Deep Auto Encoder 를 이용한 아날로그 위성 수신기 지향 항공 영상 향상 방법

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Analog Satellite Receiver Oriented Aerial Image Enhancement Method using Deep Auto Encoders

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Abstract

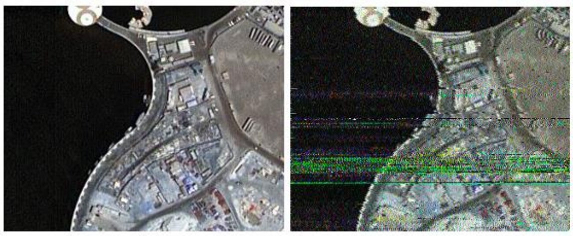
Aerial images are being one of the important aspects of satellite imagery, delivers effective information on landcovers. Their special characteristics includes the viewpoint from space which clarifies data related to land examining processes. Aerial images taken by satellites employed radio waves to wirelessly transmit images to ground stations. Due to transmission errors, images get distorted and unable to perform in landcover examining. This paper proposes an aerial image enhancement method using deep autoencoders. A properly trained auto-encoder can enhance an aerial image to a considerable level of improvement. Results showed that the achieved enhancement is better than that was obtained from traditional image denoising methods.

1. Introduction

Landcover exploration is an important activity in the human welfare facilitation. Satellite images hugely contributes such activities by providing accurate details about the surface of the earth. Satellite images include aerial images, which are images of earth's surface, taken from above usually from space by using a satellite. Land cover and land use monitoring are essential in natural resource management [1]. Based on an aerial image, different types of land coverage such as buildings, plantation, roads and water can be identified.

After taking an image, a satellite must send it to a ground station which is a radio receiver build for image reception. For convenience, a wireless connection is established between the satellite and the ground station. Image is then converted into a set of audio tones which include information about the image and send it using radio waves. During the transmission process, radio waves are vulnerable to interference and attenuation which disturbs the information transmission and eventually create a distorted image at the receiver's end. Such distorted image is less useful for landcover exploration. Figure 1(a) shows the transmitted image and (b) shows the received image.

This paper proposes and auto-encoder based image enhancement method for distorted and noisy aerial images enhancement. Convolutional layers of an auto-encoder can gradually scale down the input image and later build it up to the original size while adjusting their internal learnable parameters. These deep learning structures can be used for image denoising and enhancement [2]. Deep auto-encoders have higher noise reduction capability when compared them with total variation (TV) minimization algorithm and non-local means (NLM) algorithm [4].



(a) (b)

Figure 1. (a) Transmitted image and (b) received image.

2. Related Work

Image enhancement using auto-encoders is not a predefined output targeted task because according to the problem specification one can create different types of convolutional encoders and decoders. Unlike convolutional neural networks (CNN), auto-encoders only have convolutional layers, and they minimize their training error by correctly recreating the desired output. An image enhancement method based on auto-encoder is used in [2] for reduce noise in high resolution sonar images. Sonar images have high noise impact compared to an optical image. Auto-encoders reduced noise effectively rather than averaging filters. Deep auto-encoders can be used for noise reduction in range doper maps of some radar types [3]. This work explored better ways for radar images noise reduction including existing ones for same image type.

For low light image enhancement, a method with two auto-encoders applied in series is tested in [5]. This dual structure was effective for low light image enhancement. Also fingerprint sample enhancement is tested with auto-encoders [6]. In this case, it was used as a pre-enhancement method to achieve better quality.

3. Methodology

Main focus of deep learning model building is to create a capable model for the intended task. Used dataset is Satellite images of Dubai [8]. This dataset contains aerial images of Dubai. In order to collect images for auto-encoder training, these images are encoded into set of audio tones and frequency modulated with radio carrier and transmitted over the air. For modulation, Narrowband Frequency Modulation (NBFM) was used, and the carrier frequency was 450 MHz. Figure 2 shows the workflow. Received images are kept for the training process.

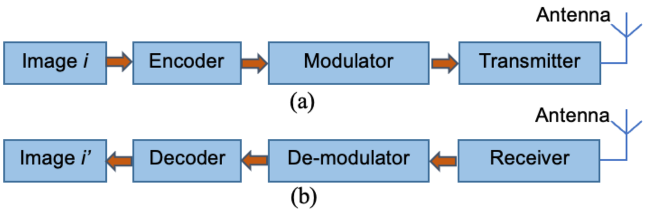


Figure 2. (a) Sender. (b) Receiver. Sent image *i* and received image *i'* are not the same.

Auto-encoder is a structure which has convolutional and deconvolutional layers to create an output similar to the input size [2]. Proposed auto-encoder structure is shown in Figure 3. Input and output sizes are 320x256. Every layer has Rectified Linear Unit (ReLU) activation function. Convolutional and de-convolutional layers have 3x3 filters. Optimizer used is Adam and loss function is Mean Squared Error (MSE) whose definition is shown below. Y is target vector, $\acute{Y}$ is recreated (output) image vector, and n is the number of images.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2$$

4. Results

Training is completed by using two cores of Intel Zeon processor at 2.3 GHz with 13 GB RAM and NVIDEA Tesla GPU. Common image size for analog image transmissions is 320x256, and this size was kept as a constant throughout the training and testing data sets. For 400 epochs, the proposed image enhancing auto-encoder's trainable parameters have achieved appropriate values successfully which was shown in Figure 4.

