Narrow-bandwidth Radio 이미지를 위한 자동 인코더 기반 이미지 향상

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Auto-Encoder Based Image Enhancement for Narrow-bandwidth Radio Images

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Abstract

Image transmission by means of telecommunications is an essential task for information sharing. For considerable distances, wireless channels can be utilized and tuned for proper uses of image data exchange. However, the disturbances that a radio wave encounter during transmission causes partial or total loss of information. Result of such communications is a distorted image at the receiver's end. This paper proposes an auto-encoder architecture as an image enhancement method for narrow-bandwidth radio images. With this method, a distorted image can be improved for better receiver satisfaction. The proposed auto-encoder is trained with many narrow-bandwidth radio image data; hence it enhances a given distorted image. Also, the results were verified with the original image data being the reference images.

1. Introduction

Data communication is being an important aspect and many forms of applications are inherited according to different needs. Narrow–bandwidth image transmission is a type of television which was designed to fit into a channel narrower than a standard analog television. It can be used to transmit or receive static images and needs only 3kHz of maximum bandwidth. Also the transmission is actually a broadcast so that it involves direct reception to a receiver.

In order to transmit an image over a transmission medium, it has to be converted into a different form which has 100% representation of the original image. One of the possible way is to convert pixel values into audio tones and then modulate the collection of tones with a carrier. Frequency modulation (FM) is suitable for such operation. During transmission, the signal is vulnerable to interference or attenuation which causes the signal not to contain 100% information about the original image when it is received. Figure 1. (a) shows the original image which was sent. Figure 1. (b), (c) and (d) shows different instances of the same image which has been received.

Auto-encoder algorithms based on convolutional neural networks (CNN) which can be used for image enhancement including noise reduction [1]. Convolutional layers of a CNN can extract different features of the input. In auto-encoders, features are then processed to upscale until they reach the size of the input. Improved auto-encoders produce better results than total variation (TV) minimization and non-local means (NLM) algorithms [3].

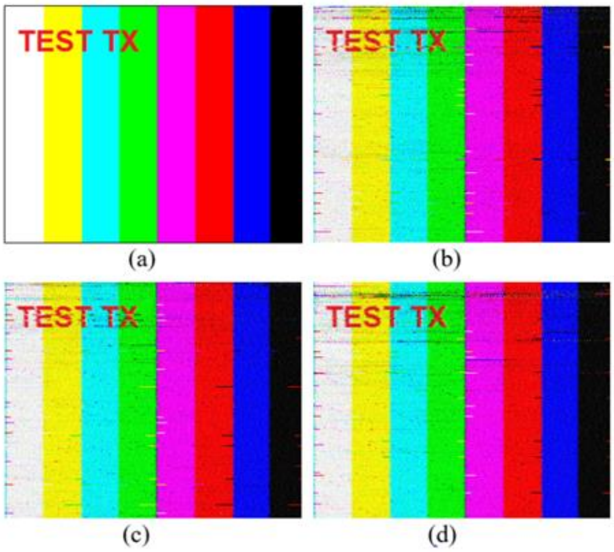

Figure 1. Different received instances (b), (c) and (d) of the same image (a).

2. Related Work

Convolutional layers of a CNN extract features to minimize the error of the network. Auto-encoders which only have convolutional layers can be trained to obtain the desired output with minimum error in a particular domain. An auto-encoder is tested for high resolution sonar image enhancing

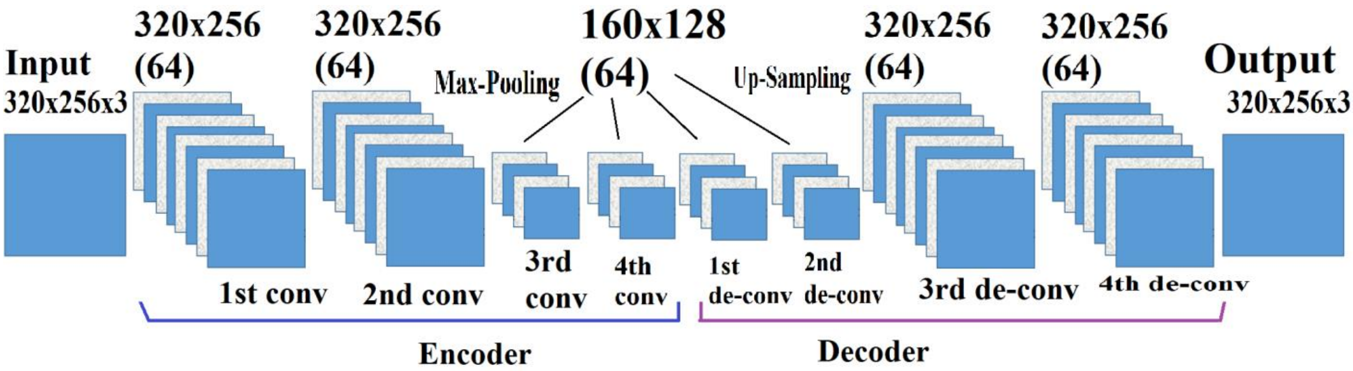

Figure 2. Structure of the proposed auto-encoder.

