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Using autoencoders to reduce noise from infrared thermal imaging of carbon fiber reinforced polymer plates

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Abstract

Noise in data can generate difficulty and even inaccuracy in its analysis. In some activities where diagnoses must have good technical precision, such as medical and dental examinations, non-destructive tests on industrial materials, agricultural monitoring, and others, noise present in the data can disturb this precision. In this work we present a statistical learning model, based on convolutional neural networks, capable of removing synthetic noise in infrared thermal images, obtained from a carbon fiber reinforced polymer plate.

1. Introduction

The presence of noise in digital images, causing loss of resolution and sharpness, has been a challenge for the scientific community in the field of data and images. With the advancement of computer technology and scientific algorithms, data has been more deeply and more carefully explored and examined [1]. Specifically for RGB or thermal image data, the detailed processing of an object is able to determine its state, for example, how healthy or deteriorated a fruit is and, even more, if this product is able for commercialization and what its market value is. In the same way, the accurate analysis of an infrared thermal image can detect, immediately and without posing risks to human health, the presence of a carcinoma or other disease.

However, in the process of producing these data, there are some factors that add noise. In thermal images, the emissivity of the object of interest, the loss of infrared signals, the oscillation of heat reflected to the sensors, among others, are some of the aspects responsible for causing noise. In addition, the processing of thermal signals performed by electronic devices is also liable to generate noise [1]. In this work we present an algorithm called Denoising AutoEncoder (DAE), based on convolutional neural networks [2], capable of reducing noise from infrared thermal images extracted from a sheet of polymer reinforced with carbon fiber.

2. Experimental Methodology

The objective proposed in this work is to build a model, based on convolutional neural networks, to reduce noise in thermal images extracted from a carbon fiber reinforced polymer plate. The steps taken in this process are defined below.

2.1. Specimens and Data Acquisition

We collect infrared thermal data using Pulsed Thermography (PT) – which consists of rapidly heating the specimen and then the heat reflected by the material is returned to the camera sensors, providing information about its surface and subsurface – using a FLIR Phoenix, InSb, 3–5 μm, 640 × 512 pixels windowed to 320 × 256 at a frame rate of 55 Hz infrared thermal camera. The inspected part is a 100 × 100 mm unidirectional laminate manufactured with carbon/PEEK (polyether ether ketone). It has a fiber volume fraction of 61%. For this experiment, 2780 thermal images extracted from the specimen were used, being 1385 images of the front surface and 1395 images of the rear surface of the specimen. Figure 1 a) presents thermal images of the front surface of the specimen.

2.2. The Denoising Autoencoder Model

Denoising AutoEncoders – DAE's are deep neural networks designed to represent, in the model's output, the data presented in its input. Its architecture is composed of three main elements: Encoder, Code and Decoder. Figure 2 shows the physical structure of an DAE. The Encoder and Decoder components are inversely similar neural networks, both in their computational architecture and in their dimensions, which operate as follows: the Encoder receives data at the network input. These data are stochastically mapped into two groups: original data and noisy data. Through function (g) with adjusted parameters (ϕ), the data are compacted and stored in a latent space called Code (or "bottleneck") [2]. The loss function reconstruction error is used for the network to learn to remove the added noise in the images, making the DAE extract the most essential features from the images. And then during the image reconstruction, through the f function and the θ parameters, the Decoder reduces the noise while recovering the initial dimensions of the input data.

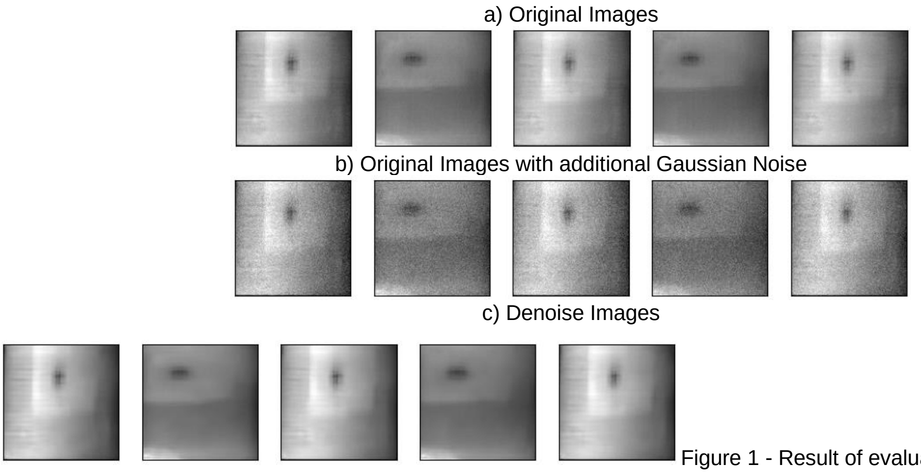

Figure 1 - Result of evaluating our model using five images from the test set with additional noise. Source: the autors.

The DAE architecture proposed in this work is based on Convolutional Neural Networks (CNN). The Encoder was contemplated with two convolutional and polling layers (to preserve the highest value for each convolutional operation), resulting in data downsampling until its intermediate encoding (latent space). Like the Encoder, the Decoder has two convolution layers where the upsampling technique is applied so that the initial dimensions are redefined [3].

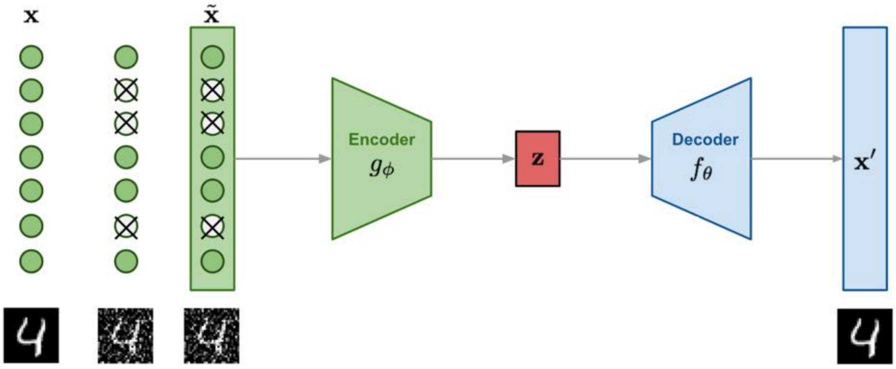

Figure 2 - Architecture of Denoising AutoEncoder model.
Source: Adapted from https://lilianweng.github.io/posts/2018-08-12-vae/denoising-autoencoder-architecture.png

To measure the uncertainty of the model we used the binary cross entropy as a cost function and to optimize the model, the Adam algorithm was chosen for the speed of convergence during network training. After training the training and validation images for 500 epochs and batches with 128 samples, our model had an accuracy of 97,43% for the training and validation data. We chose 5 images from the test dataset to run and compare the autoencoder. Note that there was a considerable reduction in the images of the test set, after the application of a Gaussian noise with the average centred in 0 and a dispersion degree of 0.1 (0.5 noise factor). Figure 1 presents five comparisons of test data. In a) are the original images. In b) are the original images with the application of the mentioned Gaussian noise. And finally, in c) we present the result of the performance of our model after reducing the noise of these five samples of the test set.

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