Deep Quantized Representation for Enhanced Reconstruction

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Outline

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 $z_i, \forall\ i = 1, 2, \cdots, n$.

Motivation

- Automated analysis requires high-quality imaging data in different domains [3, 7, 5]
- Live Cell Imaging is important to study plant development (Arabidopsis thaliana)
- Image quality degrades with deeper layers of the Shoot Apical Meristem stack [6]
  - noisy, poor contrast, blurring, etc.
- Quality issues lead to disposal of painstakingly collected imaging data [2]

Conceptual Overview

- Quantization in latent space can remove noise in image space [1].

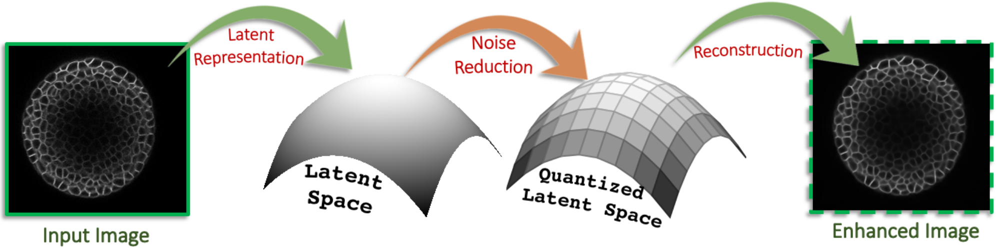
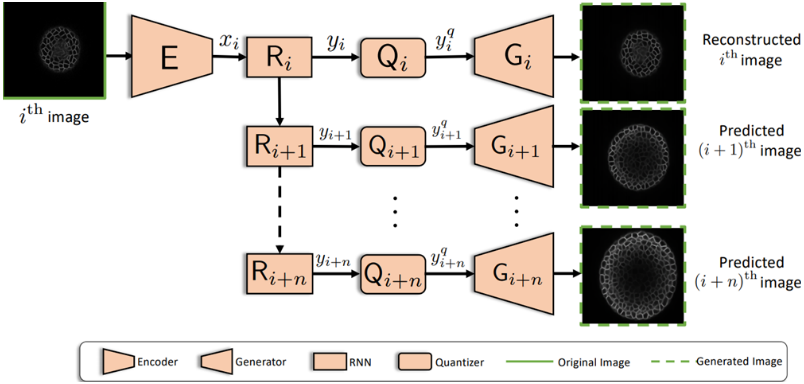


Figure: Conceptual Overview. Input image is projected on the latent space. The latent representation of the image is quantized using k-means over the entire dataset [4].The quantized representation is used to reconstruct the image.

Proposed Approach



Proposed Architecture. Encoder E encodes input image to x_i. RNN module R_i 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.

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Training Protocol

- Given a z-stack $\mathcal{Z} = \{z_i\}_{i=1}^{n}$ our target is to reconstruct enhanced z-stack, $\hat{\mathcal{Z}}$.
- Encoder E generates the latent representation, x_i.
- RNN R_i generates correlated representations for slices y_i and $(\{y_{i+j}\}_{j=1}^{n})$
  - Helps gather more information from consecutive slices
- Quantizer Q_i learns a representative dictionary embedding using correlated codes.
  - Helps gather more information from consecutive slices
- Generator G_i reconstruct enhanced image using quantized latent codes.
- Framework is trained using loss given by,

$$\mathcal{L}_{total} = \mathcal{L}_{rec} + \lambda_q * \mathcal{L}_{quant} \quad (1)$$

$$\mathcal{L}_{rec} = \mathcal{L}_{mse} + \lambda_{ssim} * \mathcal{L}_{ssim} \quad (2)$$

$$\mathcal{L}_{quant} = \text{quantization loss as in [4]} \quad (3)$$

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Results with Quantization

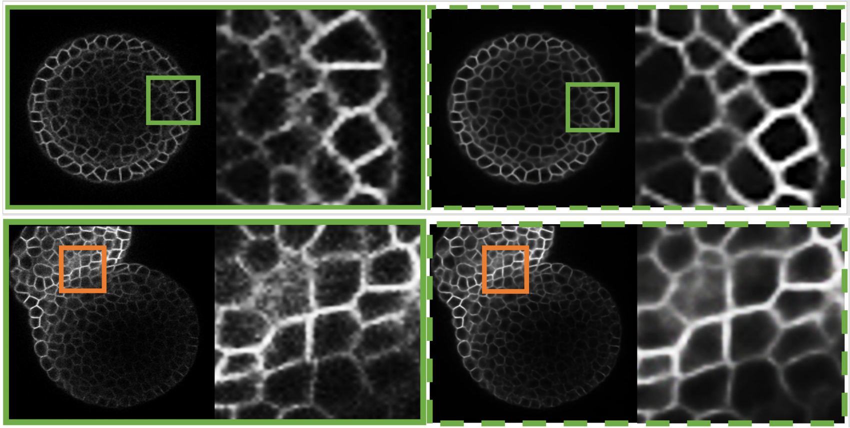

Figure: Reconstruction Results. Original image (left) and Reconstructed image (right) with corresponding zoomed parts are presented here.

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Results without Quantization

- Without quantization the reconstructed image is blurry.
- Typically using Mean Square loss smoothen the image in AE.

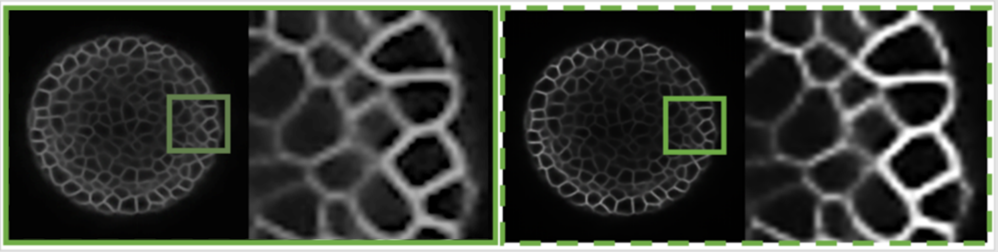

Figure: Reconstruction Results without quantization. Reconstructed image without quantization (left) and Reconstructed image with quantization (right) with corresponding zoomed parts are presented here.

References

- Abhishek Aich et al. “Non-Adversarial Video Synthesis with Learned Priors”. In: *arXiv preprint arXiv:2003.09565* (2020).
- Andrey Ignatov and Radu Timofte. “Ntire 2019 challenge on image enhancement: Methods and results”. In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*. 2019, pp. 0–0.
- Neeta P Kulkarni. “Advanced Method for Image Resolution Enhancement”. In: *Techno-Societal 2018*. Springer, 2020, pp. 231–238.
- Aaron van den Oord, Oriol Vinyals, et al. “Neural discrete representation learning”. In: *Advances in Neural Information Processing Systems*. 2017, pp. 6306–6315.
- Leonardo Rundo et al. “MedGA: a novel evolutionary method for image enhancement in medical imaging systems”. In: *Expert Systems with Applications* 119 (2019), pp. 387–399.
- 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.
- Tianfan Xue et al. “Video enhancement with task-oriented flow”. In: *International Journal of Computer Vision* 127.8 (2019), pp. 1106–1125.

Thank You!

Code Available at: https://github.com/agupt013/enhancedRec

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