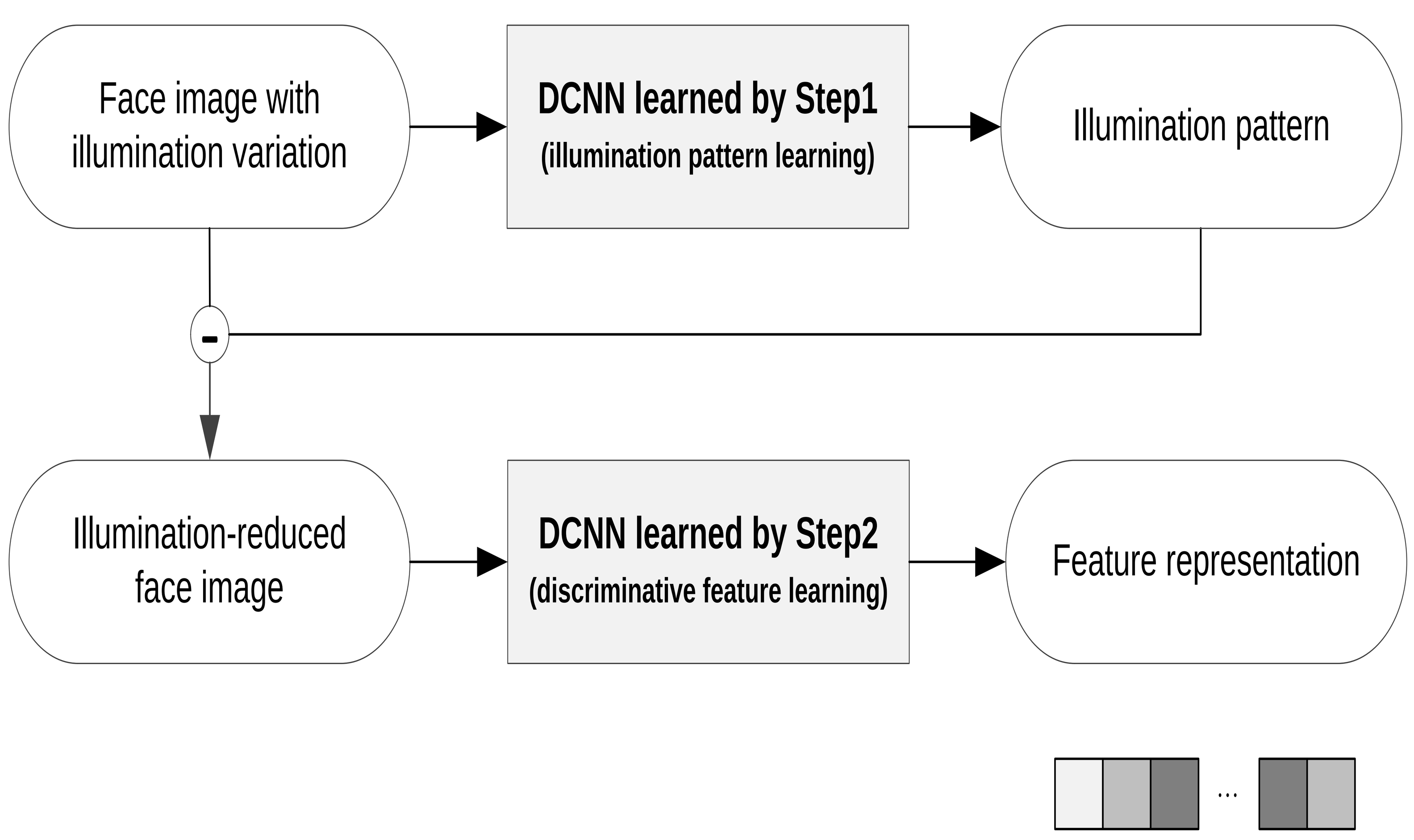
Deep learning based Image processing in IVY Lab