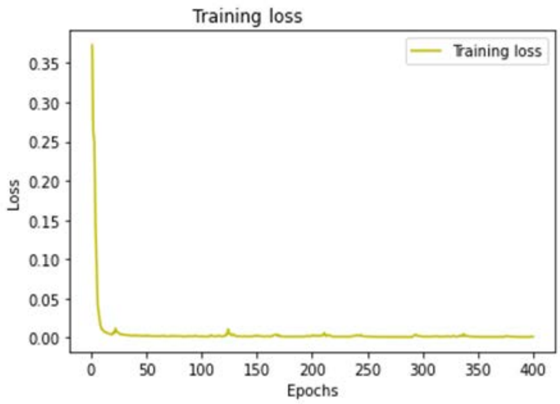


Figure 4. Training progress for 400 epochs.

Enhancement results are compared with mean filter, Gaussian filter, bilateral filter, non-local means (NLM) algorithm and total variation (TV) minimization algorithm with the metrics, Root Mean Squared Error (RMSE) (Shown in Table 1) and Peak Signal to Noise Ratio (PSNR) (Shown in Table 2). Results showed that the proposed auto-encoder based method achieved better enhancement.

5. Conclusion.

This paper proposed an auto-encoder based image enhancement method for aerial images received from analog satellites. From an existing dataset, transmission operation

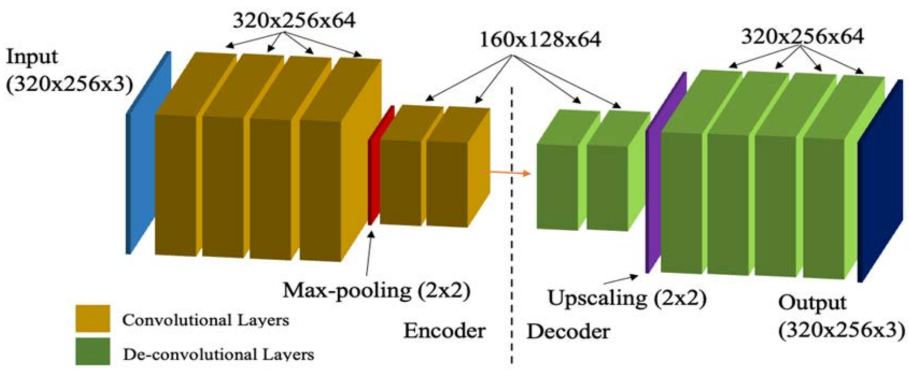


Figure 3. Proposed Encoder-Decoder Structure.

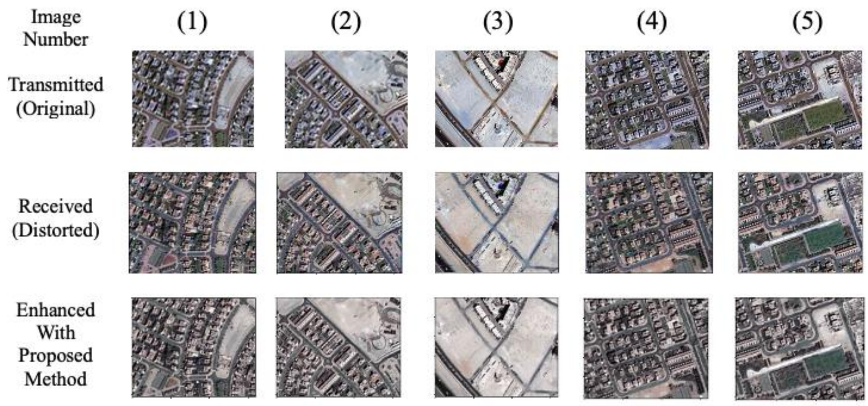


Figure 5. Results obtained for five testing images.

Table 1. Evaluation of the performance using RMSE for five testing images.

Method	(1)	(2)	(3)	(4)	(5)
Median (3x3)	0.2235	0.1896	0.1182	0.2357	0.2102
Gaussian(sigma=1)	0.2348	0.2017	0.1262	0.2499	0.2235
Bilateral	0.2427	0.2095	0.1305	0.2592	0.2323
NLM	0.2317	0.1989	0.1268	0.2439	0.2186
TV	0.2369	0.2009	0.1201	0.2531	0.2245
Proposed method	**0.1418**	**0.1186**	**0.0835**	**0.1544**	**0.1392**

Table 2. Evaluation of the performance using PSNR for five testing images.

Method	(1)	(2)	(3)	(4)	(5)
Median (3x3)	19.43	19.53	21.71	19.34	19.58
Gaussian(sigma=1)	19.00	19.00	21.14	18.83	19.05
Bilateral	18.71	18.67	20.85	18.52	18.72
NLM	19.11	19.12	21.10	19.05	19.25
TV	18.92	19.03	21.57	18.72	19.01
Proposed method	**23.38**	**23.60**	**24.73**	**23.02**	**23.16**

was performed to capture training data for the deep learning model. After training, results were compared with traditional image enhancement methods' results and the proposed method produced considerable achievement in enhancement.

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