Noise Suppression by Artificial Intelligence

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Noise suppression algorithms have been used in various tasks such as computer vision, industrial inspection, and video surveillance, among others. Noise suppression has become a dynamic field within the domain of image processing. This is due to the fact that as technological advances emerge, a greater understanding of the scene in which a vision system is interacting is required.

denoising vanilla autoencoder images noise

1. Introduction

Currently, there is a growing interest in the use of artificial vision systems for application in daily tasks such as industrial processes, autonomous driving, telecommunication systems, surveillance systems, and medicine, among others [1]. Recent developments in the field of artificial vision have stimulated the need to make increasingly robust systems to meet established quality requirements, which is an essential part of why systems fail to cover these types of requirements, mainly in data acquisition. Among image acquisition systems, there are several factors that can alter the result of the capture, including failures in the camera sensors, adverse lighting conditions, electromagnetic interferences, noise generated by the hardware, etc. [2]. All of these phenomena are described using distribution models and are known, in a general way, as noise. The procedure in the image processing field to try to diminish the effect of the noise is known as the pre-processing stage in any image processing system. In recent years, various algorithms have been developed in denoising images, and recently, a new field has taken much interest in the scientific community. In this way, deep learning methods emerge [3][4].

Deep learning methods particularly present an inherent ability to overcome the deficiencies contained in some traditional algorithms [5]; however, despite their significant improvements compared to traditional filters, deep learning methods have practical limitations to their credit, which fall in high computational complexity. Although, as previously mentioned, various methods have focused on noise suppression [6][7][8].

2. Noise Suppression

In recent years, noise suppression has become a dynamic field within the domain of image processing. This is due to the fact that as technological advances emerge, a greater understanding of the scene in which a vision system is interacting is required [9]. For the suppression of noise, several processing techniques have been proposed. These techniques are known as filters that depend on the noise present in the image and are mainly classified into two types.

2.1. Spatial Domain Filtering

Spatial filtering is a traditional method for noise suppression in images. These filters suppress noise by being applied directly to the corrupted image. They can generally be classified into linear and non-linear. Among the most common filters are:

- Mean Filter: For each pixel, there are samples with a similar neighborhood to the pixel's neighborhood, and the pixel value is updated according to the weighted average of the samples [10].

- Median Filter: The use of this filter is that the central pixel of a neighborhood is replaced by the median value of the corresponding window [11].

- Fuzzy Methods: This type of filter is different from those mentioned above since it is mainly constituted by fuzzy rules with which it is possible to preserve the edges and fine details in an image. Fuzzy rules are used to derive suitable weights for neighboring samples by considering local gradients and angle deviations. Finally, directional processing is used with which it improves the precision of the same filter [12].

2.2. Transform Domain Filtering

Transform domain filtering is a very useful tool for signal and image processing due to its extensive analysis of multiple resolutions, sub-bands, and location in the time and frequency domains. An example of this type of filtering is the Wavelet method, which is performed based on the frequency domain and attempts to distinguish the signal from noise and preserve said signal in the noise suppression process. As a first step, a wave base is selected to determine the decomposition of its layers to later select the level of decomposition, establishing a threshold in all the sub-bands for all levels [13].

2.3. Artificial Intelligence

A new method of processing images has emerged, called artificial intelligence. To address the issue of noise suppression, it is necessary to distinguish between artificial intelligence, machine learning, and deep learning, because people tend to use these terms synonymously, but there exists a subtle difference. Artificial intelligence involves machines that can perform tasks with characteristics of human intelligence, such as understanding language, recognizing objects, gestures, sounds, and problem solving [14][15]. Machine learning is a subset that belongs to artificial intelligence. The function is to obtain better performance in the learning task. The algorithms used are mainly statistical and probabilistic ones, making the machines improve with experience, allowing them to act and make decisions based on the input data [16]. Finally, deep learning is a subset of machine learning that uses techniques and algorithms of automatic learning that have high performance in different problems of image recognition, sound recognition, etc., since the basic functioning and structure of the brain and the visual system of animals are imitated [17].

There are two types of deep learning: the first type is supervised, learning which takes a direct approach using labels on learning data to build a reasonable understanding of how machines make decisions, and the second is unsupervised learning, which takes a very different approach by learning by itself how to make decisions or perform specific tasks without the need to contain labels in a database [18].

Autoencoders

Autoencoders are unsupervised neural networks, and the main function of autoencoders is that the input and the output are the same [19]. This is taken as an advantage against other models because, in each training phase of the neural network, the output is compared with the original image version, and through a calculation error, the weights found in each of the layers that make up the autoencoder are adjusted. This adjustment is carried out by means of the backpropagation method. There are different types of autoencoders, which are:

- The Vanilla Autoencoder (*VA*) comprises only three layers: the encoding layer, in charge of reducing the dimensions of the input information; the hidden layer, better known as latent space, in which are the representations of all characteristics learned by the network; and the decoding layer, which is in charge of restoring the information to its original input dimensions, as shown in **Figure 1** [20].

- The Convolutional Autoencoder (*Conv AE*) makes use of convolution operators and extracts useful representations from the input data, as shown in **Figure 2**. The input image is sampled to obtain a latent representation and is forced to learn that representation [21].

- The Denoising Autoencoder (*DA*) is a robust modification of *Conv AE* that changes the input data preparation. The information the autoencoder is trained in is divided into two groups: original and corrupted. In order for the autoencoder to learn to denoise an image, the corrupted information is sent to the input of the network to be processed. Once the information is in the output, it is compared with the original [22]. This type of autoencoder is capable of generating clean images from noisy images, ignoring the type of noise present as well as the density in which the image was affected.

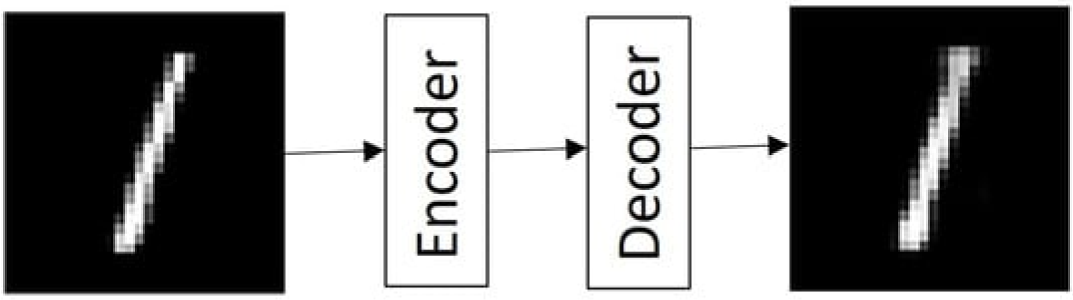

Figure 1. Architecture of the vanilla autoencoder.

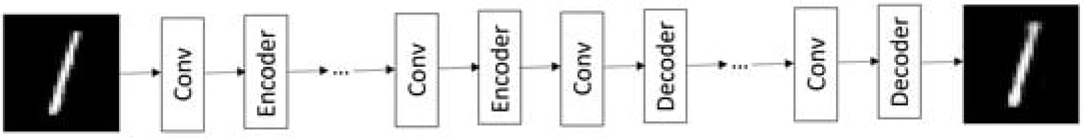

Figure 2. Architecture of the convolutional autoencoder.

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