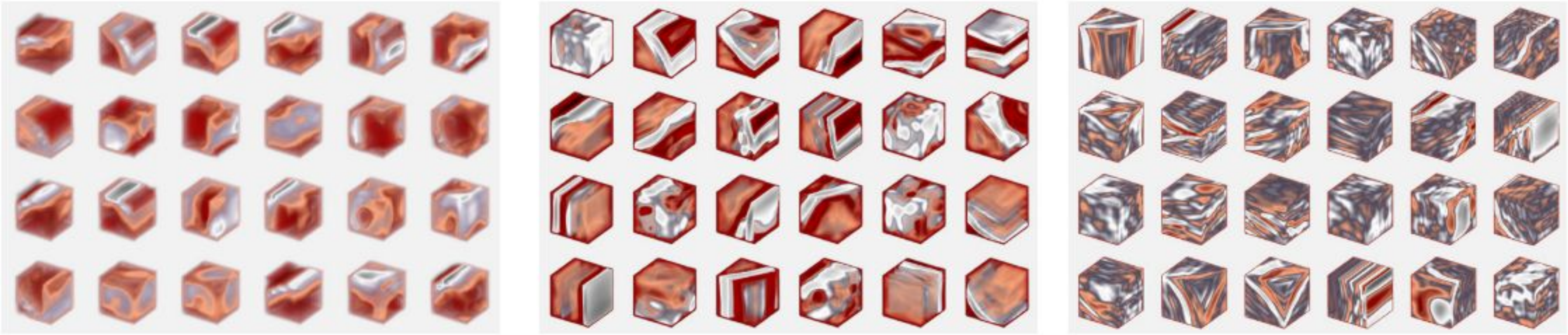
- Color and Alpha is determined by the probability of label n:

$$v.Color = \sum_n TableColor(n, v.Prob_n) \times v.Prob_n$$
$$v.Alpha = \sum_n TableAlpha(n, v.Prob_n) \times v.Prob_n$$

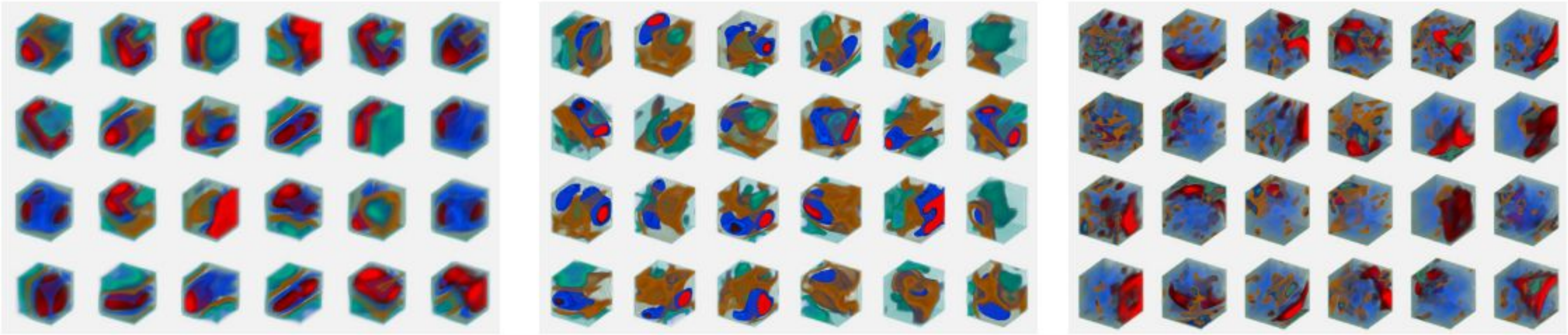
- Smoother transition.

