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Tunable Models for Image Processing

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1 Introduction

In many image restoration tasks, such as denoising [9, 6] and super-resolution [4, 10], the state of the art results are based on deep learning based models. The most common approach is to train the model in a supervised manner, where the input is an image with a fixed pre-determined corruption level and the output is the clean image, so that most deep learning based image processing models are optimized for only a single degradation level. In reality, the degradation level is not known a-priori and therefore at inference time, the model can underperform. As an example, consider low-light image processing where the captured image has low photon count and low SNR. Deep learning based models have been proposed to process low-light images [1]. However, since the desired optimal output exposure is unknown a-priori, at inference time the output image might suffer from a too short exposure which results in a noisy image, or from a too long exposure which results in a blurry image. As another example, in denoising the noise level of the corrupted image is not known a-priori. In order to overcome this limitation, continuous-level based models have been proposed. In such models, the output image is based on a target parameter (e.g. noise or exposure level) which can be adjusted at inference time.

2 Related Works

Recently, various models have been proposed to output an image based on the continuous modulation of a parameter. These models often train CNNs based on images with an initial degradation level. Then, they fine tune the model by fixing the exiting parameters and train the same model with or without additional architectural changes, based on images with the final degradation level. At inference time, the input parameter determines the weight between the initial degradation level network and the final one. The key observation that stands in the basis of the aforementioned techniques is that the kernels in both networks, the initial and the final one, exhibits a similarity which might be approximated by interpolating the latent space.

אם נסתכל על מודלישם אומרנו על נניח רעש בדרגות שונות.
ונתסכל על הפילטרים שלהם אחרי האימון. תהיה קורליציה טובה ומעבר הדרגתי בין הפילטרים האלה.
וזה מה שנתן את ההרגשה שאפשר לבצע אינטפרולציה בין הפילטרים הללו כדי לקבל transition במשימה הספיציפית.

Finetuning means taking weights of a trained neural network and use it as initialization for a new model being trained on data from the same domain (often e.g. images). It is used to speed up the training and overcome smaill datasets

In the following we consider the latest related papers. Dynamic Network Interpolation (DNI) [8] train the same model with different degradation levels, where the final level is fine-tuned from the initial one. At inference time, it linearly interpolates all the parameters of the networks. This simple strategy can fail when the required interpolation is not linear. AdaFM [2] introduces an additional tuning layer for the final level. The layer is a linear transition block with depth-wise convolution. Due to the linear interpolation method, it might also fail to overcome non-linear interpolation requirements. CFSNet [7] uses an additional network incorporated into the existing one, and interpolates the feature maps and not the model parameters. Dynamic-Net [5] adds additional modulation blocks after the exiting ones, to interpolate the feature maps as well. The final model in both approaches requires additional computational resources, which might be significantly larger, than the initial models. Recently. FTN [3] introduced a dedicated modulation module, similarly to AdaFM[2], which enables interpolation of the kernels between initial and final one in a non-linear manner and tries to achieve this task without significant overhead relative to the baseline network.

prediction

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