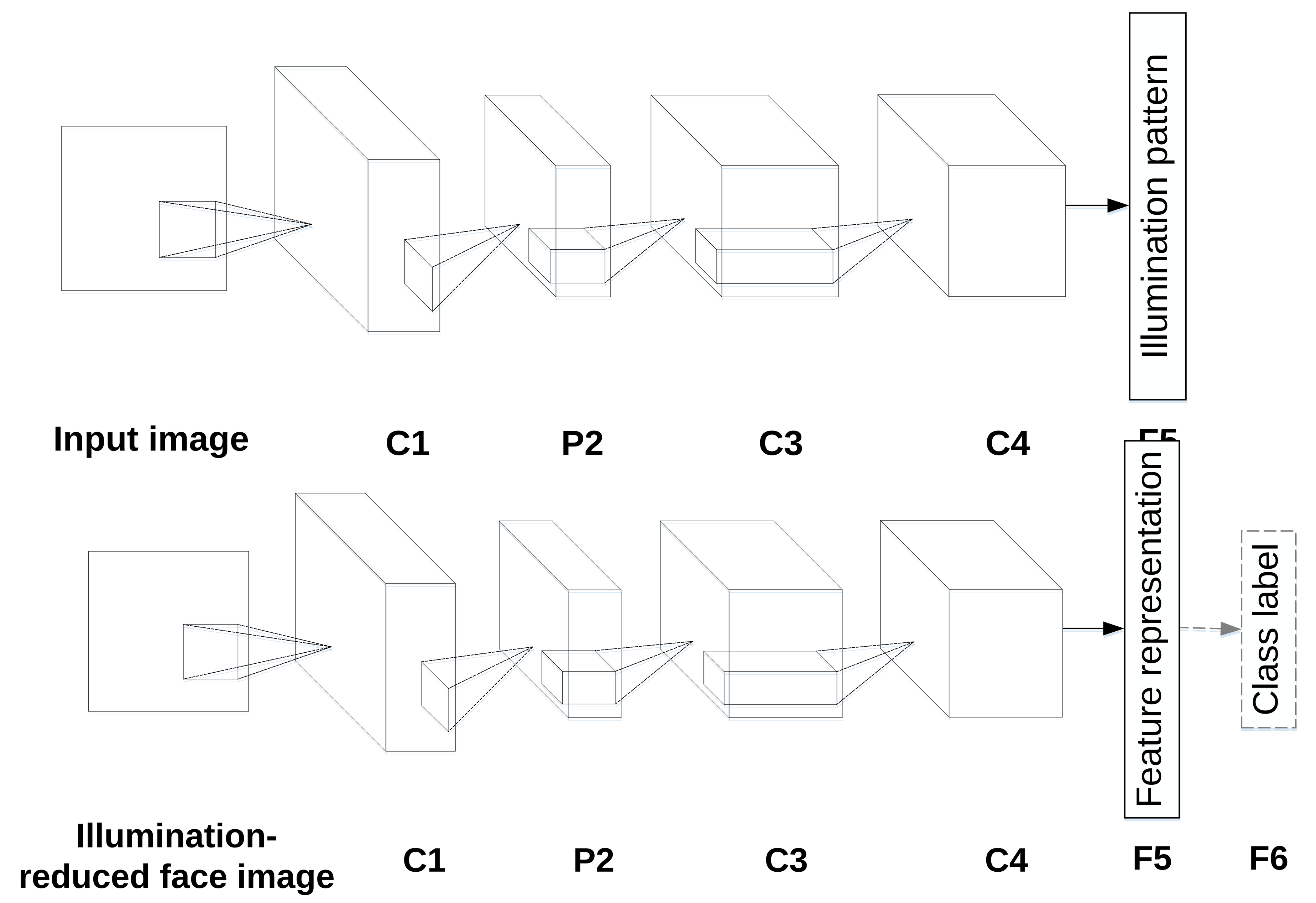
Digested from our publications ('15-'16) of topics in face recognition, medical mass detection, image in-painting, 3D.

Prof. Yong Man Ro

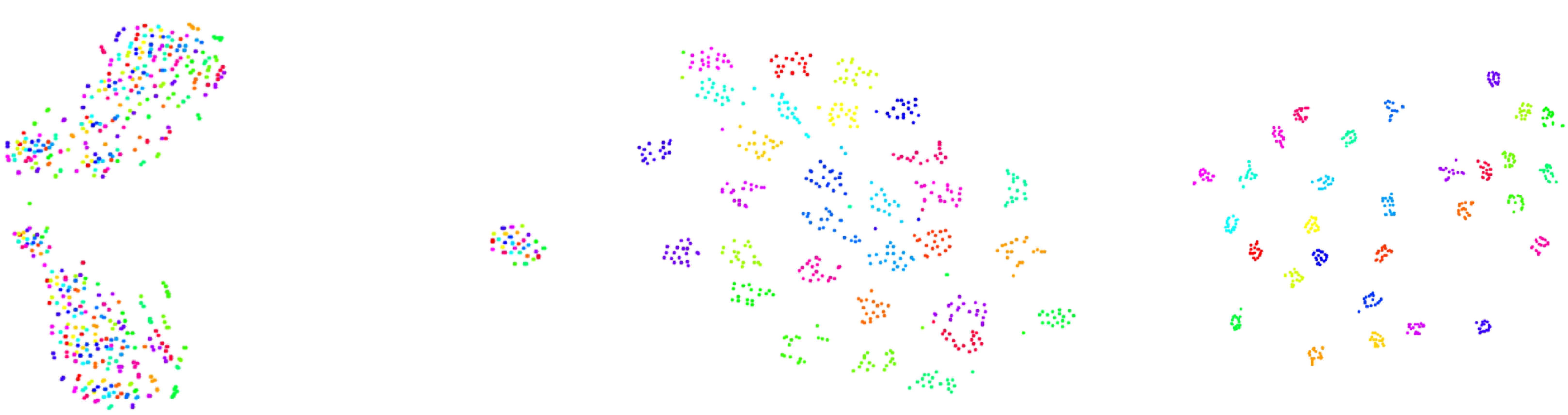
Two-step Learning of Deep Convolutional Neural Network for Discriminative Face Recognition under Varying Illumination



FR method robust to illumination variations learned with the proposed two-step learning method.



DCNN architectures adopted in the proposed learning method. (a) DCNN for learning illumination patterns. (b) DCNN for maximizing the discriminative power of feature representation.



(a) Original 2D feature space under illumination variations.

(b) 2D feature space learned with the proposed method (after Step 1).

