CURRICULUM LEARNING AND OTHER TRAINING STRATEGIES FOR NOISE REMOVAL IN IMAGES

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Objectives

Developing an effective architecture for a Denoising Autoencoder (DAE) is the first step in building robust machine learning models. This type of neural network aims to remove noise from input data through a reconstruction function, comparing the output data to the original noise-free data. Furthermore, it's crucial to accurately select hyperparameters and network layers to ensure the model learns meaningful data representations.

In addition to conventional training with all available data, the use of Curriculum Learning (CL) can enhance DAE performance by allowing the network to develop a gradual and refined understanding of the data. However, it is essential to compare this approach to assess its impact on the model. A rigorous analysis of performance metrics can reveal the benefits of CL. If it demonstrates significant advantages over traditional methods, we can conclude that training with CL is beneficial for DAEs.

Materials and Methods

One initial step is to determine the base architecture for the noise removal study. As a result, a neural network architecture with 8 layers, each containing 8 filters of size 3x3, was selected as the model to be used. Following that, implementations related to Curriculum Learning (CL) are necessary. This supplementary training technique consists of two functions: pacing and scoring. The first function determines the rate at which data is incorporated into the training, starting with a portion of the images and gradually increasing until the entire dataset is included. The scoring function aims to score the difficulty level of the instance, meaning that easier examples are provided at the beginning of training and more challenging ones are introduced gradually. This provides a direct simulation of the learning curriculum in a discipline, for example. In our study, we applied different pacing functions (linear, log, ladder, and ladderlog), as well as scoring functions: RMSE and CHISC (from Santos and Ponti, 2019).

Results

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In Tables 1 to 4, we can observe the results obtained through conventional (constant) training and various pacing functions. These tables illustrate the diverse performances achieved by employing different pacing strategies and noise.

Metric	Constante	Linear	Log	Ladder	Ladder Log
RMSE	0,1855	0,1748	**0,1713**	0,1762	0,1741
PSNR	62,951	63,427	**63,610**	63,367	63,465

SSIM	0,5360	0,5590	**0,5734**	0,5487	0,5557

Table 1: Application with 10% noise, scoring function RMSE.

Metric	Constante	Linear	Log	Ladder	Ladder Log
RMSE	0,1855	**0,1735**	0,1803	0,1768	0,1737
PSNR	62,951	**63,500**	63,177	63,316	63,492
SSIM	0,5360	**0,5593**	0,5485	0,5503	0,5558

Table 2: Application with 10% noise, scoring function CHISC.

It's evident that the application of Curriculum Learning (CL) had a positive impact on learning. As the RMSE metric values decreased, it indicates improved performance. The best scenario was achieved with the RMSE scoring function, showing a reduction of 0.014155 in Table 1, while the worst scenario was observed with the CHISC scoring function, which showed a reduction of 0.011966 in Table 2.

Metric	Constante	Linear	Log	Ladder	Ladder Log
RMSE	0,2110	0,2118	0,2125	0,2159	**0,2104**
PSNR	61,760	61,731	61,707	61,579	**61,793**
SSIM	0,4693	0,4641	0,4555	0,4508	**0,4663**

Table 3: Application with 30% noise, scoring function RMSE.

Metric	Constante	Linear	Log	Ladder	Ladder Log
RMSE	0,2110	0,2099	0,2119	0,2138	**0,2099**
PSNR	61,760	61,813	61,731	61,658	**61,807**
SSIM	0,4693	0,45505	0,4639	0,4579	**0,4716**

Table 4: Application with 30% noise, scoring function CHISC.

The CL technique yielded satisfactory results for Gaussian noise removal with both RMSE and CHISC scoring functions. It's evident that the results obtained outperformed those achieved by the constant method. Additionally, we observed that the RMSE metric demonstrated its most notable performance in scenarios with lower noise levels, as illustrated in Table 1. On the other hand, in situations with higher noise levels, the CHISC metric showed more satisfactory results. This is evident in the analysis of Table 4, where we observed a decrease of 0.001147 in RMSE, an increase of 0.05345 in PSNR, and an increase of 0.014311 in SSIM. These results solidify the improvement in performance.

Conclusions

Based on these results, we conclude that the Curriculum Learning (CL) training method is applicable to Denoising Autoencoders (DAEs) and yields results equal to or better than the traditional method. Furthermore, we observed that CL is sensitive to the hyperparameters used, with superior performance when using the CHISC metric for higher noise levels and the RMSE metric for lower noise levels.

Another noteworthy factor is that the use of this methodology reduces training time since data is gradually incorporated, resulting in a significantly smaller number of images used in the initial epochs.

References

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