

DEEP QUANTIZED REPRESENTATION FOR ENHANCED RECONSTRUCTION

Akash Gupta Abhishek Aich Kevin Rodriguez G. Venugopala Reddy Amit Roy-Chowdhury

University of California, Riverside

ABSTRACT

In this paper, we propose a data driven Deep Quantized Latent Representation (DQLR) for high-quality data reconstruction in the Shoot Apical Meristem (SAM) of *Arabidopsis thaliana*. Our proposed framework utilizes multiple consecutive slices to learn a low dimensional latent space, quantize it and perform reconstruction using the quantized representation.

Index Terms— Cell reconstruction, quantized representation, shoot apical meristem, *arabidopsis thaliana*

1. PROBLEM OVERVIEW

Introduction. One of the major challenges in imaging of the SAM plant is that deeper slices in the z -stack suffer degradation due to different quality-related problems like blurring. Such issues often lead to disposal of painstakingly collected data and delay the research. Therefore it is necessary to design techniques that can enhance these stack of images to make them suitable for further analysis.

Problem Statement. Given a z -stack $\mathcal{Z} = \{z_i\}_{i=1}^n$, where z_i is the i^{th} slice in the stack from the top, the task is to reconstruct this z -stack, $\hat{\mathcal{Z}} = \{\hat{z}_i\}_{i=1}^n$ such that \hat{z}_i is the visually enhanced slice compared to $z_i, \forall i = 1, 2, \dots, n$.

2. METHODOLOGY AND RESULTS

Proposed Approach. An overview of our approach is illustrated in Figure 1. We assume that the latent representation x_i of a noisy image z_i is composed of two parts, quantized latent code, $y_i^q = Q_i(y_i)$, corresponding to the enhanced version of z_i , and noise latent code, y_i^n , corresponding to the noisy part [1]. The consecutive slices in the z -stack are correlated which implies that they must be correlated in the latent space as well. We employ a recurrent neural network (RNN) R to learn this correlated representations $\{y_{i+j}\}_{j=0}^n$ by passing latent vector $\{x_i\}_{i=1}^n$ to R.

We present a framework similar to deep auto-encoder to reconstruct z -stack \mathcal{Z} with enhancement. Our encoder E compresses i^{th} input slice image to a latent representation x_i . The compressed representation x_i is processed through R_i to learn the inter-correlation between this latent representation of the consecutive slices ($\{i+j\}_{j=0}^n$) during training. RNN generated correlated latent codes ($\{y_{i+j}\}_{j=0}^n$) are then used as an input to quantization module Q_i . Q_i learns a vector dictionary for quantized representation during training of the network and generates a quantized latent code y_i^q . Our assumption

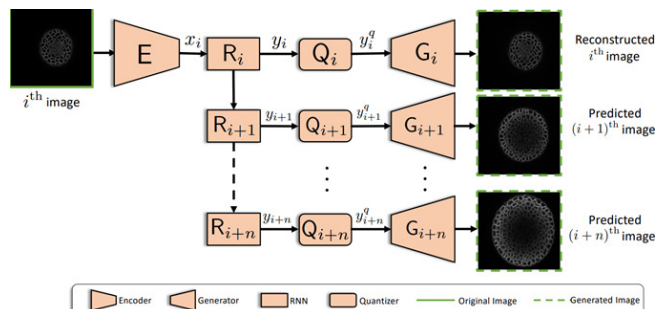


Fig. 1: Overview of the proposed approach from one slice of the stack. Encoder E encodes input image to x_i . Recurrent Neural Network (RNN) module generates correlated codes for reconstruction (y_i) and prediction ($\{y_{i+j}\}_{j=1}^n$). Quantizer module Q_i quantize the latent codes and Generator G reconstructs/predicts the images.

is that the quantization of latent code will remove the noisy component y_i^n and the reconstructed/predicted images using the quantized latent codes by generator G should be enhanced.

Qualitative Results. We used a publicly available Confocal membrane dataset [2] consisting of 6 plants. We train our model using 4 plant stacks, and use 1 plant stack each for validation and test data each. Experiments confirms that the generated images using our proposed approach are enhanced and hence, visually better. Qualitative results on the test set is shown in the Figure 2.

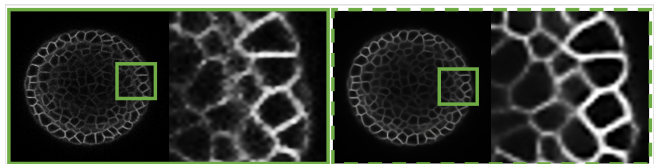


Fig. 2: Reconstruction result. Original image (left) and Reconstructed image (right) with corresponding zoomed parts are presented here.

Acknowledgement. We thank Prof. B.S. Manjunath from UCSB for valuable discussions and helpful suggestions.

3. REFERENCES

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