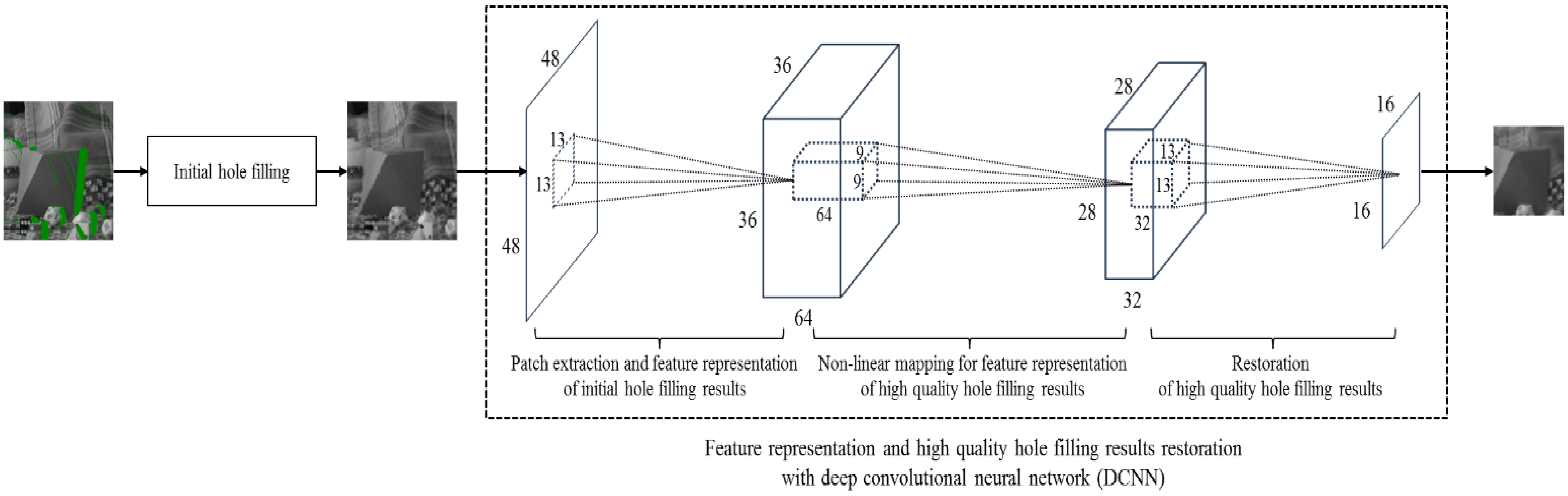
(c) 2D feature space learned with the proposed method (after Step 2).

Visualization of 2D feature spaces. Each dot represents a feature from 30 different classes under 20 illumination variations. (Best viewed in color.)

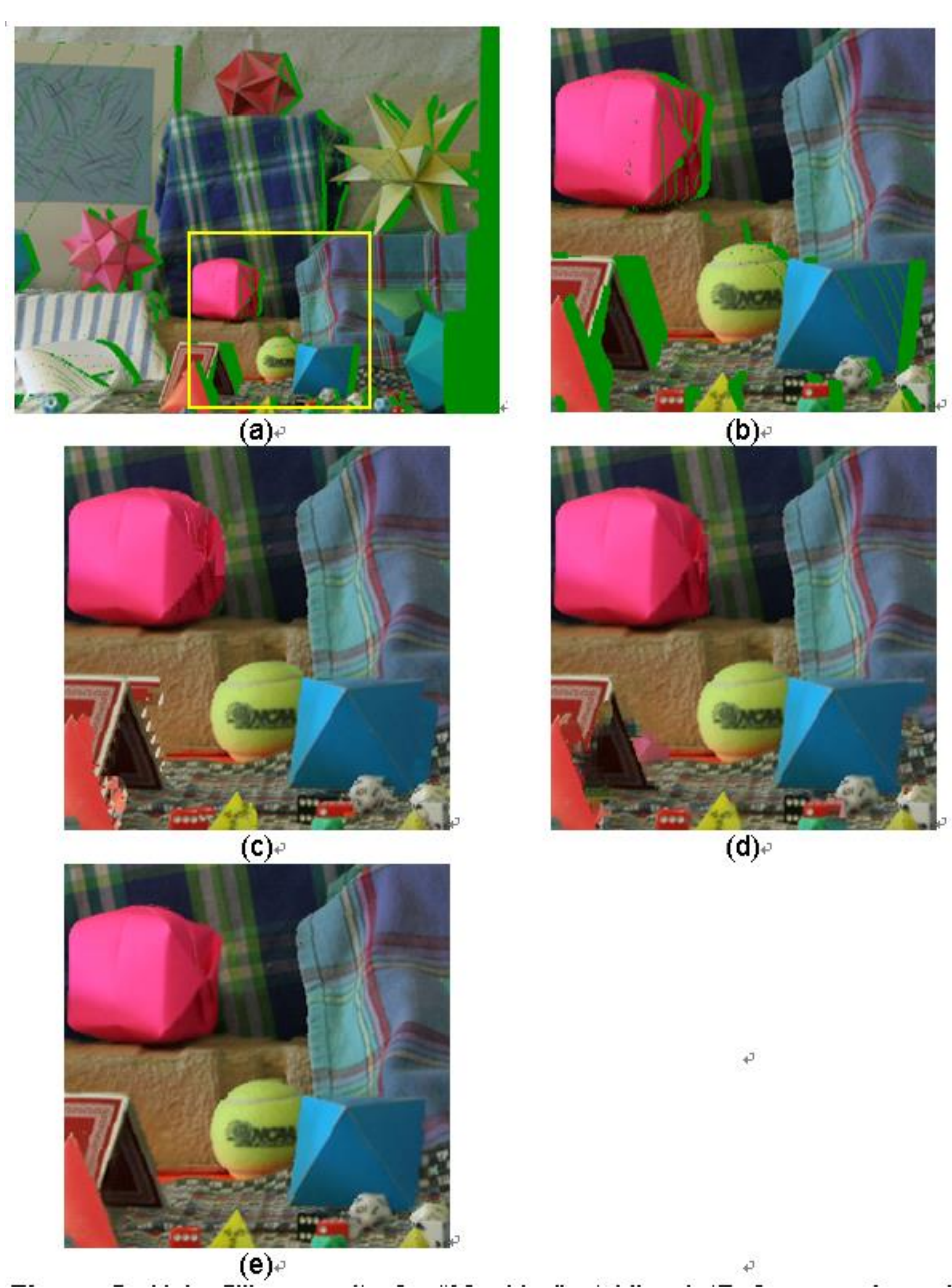
Table 1. FR accuracy comparisons with the proposed method and the previous works.

