Image Denoising using Autoencoders and Singular Value Decomposition (k-SVD)

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Abstract

Image denoising, a fundamental task in image processing, involves restoring the original image by removing noise from a noise-affected version. It holds immense significance in enhancing image quality, especially in biomedical contexts, where clearer images can lead to more accurate medical diagnoses. Noise sources, both intrinsic (like sensors) and extrinsic (like environmental factors), can introduce distortions that are often unavoidable.

Autoencoders, a class of artificial neural networks, are adept at unsupervised learning. They are trained to reconstruct their input at the output, making them ideal for denoising tasks. In this endeavor, our focus lies in crafting a denoising model by combining denoising singular value decomposition (SVD) and denoising autoencoder on a X-ray image small dataset.

The result shows that combining the denoising SVD with autoencoder performed better than using only denoicing autiencoder on small X-ray image dataset.

1 Introduction

Medical imaging techniques, encompassing X-rays, Magnetic Resonance Imaging (MRI), Computer Tomography (CT), ultrasound, and more, are notably vulnerable to the intrusion of noise [8]. This susceptibility arises from a myriad of factors, spanning diverse image acquisition methods to endeavors aimed at minimizing patient radiation exposure. Notably, the reduction of radiation levels can inadvertently lead to an escalation in noise [7]. Consequently, the need for denoising emerges as a crucial demand for accurate image analysis, serving both human interpretations and machine-based assessments.

During the stages of acquisition and transmission, images inevitably encounter noise, which can compromise their quality. As a vital preliminary measure to enhance the precision of subsequent processing, image denoising becomes imperative across a wide array of applications. These encompass visual refinement, feature extraction, and object recognition

The primary objective of denoising is to meticulously restore the original image from its noisy manifestation, striking a delicate balance between accuracy and the retention of crucial details like edges and textures. Pursuing this goal, the domain of image denoising has been a subject of extensive exploration within the signal processing community over the past decades. The culmination of these efforts has yielded a diverse denoising techniques, each contributing to the body of knowledge in this field.

The primary aim of this study is to combine denoising SVD with denoising autoencoder on small X-rays images and comapre the output with when using only denoising autoencoder on small dataset.

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2 Literature

While BM3D [1] is recognized as a cutting-edge technique in image denoising and has been meticulously designed, Burger et al. [2] demonstrated that a plain multi-layer perceptron (MLP) can achieve comparable denoising performance.

Denoising autoencoders, a recent addition to the field of image denoising, were introduced by Vincent et al. [3] as an extension of classic autoencoders and have been utilized as foundational elements in deep networks. The stacking of denoising autoencoders was explored [4], enabling the construction of deep networks by feeding the output of one denoising autoencoder to the one below it.

Jain et al. [5] proposed image denoising using convolutional neural networks and observed that, with a limited set of training images, performance equivalent to or surpassing state-of-the-art methods based on wavelets and Markov random fields can be achieved. Meanwhile, Xie et al. [6] employed stacked sparse autoencoders for image denoising and inpainting, delivering comparable results to SVD.

Another approach by Agostenelli et al. [7] involved adaptive multi-column deep neural networks for image denoising, constructed through a combination of stacked sparse autoencoders. This system demonstrated robustness across various noise types.

3 Method

This project will investigate the use of autoencoders for denoising medical images. The goal is to see if an autoencoder can improve the quality of noisy medical images, and how this affects the accuracy of subsequent image analysis. This project will start by systematically introducing noise into a medical image dataset, creating a 'noisy' version of the original images.Firstly, singular value decomposition (SVD) was employed for denoising the images, followed by the utilization of an autoencoder model on the SVD outcomes. This was then compared to the scenario where solely an autoencoder model was used. The autoencoder model was trained to 'denoise' the noisy images, aiming to reconstruct the original images from their noisy counterparts. Subsequently, after training the autoencoder, the accuracy of image analysis outcomes from the original images, noisy images, and denoised images was compared. This comparison aimed to ascertain whether the combined approach of autoencoder and SVD was more efficient and effective in enhancing the quality of noisy medical images, and whether it resulted in more accurate image analysis outcomes compared to employing only an autoencoder model.

