Deep Quantized Representation for Enhanced Reconstruction

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Abstract

- 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.

Motivation

Major challenges in analysis of images of SAM plant:

- Deeper slices in the z-stack are often noisy
- Noisy data hinders the quality of analysis
- Disposal of painstakingly collected data

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, $\hat{\mathcal{Z}} = \{\hat{z}_1\}_{i=1}^{n}$ such that $\hat{z}_i$ is the **visually enhanced slice** compared to $z_i, \forall\ i = 1, 2, \cdots, n$.

Approach

- We assume that the latent representation x_i of a noisy image z_i is composed of two parts, quantized latent code, $y_i^q = \mathsf{Q}_i(y_i)$, 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.

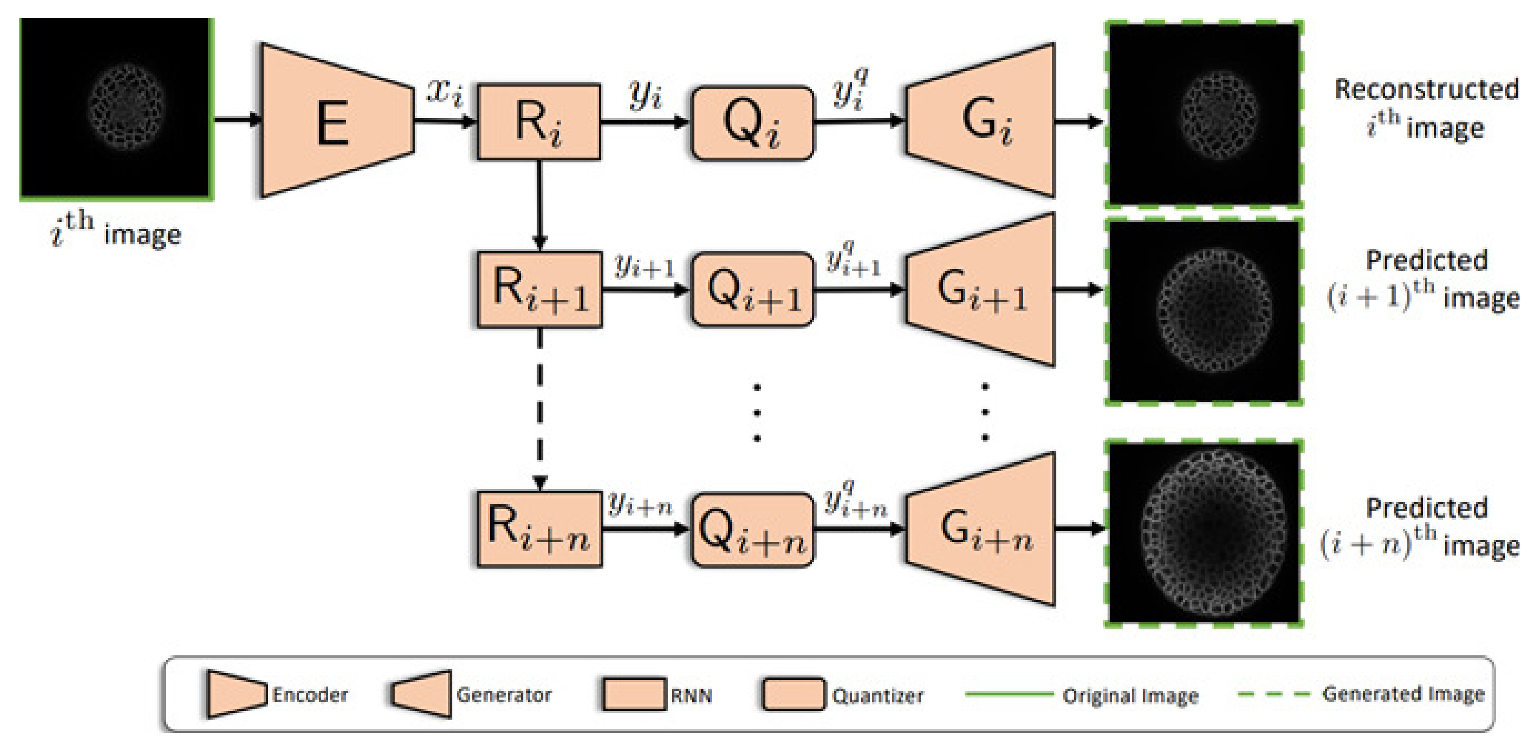

Figure 1: Overview of the proposed approach. Encoder E encodes input image to x_i. Recurrent Neural Network (RNN) module generates correlated codes for reconstruction (y_i) and prediction ($\{y_{i+j}\}_{j=1}^{n}$). Quantizer module Q_i quantize the latent codes and Generator G reconstructs/predicts the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

Results

- We used a publicly available Confocal membrane dataset [2] consisting of 6 plants. We train our model using 4 plant stacks, and keep 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.