Method	Recognition rate
Histogram equalization [5]	43.10%
Multi-scale retinex [7]	60.55%
GradientFace [8]	84.75%
Weber-Face [9]	90.47%
Conventional CNN [18]	72.22%
Proposed method	96.24%

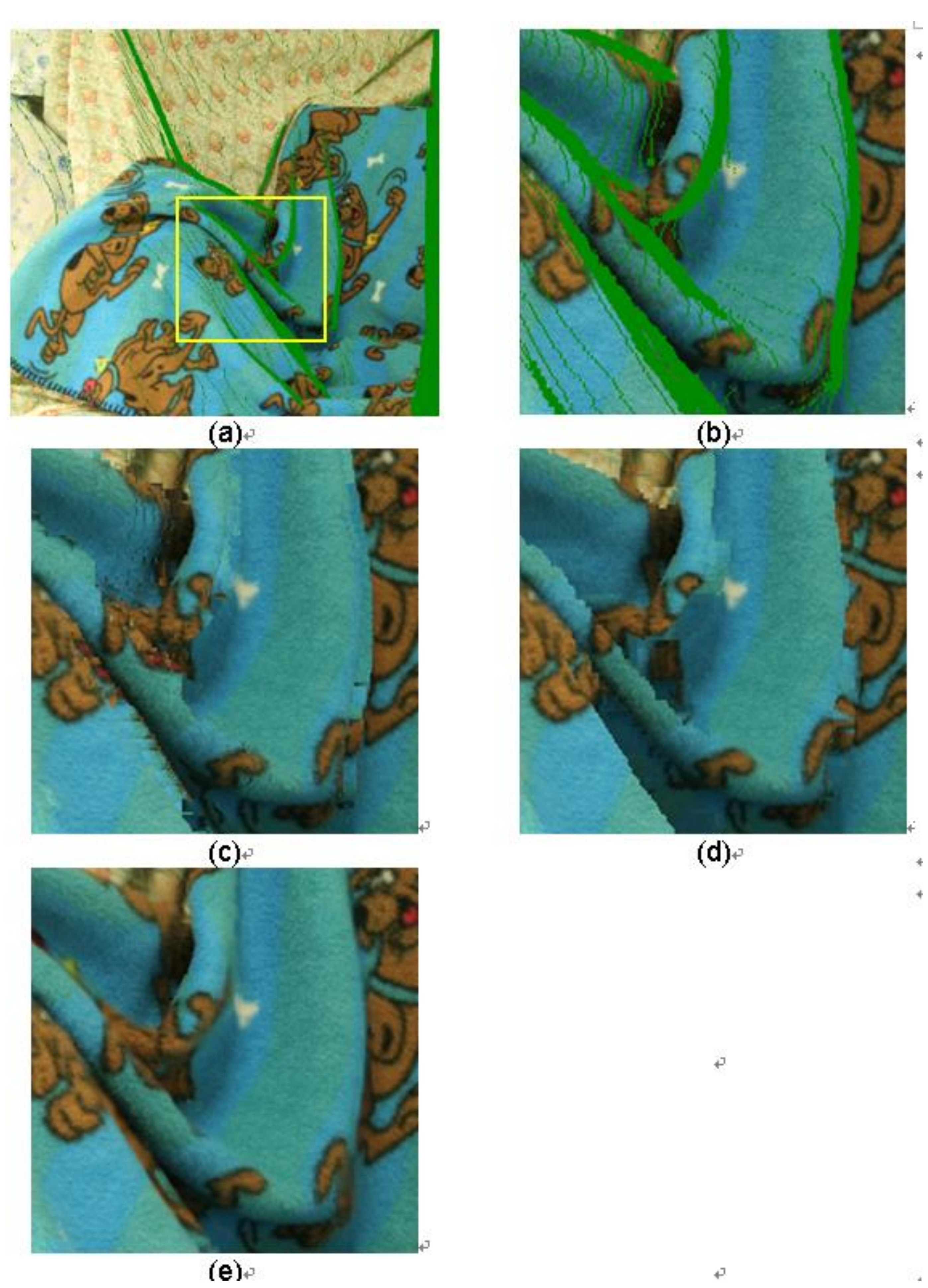
Learning based hole filling method using deep convolutional neural network for view synthesis