3.1 SVD Denoising

Every two-dimensional image A of size $M \times N (M \geq N)$ can be decomposed into three matrices by SVD:

$$A = USV^T$$

where U and V are the left and right singular matrices of A, with column vectors $\vec{u}_i$ and $\vec{v}_i$, respectively. The rank of A is $R(R \leq N)$, and when the diagonal SV matrix $S = diag\,(s_1, s_2, \ldots, s_R)$ is a non-negative matrix, the nonzero singular values can be arranged as $s_1 \geq s_2 \geq \cdots \geq s_R > 0$. These SVs reflect the energy distribution of the image, and s_i can be considered the representation coefficient. Therefore, image A can be expressed by ignoring SVs having value zero as follows:

$$A = \sum_{i=1}^{R} s_i u_i v_i^T.$$

[9] proposed an improved image denoising method based on wavelet and SVD transforms using the directional features [15]: use the SVD to filter the noise of the highfrequency parts with image rotations and the enhancement of the directional features; then rotate it back after filtering.

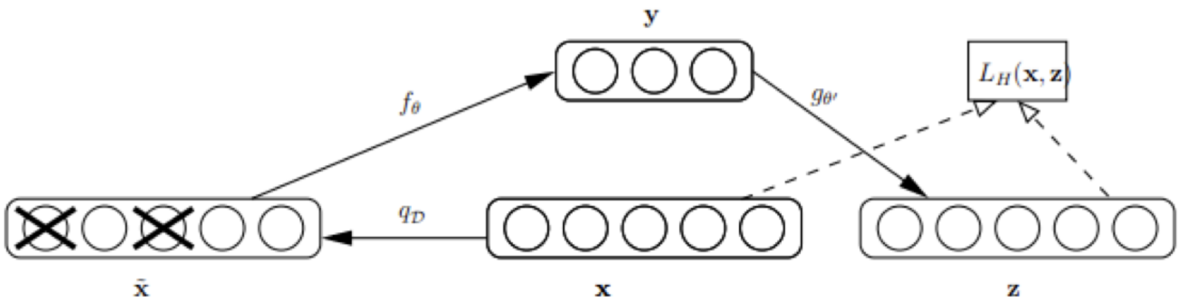

Figure 1: Denoising autoencoder

3.1.1 Autoencoders

An autoencoder represents a specific class of neural networks designed to learn an approximation of the identity function through backpropagation. In other words, it aims to replicate its input data without labels, using a set of training inputs that lack explicit annotations.

Denoising Autoencoders: A denoising autoencoder can be seen as an expanded version of the traditional autoencoder [10], wherein the model is compelled to grasp the art of reconstructing inputs when presented with their noisy counterparts. This involves introducing a stochastic corruption step that randomly nullifies certain input elements. Consequently, the denoising autoencoder is then tasked with predicting the absent (corrupted) information, focusing on randomly chosen sets of these absent patterns. Basic architecture of a denoising autoencoder is shown in Fig. 1

4 Evaluation and Results

4.1 Data

I used X-ray Covid-19 dataset from Kaggle, with 100 normal X-images images collected from patients with a resolution of 1935 × 2400.

4.2 Experimental Preparation:

Before commencing with the modeling process, all images underwent a preprocessing stage. This preprocessing involved resizing all images to dimensions of 64 × 64, primarily driven by considerations related to computational resources. The corruption process, characterized by various parameters as outlined in Table I, was then employed for further experimentation.

Rather than applying corruption to individual images sequentially, a flattened dataset was utilized, where each row corresponded to an image. This approach involved simultaneously introducing perturbations to all images within the dataset. Subsequently, the corrupted datasets were employed in the modeling process. For the convolutional denoising autoencoder (CNN DAE), a relatively straightforward architecture was adopted. The Gaussian noise ($\sigma = 1, \mu = 0$ p=0.1) was used to add noise to the original image. The evaluation of images was carried out using the structural similarity index measure (SSIM), which was preferred over the peak signal-to-noise ratio (PSNR) due to its heightened consistency and accuracy [11]. SSIM, a composite index derived from three measurements, assesses the visual impact of alterations in image luminance, contrast, and other residual discrepancies, collectively referred to as structural modifications. The foundational configurations remained consistent across all experiments, utilizing 50 epochs and a batch size of 16. The absence of fine-tuning was deliberate to ensure the comparison results were obtained on a rudimentary architecture, which should be accessible even to less experienced users. The average SSIM scores across the test image set were computed and reported for the purpose of comparison.

5 Result

The result presented in this for this experiment is presented in this section. The table 1 shows the SSIM using K-SVD on the image, denoising autoencoder and combination of the two method.