[1]. A sonar image contains a plenty of random noise compared to an optical image. Auto-encoders reduced noise in sonar images better than averaging filters.

Noise in Range-Doppler maps of some radars can be reduced by using deep convolutional auto-encoders [2]. The purpose of this work is to find better ways of noise reduction rather to use existing ones for the same image type. A dual auto-encoder method was proposed for enhancing low-light images [4]. In this work, two auto-encoders were applied in series to enhance the image. Also enhancement of fingerprint samples was tested with auto-encoders [5] as a pre-processing step for better quality.

3. Methodology

With the given priority and its own importance, an image enhancing auto-encoder is proposed for the narrow-bandwidth radio images. Following sub sections describe the consequential steps for the experiment.

3.1 Image Enhancing Auto-encoder

Auto-encoder is a neural network model which contains convolutional layers and deconvolution layers to restore the original input size [1]. Input provided to the network has the size of 320x256. This input is convolved two times with 64 convolutional filters. Then it is applied max-pooling of size 2x2 and convolved four times with 64 convolutional filters. After it is up-sampled with size 2x2 and de-convolved two times with 64 filters with the size of 320x256. Each convolutional layer has Rectified Linear Unit (ReLU) activation function. Finally, the original size of the input is restored. Figure 2 shows the proposed auto-encoder structure and table 1 gives the description.

Table 1. Proposed auto-encoder architecture.

Layer	Output size	# of filters	Filter size
1st conv layer	320x256x64	64	3x3
2nd conv layer	320x256x64	64	3x3
Max-pooling	160x128x64	-	2x2
3rd conv layer	160x128x64	64	3x3
4th conv layer	160x128x64	64	3x3
1st de-conv layer	160x128x64	64	3x3
2nd de-conv layer	160x128x64	64	3x3
Up-sampling	320x256x64	-	2x2
3rd de-conv layer	320x256x64	64	3x3
4th de-conv layer	320x256x64	64	3x3

3.2 Device Setup

In order to collect training data, a proper device setup is needed. Figure 3 (a) shows a sender, which transmit images over the air, and figure 3 (b) shows the receiver. Input image is converted to a collection of wave forms and modulated with a carrier. Narrowband frequency modulation (NBFM) scheme is used in the transmitter with 450 MHz carrier frequency.

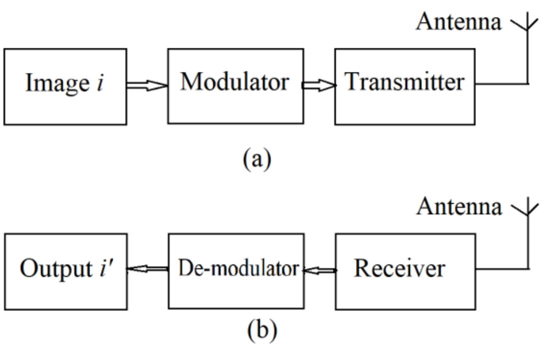

Figure 3. Image transmitter (a), and image receiver (b).

3.3 Data Collection.

If an image i is sent, corresponding received output is i'. Many outputs for a single image are collected by sending the same image many times. A total of 111 demodulated samples were collected. Same image is sent multiple times, because resulting output is different for each transmission.

4. Results

4.1 Training

Proposed auto-encoder is trained by using 2 x Intel Zeon 2.3 GHz CPU cores, 13 GB RAM system, with NVIDEA Tesla K80 GPU. All training images were size of 320x256 pixels.

4.2 Loss Function

Training loss is calculated by using Mean Squared Error (MSE) function. Also Adam optimizer is used in the training process for optimization. Proposed auto-encoder is trained 400 epochs. Training progress is shown in figure 4.

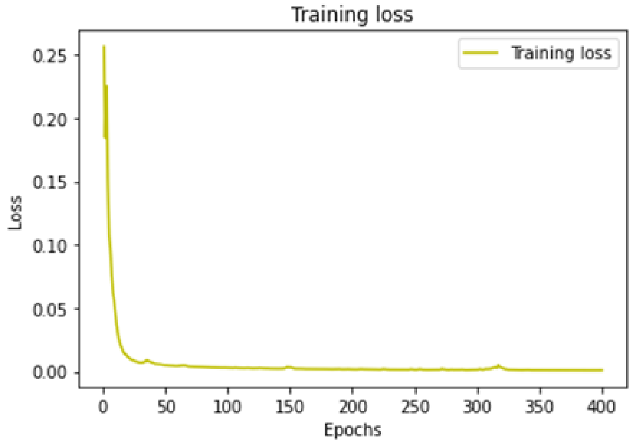

Figure 4. The plot of training loss obtained for 400 epochs.