Proposed hole filling method with deep convolutional neural network (DCNN) for view synthesis

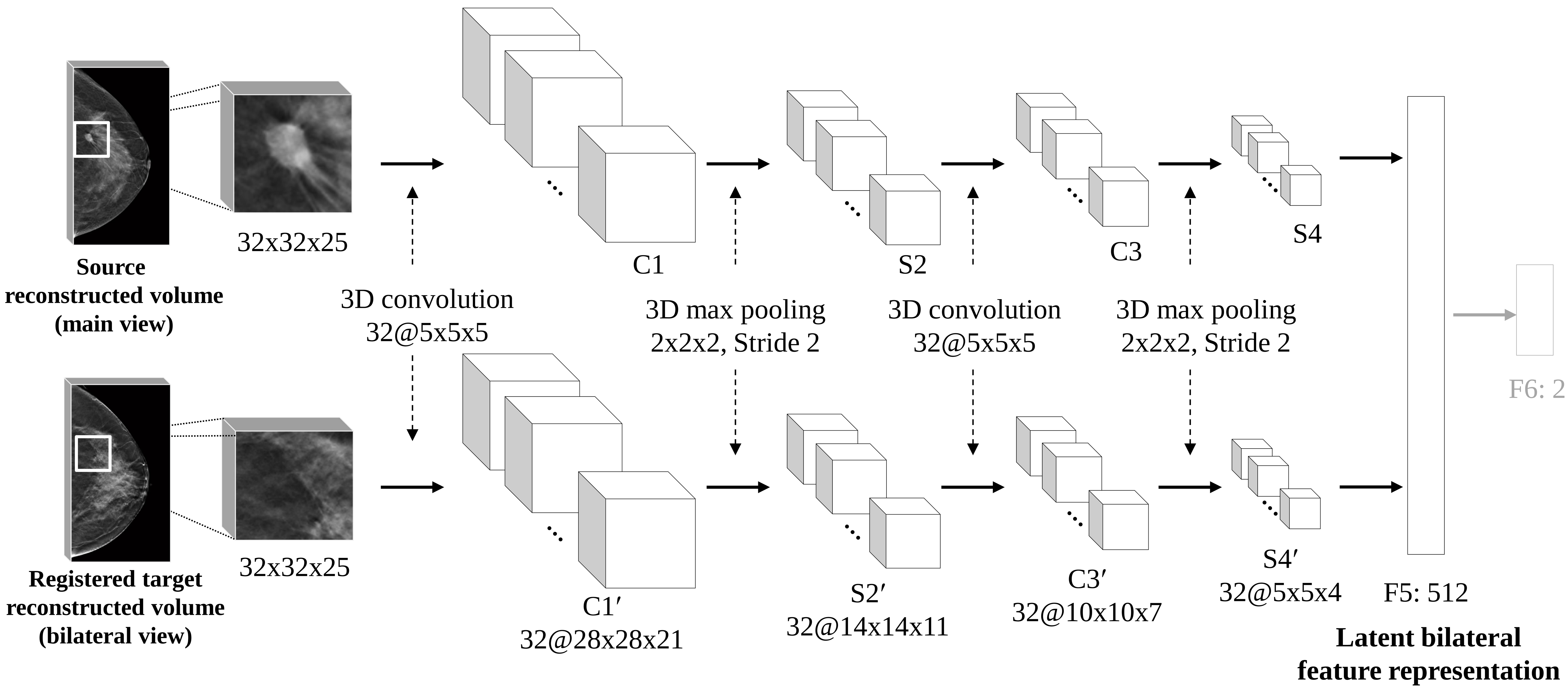


Hole filling results for “Moebius” at View4 (Reference viewpoint: View1). (a) Warped view. (b) Magnified part of (a). (c) Local greedy method [11]. (d) Global optimization-based method [13]. (e) Proposed hole filling method.