Here are the results obtained from the denoising methods, as shown in Table 1:

Table 1: COMPARING MEAN SSIM SCORES DENOISING METHODS

Image type	SSIM
Noised	0.1053
K-SVD	0.1702
DAE	0.1124
K-SVD+DAE	0.3358

Our hard work has led us to a significant finding: when we combined K-SVD and DAE methods on smaller images, we got better results than using them separately. The SSIM score of 0.3358 shows that this combination works better than just using K-SVD or DAE alone.

Although the denoised images are not entirely clear due to their small size, it's important to know that we were aiming for a comprehensive approach rather than perfect clarity. Our success lies in navigating the complex world of denoising by considering various factors. The SSIM score of 0.3358 shows that we have made progress.

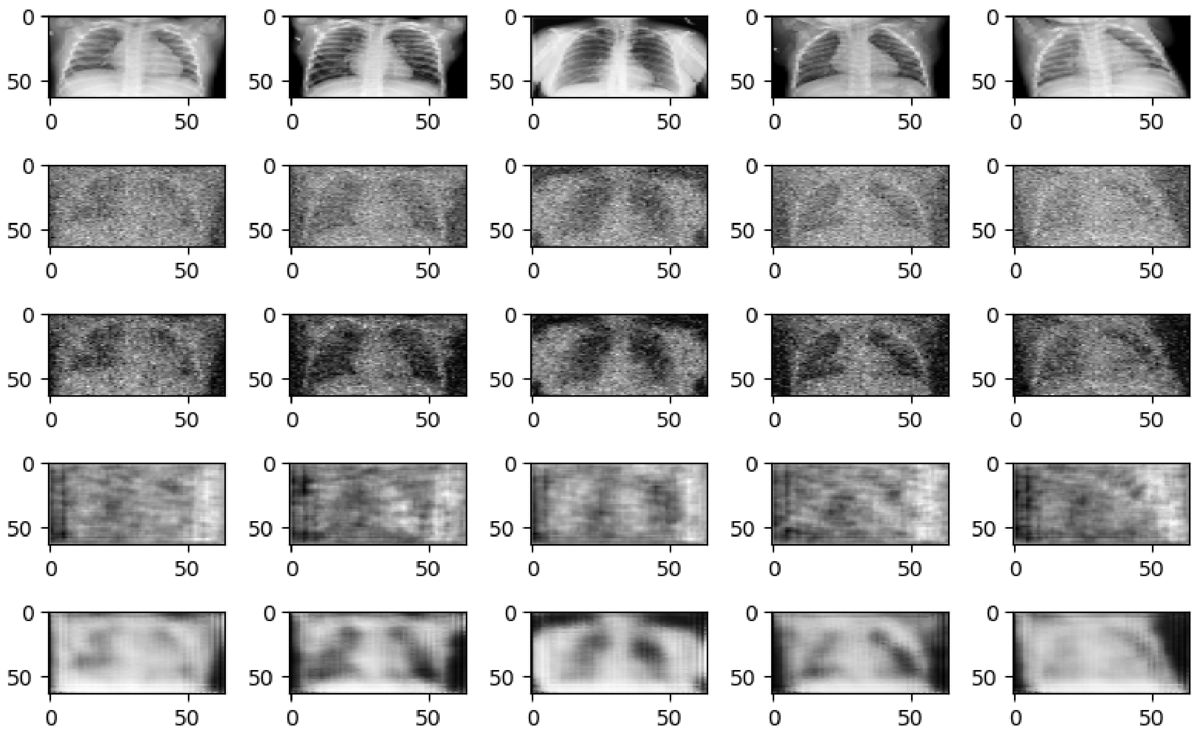

Figure 2: The first row contains the real image, the second row is the noised image, the third is the K-SVD denoised, the fourth row is the DAE, and the last row is the combination of K-SVD.

6 Conclusion

In conclusion, our exploration into the amalgamation of K-SVD and DAE techniques for denoising smaller images has yielded promising results. The enhanced outcomes achieved through this combined approach, as indicated by the higher SSIM score of 0.3358, suggest its potential in addressing the challenges of noisy image restoration.

As we move ahead, future research endeavors can capitalize on this foundation. Emphasizing the utilization of larger datasets could lead to improved accuracy in denoising, thus refining the quality of reconstructed images and further strengthening the robustness of the techniques. By broadening our horizons and harnessing the power of expansive data, we can continue to advance the field of medical image denoising and contribute to enhanced diagnostic and analytical applications.

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