Embedded CycleGAN for Shape-Agnostic Image-to-Image Translation

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Introduction

Cycle-consistent GANs demonstrated impressive performance in unpaired image-to-image translation. Such models work extremely well when color and texture changes are required for translation but fail in cases where shape changes are required. This work analyzes the trade-offs between the cycle-consistency importance and the necessary shape changes required for natural looking imagery. The results demonstrate improved translations between domains that require shape changes. Additionally, our model learns interesting attention/segmentation information about the translated images in its embeddings.

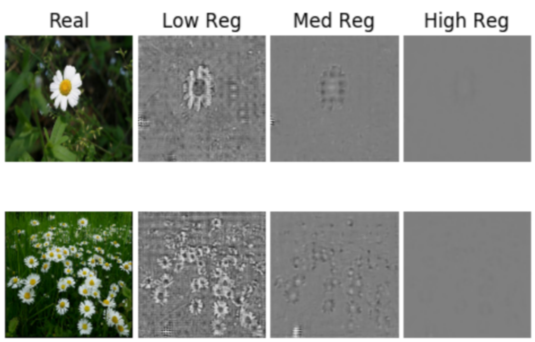

Fig.2 Various levels of regularization on the embedding channel.

Proposed Model and Methodology

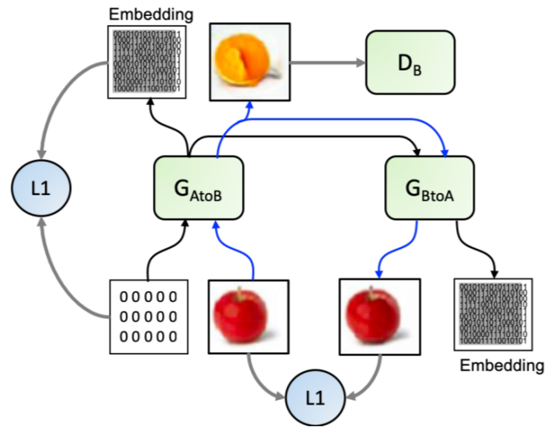

Fig.1 General flow of the proposed model.

A zero mask is added as a 4th dimension to each sample, which is then fed to a generator that produces a 4-dimension output. Three of the channels are the RGB channels of the generated fake image and the last channel is an embedding learned by the generator. The fake image is evaluated against the discriminator without the embedding channel while they are both used as input to the second generator for reconstruction of the original image. An L1 loss is applied on the embedding channel to force the model to learn only the necessary information to help in reconstruction and make sure that the model doesn't memorize the entire structure of the image in that embedding.

Experiments and Results

- **Cycle-Consistency Strength**: As it increases the model changes shapes in translation less.
- **An Embedding Channel:** Helps in reconstruction and shape changing per lower cycle-consistency levels.
- **Regularization:** different levels of regularization on the embedding channel force the model to learn efficient embeddings. Information about the subject of translation is last to be lost (Fig. 2).
- **Variations:** different methods of regularization learn different embeddings and affect the model differently.
- **Dog Breeds:** The model can change shapes better between different dog breeds (Fig. 3).

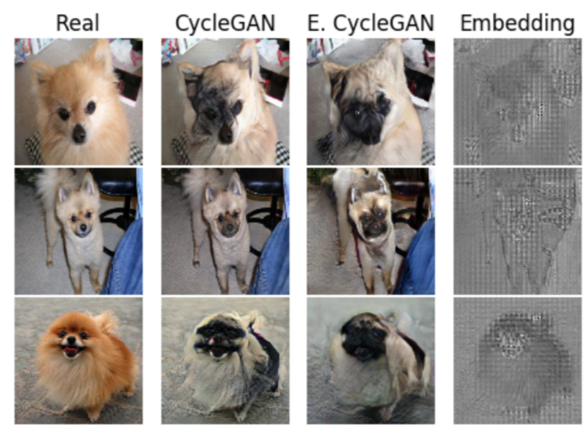

Fig.3 CycleGAN vs. Embedded CycleGAN.