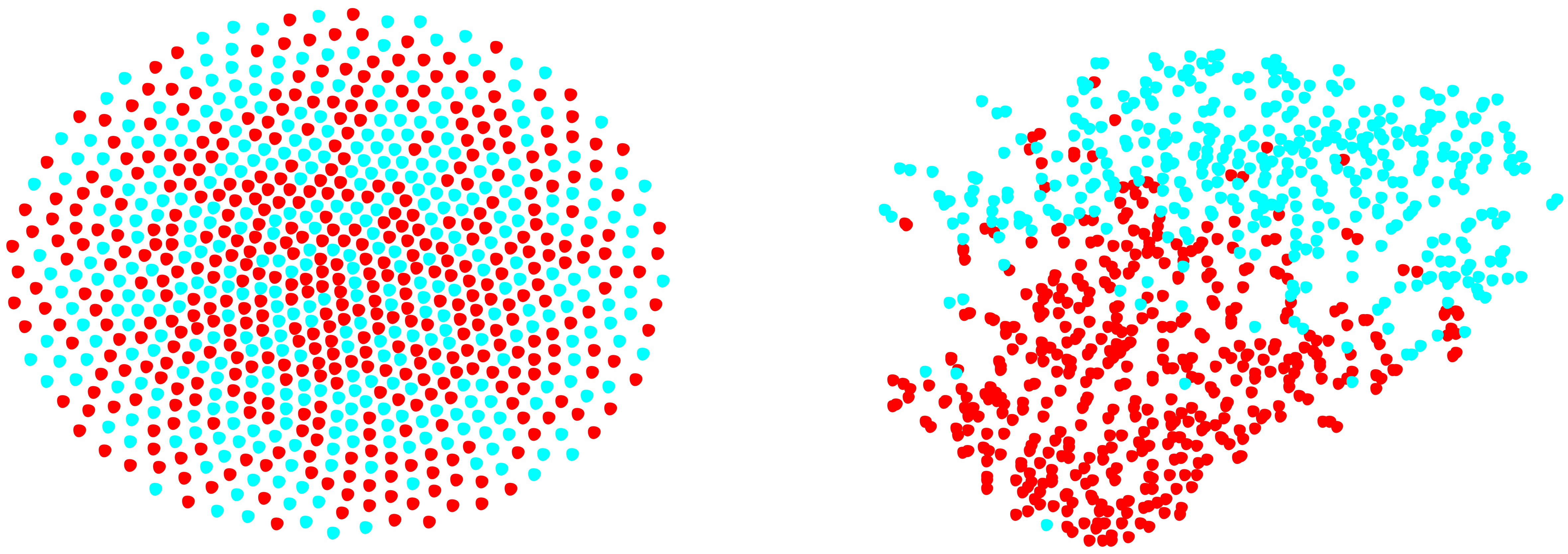


Hole filling results for “Cloth3” at View4 (Reference viewpoint: View1). (a) Warped view. (b) Magnified part of (a). (c) Local greedy method [11]. (d) Global optimization-based method [13]. (e) Proposed hole filling method.

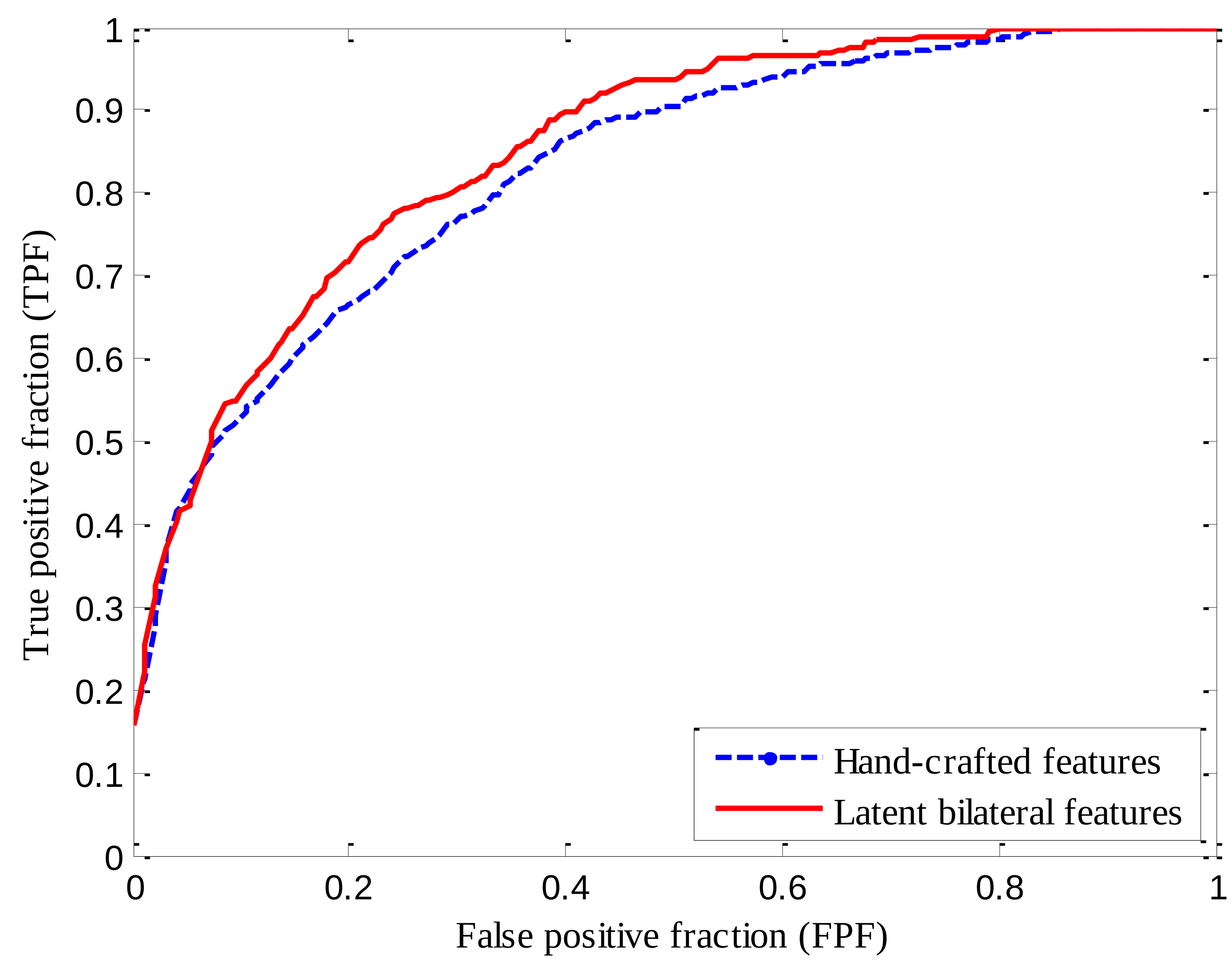
Latent Feature Representation With 3-d Multi-view Deep Convolutional Neural Network For Bilateral Analysis In Digital Breast Tomosynthesis



Proposed latent bilateral feature representation framework with 3-D multi-view DCNN



t-SNE feature visualization [14] of (a) original input data for the training set, (b) outputs of the fully-connected layer (F5) for the training data with the proposed DCNN. Red colored dots denote the mass samples and blue colored dots denote the normal breast tissues.