4.3 Testing Images

Proposed method is tested with separate set of transmitted images which were not used for training. Results of the proposed method are compared with mean filter, Gaussian filter, bilateral filter, non-local means (NLM) algorithm and total variation (TV) minimization algorithm. Figure 5 shows results for five testing images. For the same testing images, table 2 shows Root Mean Squared Error (RMSE) values calculated, and table 3 shows Peak Signal to Noise Ratio (PSNR) values calculated for each method. For every calculation, the referencing image was the original image transmitted by the sender.

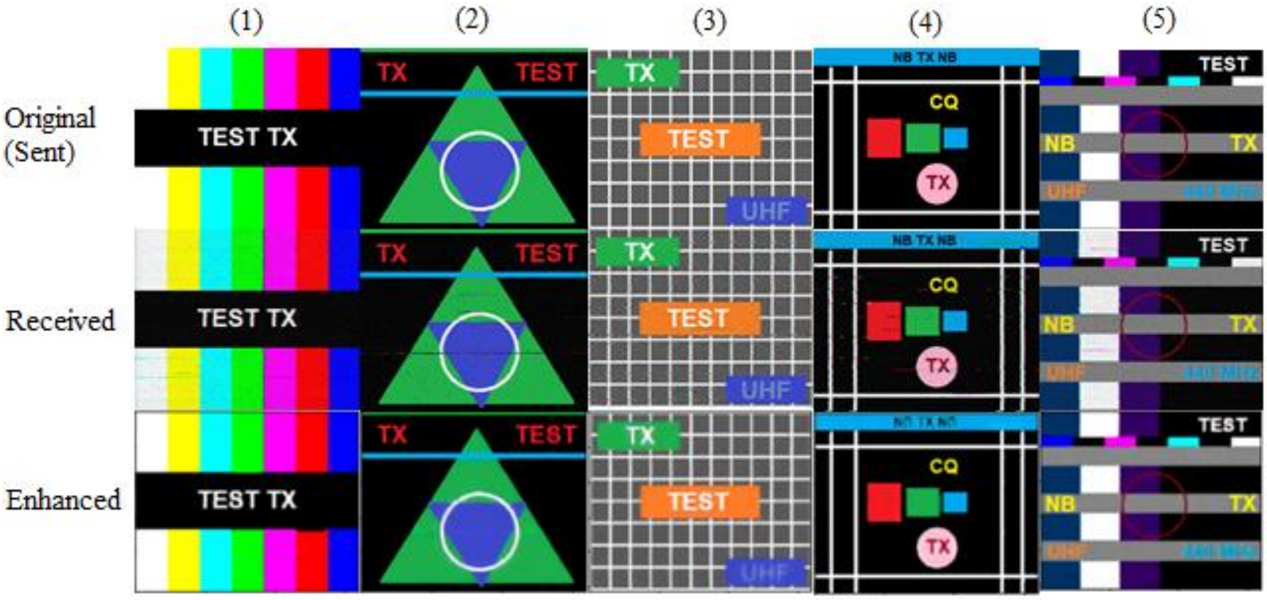

Figure 5. Results for five testing images.

Table 2. Evaluation of the performance using RMSE for five test images.

Method	(1)	(2)	(3)	(4)	(5)
Median (3x3)	0.1159	0.1520	0.1646	0.2546	0.1317
Gaussian (σ=1)	0.1533	0.1923	0.2043	0.3166	0.1654
Bilateral	0.1554	0.1979	0.2090	0.3218	0.1696
NLM	0.1304	0.1889	0.1662	0.2774	0.1520
TV	0.2102	0.2797	0.1862	0.2910	0.1775
[1]	0.0855	0.1995	0.1324	0.1319	0.1342
Proposed method	**0.0719**	**0.1389**	**0.0980**	**0.1106**	**0.0947**

Table 3. Evaluation of the performance using PSNR for five test images.

Method	(1)	(2)	(3)	(4)	(5)
Median (3x3)	22.62	25.63	20.41	19.52	23.15
Gaussian (σ=1)	20.20	25.58	18.53	17.63	21.87
Bilateral	20.08	23.33	18.33	17.49	21.65
NLM	21.61	23.73	20.32	18.78	22.60
TV	17.46	20.33	19.34	18.36	21.25
[1]	25.27	23.26	22.23	25.23	23.68
Proposed method	**26.77**	**26.41**	**24.90**	**26.76**	**26.71**

5. Conclusion.

In this paper, an auto-encoder based image enhancement method is proposed for narrow-bandwidth radio images. A custom image data set was generated and a transmission operation was performed to collect training data. Then the auto-encoder was trained and results were obtained. Results showed a significant enhancement in the received images. Finally, it shows using an auto-encoder based image enhancement method for narrow-bandwidth radio images is greatly effective.

References

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