Results

Visualization of dictionaries



(a) Dictionaries of LdCT-Chest dataset

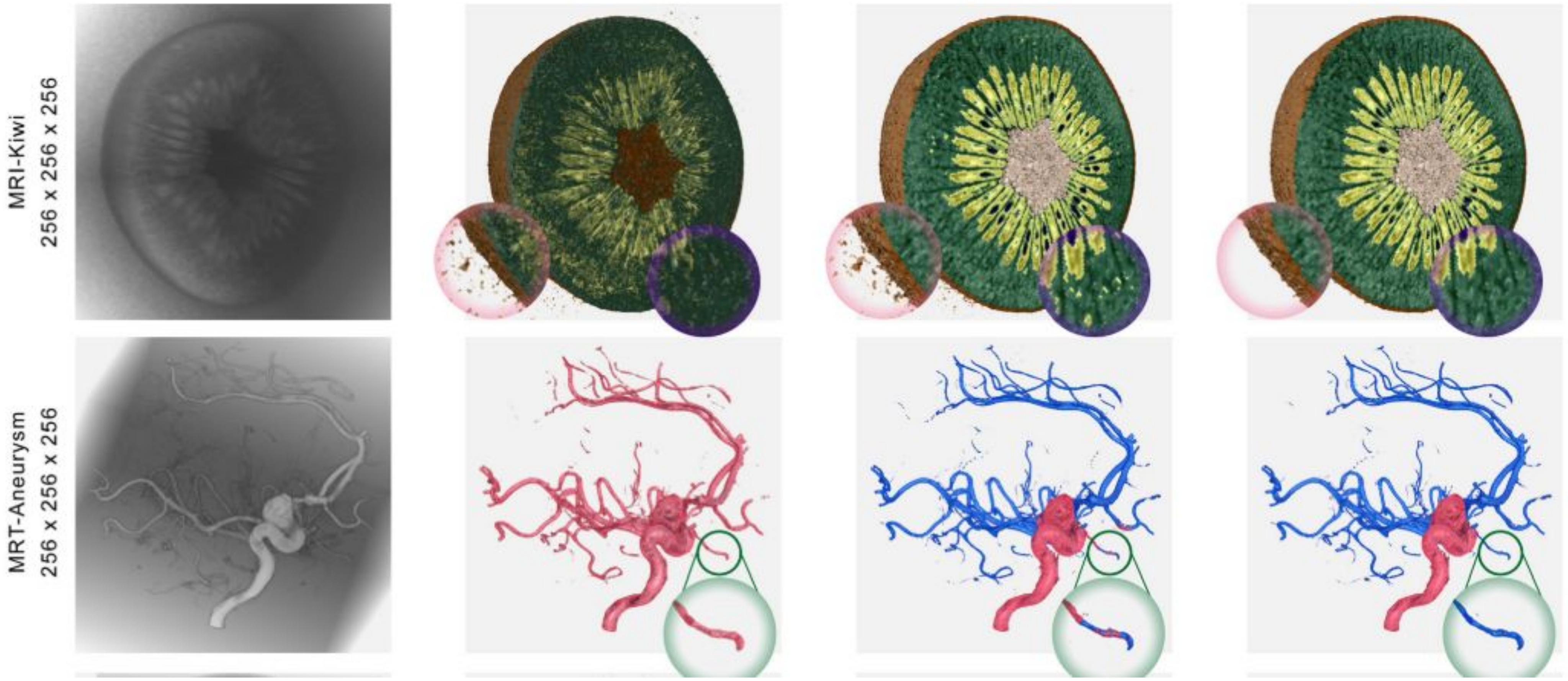


(b) Dictionaries of CT-Bonsai dataset

Resistance to noise

Fig. 10: Rendering of the noisy spiral dataset. From left to right: Kniss et al. [17], Soundararajan and Schultz [29], and ours. Our method is robust to noise due to the nature of learned dictionary.

Better rendering results



User Study

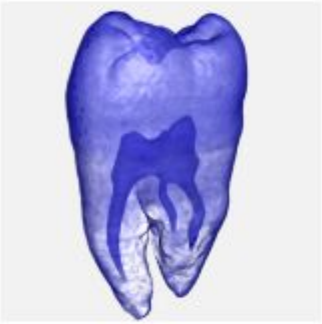
- Task 1: Subjects were asked to visualize the letter “a” only:

(a) Task 1 input

- Task 2: Object the same but “a” and “b” are overlapped.

(b) Task 2 input

- Task 3: The participants were asked to separate three structures in the CT-Tooth dataset



(c) Task 3 input

(f) Task 3 model answer

User Study Results

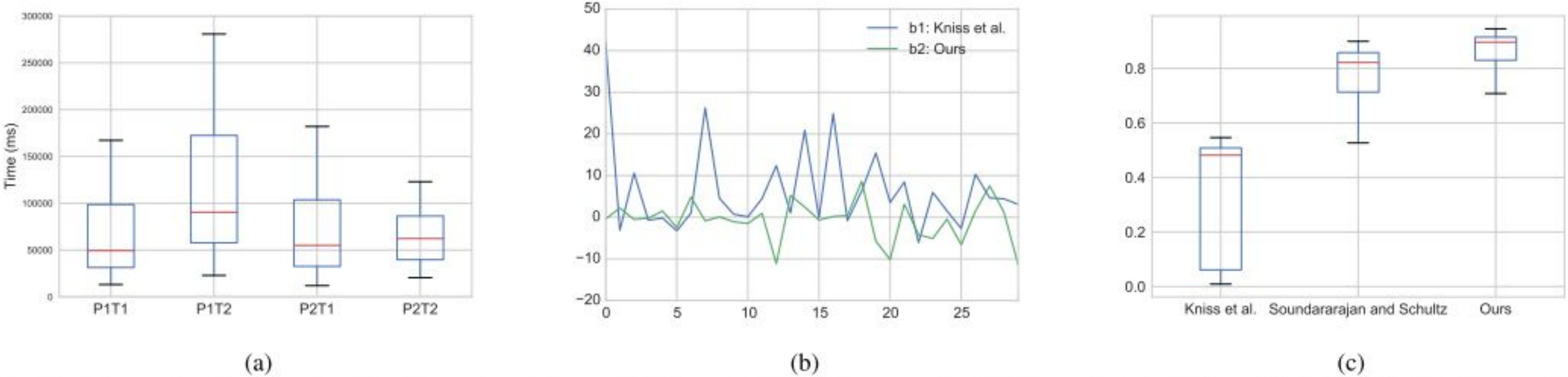


Fig. 13: User evaluation results. (a) : Experiment time of Kniss et al.(P1) and our method (P2) on Task 1 (T1) and Task 2 (T2), (b): Comparison of b values from Fitts' law analysis on Task 1 and 2. b1: Kniss et al., b2: ours, and (c): Accuracy result of Task 3.

Discussion

Connection to DNN

- The method used in this paper is designed to mimic multi-scale feature learning in DNN.
- However, CSC replaces the gradient descent in DNN with the global energy minimization problem.
- Easier to train compared with DNN

Limitation

- The running time for the dictionary learning and high-dimensional feature construction is about 30 minutes on a single CPU core and 10 minutes with GPU acceleration