Comparisons of ROC curves of FP reduction using hand-crafted features and proposed latent bilateral features

IVY Lab, EE, KAIST, http://ivylab.kaist.ac.kr/main.asp

Pose-robust and Discriminative Feature Representation by Multi-task Deep Learning for Multi-view Face Recognition

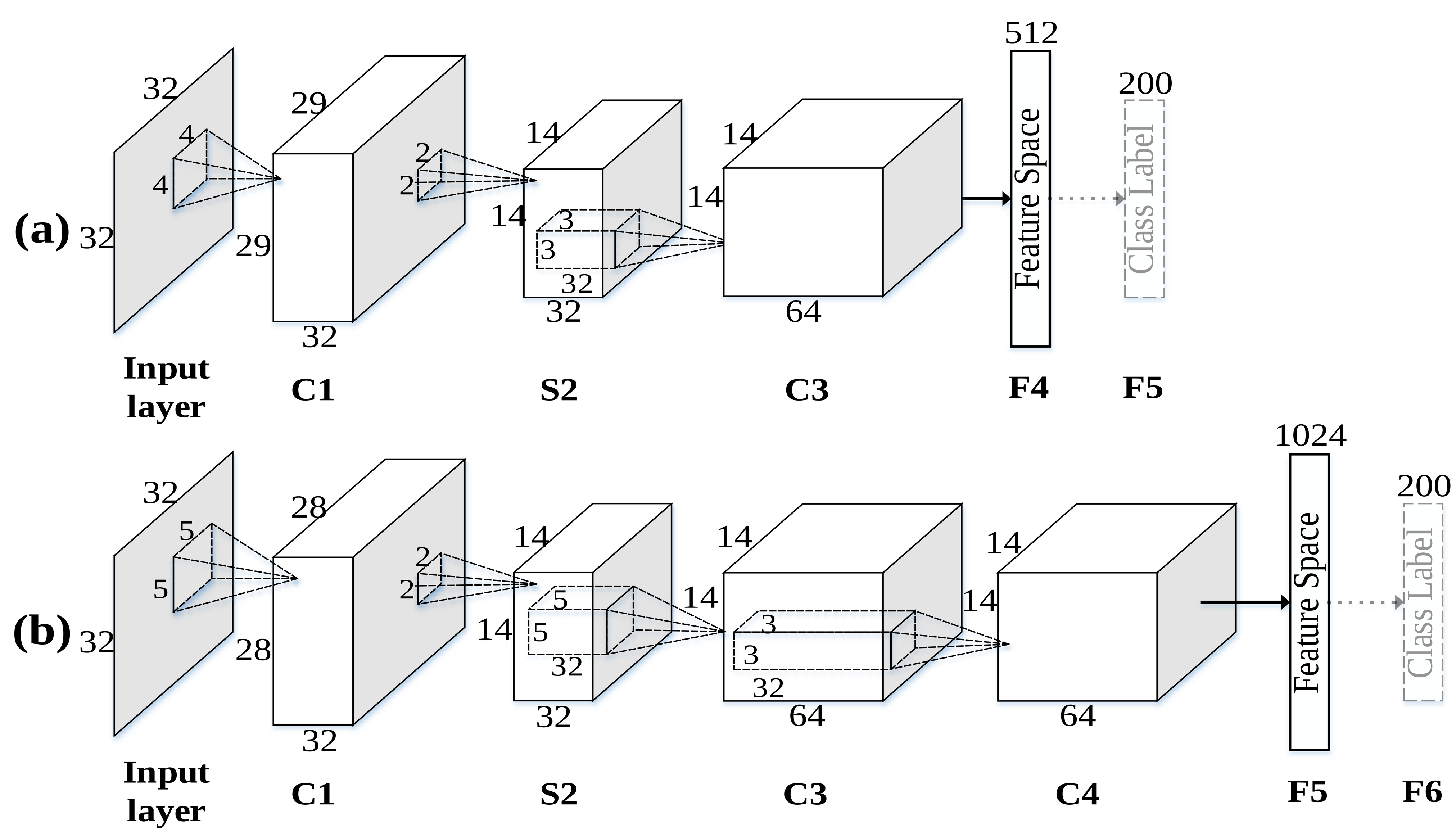
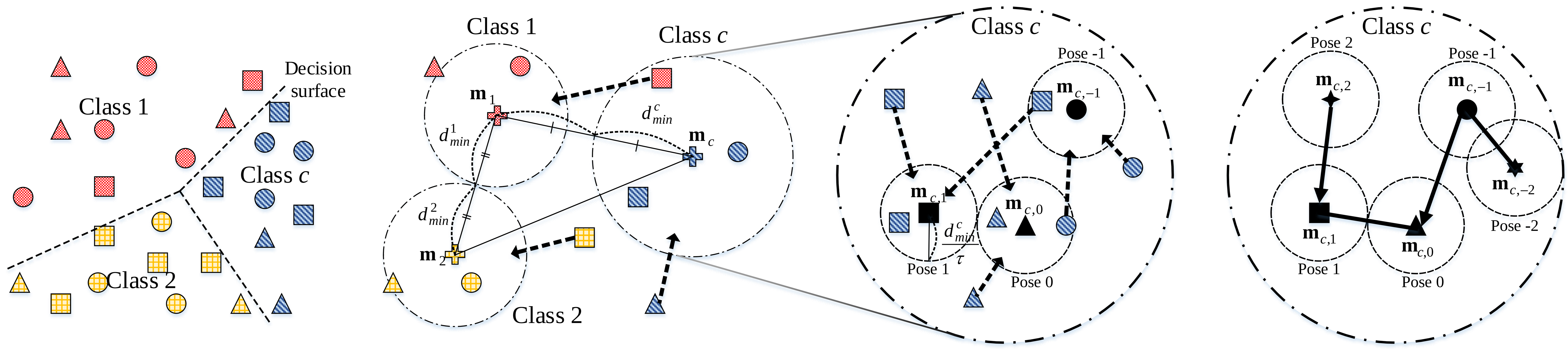
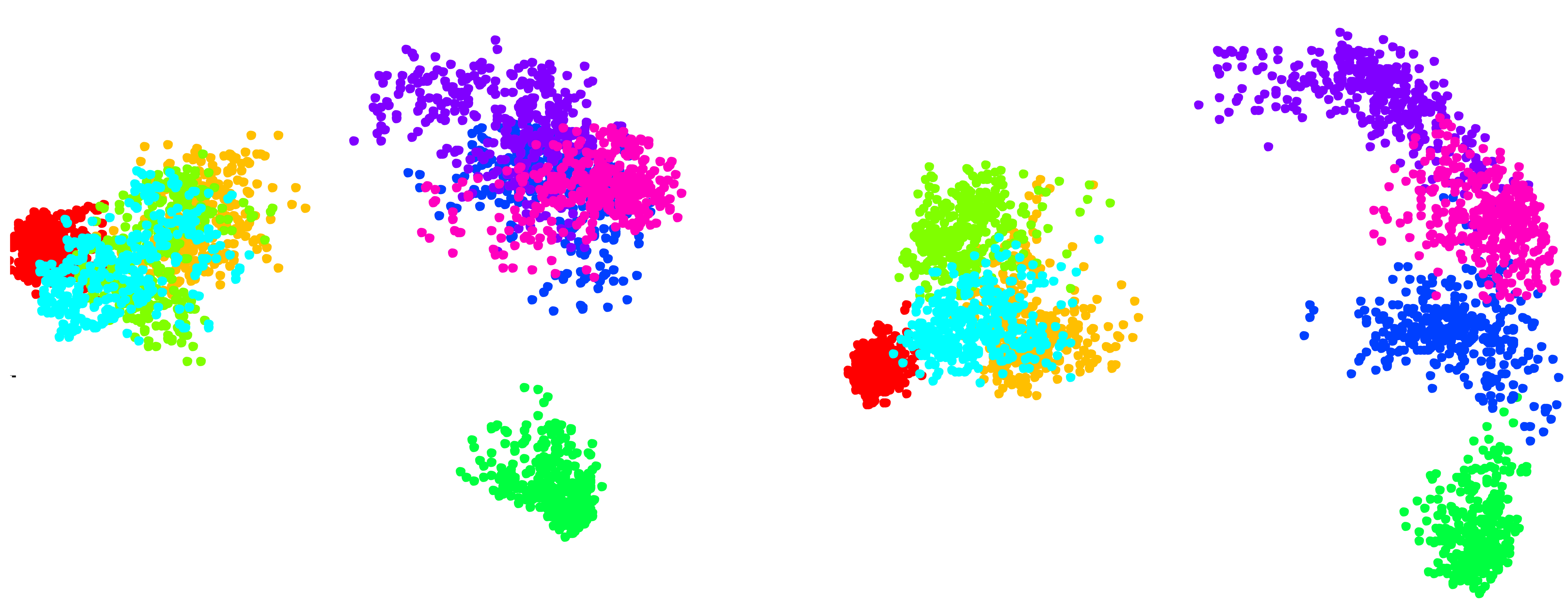


Figure 3. Architectures of ConvNets in our experiments. (a) ConvNet for Setting-I (b) ConvNet for Setting-II. (C: convolutional layer, S: subsampling layer, F: fully-connected layer)



(a) Inter-class variation (b) Intra-class variation (c) Intra-pose variation (d) Pose continuity

Visualization of error functions for our multi-task learning in deep ConvNet. The feature vector of the samples in each class are represented by the same color, and various poses are represened by different shapes.



(a) Conventional deep ConvNet (task1) (b) Proposed Multi-task deep ConvNet (all tasks)

Visualization of sample distribution in learned feature space. Each dot represents a sample, and 8 classes are plotted with different colors. (a) Results of conventional deep ConvNets. (b) Results of the proposed multi-task deep ConvNets (best viewed in color).