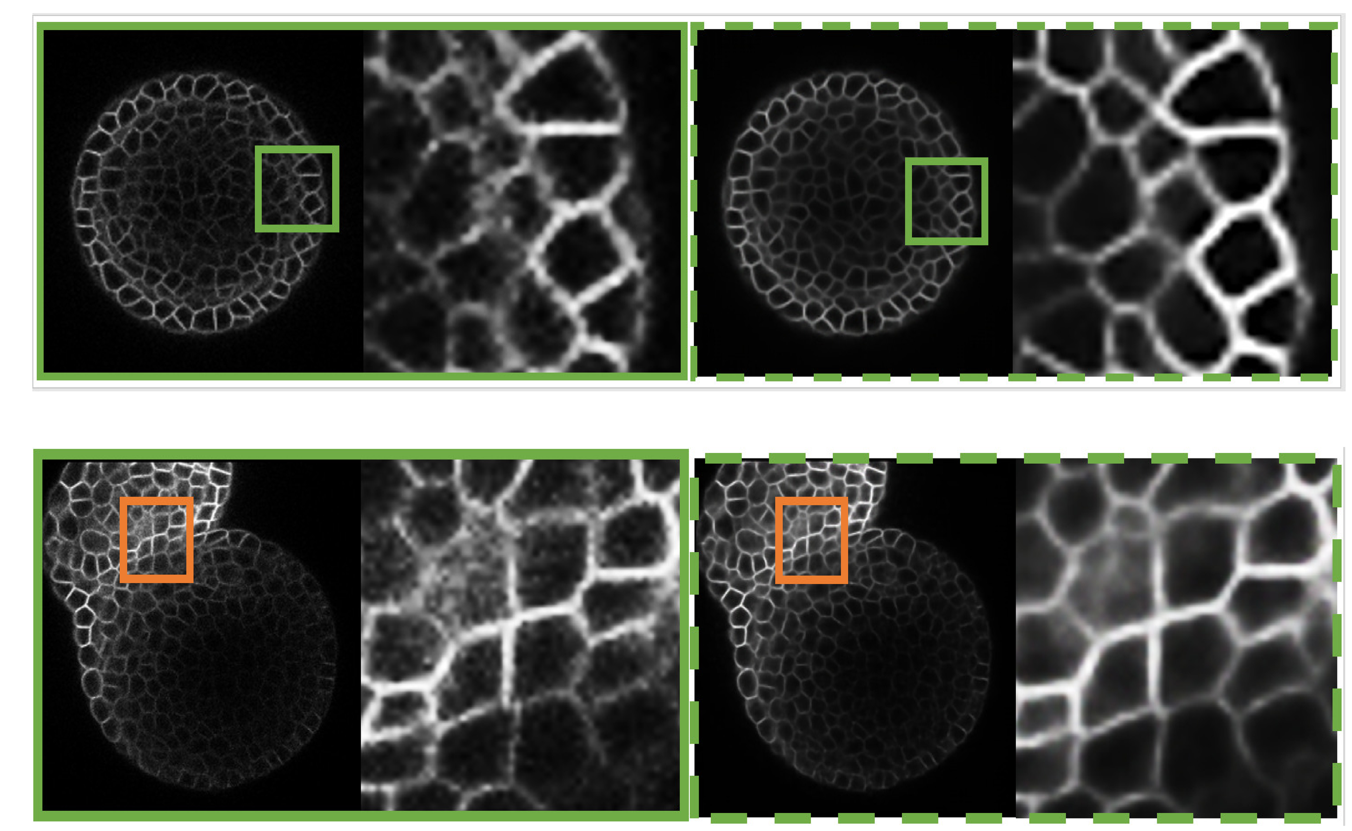

Figure 2: Reconstruction result. Original image (left, -) and Reconstructed image (right, --) with corresponding zoomed parts (square boxes) are presented. The reconstructed images are sharper and visually clearer.

References

[1] Aaron van den Oord, Oriol Vinyals, et al. "Neural discrete representation learning". In: *Advances in Neural Information Processing Systems*. 2017, pp. 6306–6315.

[2] Lisa Willis et al. "Cell size and growth regulation in the Arabidopsis thaliana apical stem cell niche". In: *Proceedings of the National Academy of Sciences* 113.51 (2016), E8238–E8246.

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