Denoising Auto-Encoder Based Image Enhancement For High Resolution Sonar Image

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***Abstract*—A typical sonar image has a plenty of random noise compared to an optical image. Due to poor picture quality, there is a large restriction on recognizing any object. Pattern recognition is exceedingly difficult not only in computer image processing but even in human eyes. Numerous researchers have attempted to apply various types of average filters to sonar images, and have also removed noise by using multiple images in succession. However, each of the algorithms has a limitation in that the resolution of the image itself is degraded or the image of the object is difficult to remove noise. Finally, We performed sonar image noise reduction with the auto-encoder algorithm based on convolutional neural network, which as recently been attracting attention. With the algorithm, we obtained sonar images of superior quality with only a single continuous image. We simply learned a ton of sonar images in a neural network of auto-encoder structures, and then we could get the results by injecting the original sonar images. We verified the results of image enhancement using the acoustic lens based multibeam sonar images.**

***Keywords*—sonar image; noise reduction; image enhancement; denoising auto-encoder; machine learning.**

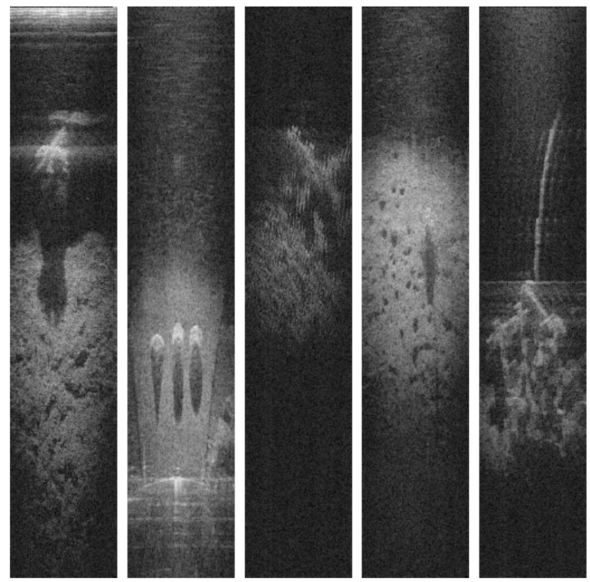

Fig. 1. The acoustic lens based multibeam sonar images. They were taken by AUV 'Cyclops' [1].

1. Introduction

The Autonomous Underwater Vehicle (AUV) and Remotely Operated Vehicle (ROV) have plenteous sensors to gather the oceanic information. Specifically, they are divided into two types. The first type sensors are navigation sensors for operating vehicles. This leads to accurate movement of the robot, and it is possible to operate the vehicle by grasping the desired position. The other sensors are oceanic data collecting sensors for gathering environmental data or underwater images.

Oceanic observation shows the marine ecosystems and physical environments. Different environmental conditions include submarine topography and tidal currents. In the submarine topography, we can see several submarine volcanoes and inhabited creatures, and it has great historical significance in geomorphology. After exploration of underwater and gathering data, we can find the correlation between the ecosystems and environments.

The underwater images include optical images and sonar images. The optical images are high resolution and colored. However, it can not be taken in the turbid stream and see the long range. In addition, there is little light in the sea, then it needs to have a strong light. However, it is possible to observe the actual ecosystem in detail and computer image processing is somewhat easy. Specially the sonar images can show the object of the turbid water and have a long range of sight [2]. Furthermore, it is possible to obtain an image without the light, and if it is on the floor, you can figure out the approximate height of the object. Nevertheless they have hardness of recognition because of low resolution and high noises. In addition, if the difference between water and density is not large, the shape will not appear in detail, and the shadow, highlight, and background are greatly depending on the viewing angle.

In this study, we proposed image enhancement of high resolution sonar image based on denoising auto-encoder. By enhancing the image, the quality of the image can be improved and the results of the exploration can be seen effectively. The auto-encoder is a neural network based algorithm that conducts unsupervised machine learning. It includes convolution networks and deconvolution networks with the same input and output matrix. We have trained the network with the acoustic lens based multibeam sonar images and tested

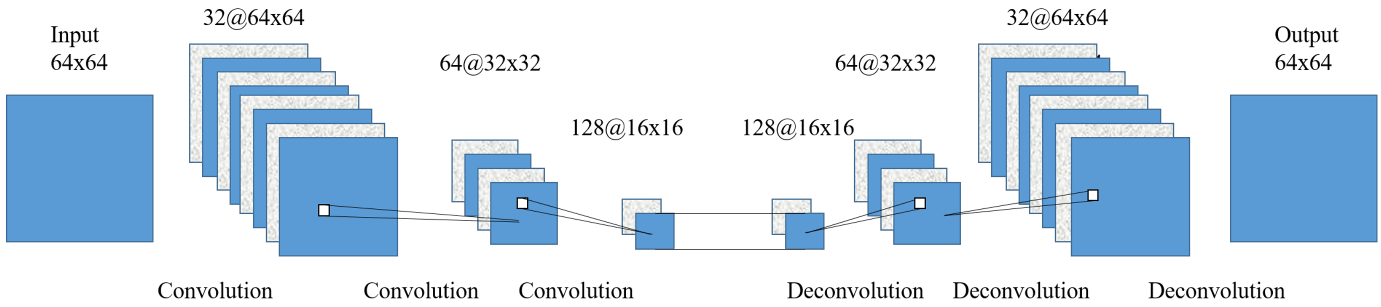

Fig. 2. The auto-encoder neural network structure.

the enhancement of output. As a result, we found the high clearance of noise reduction and generated even clear sonar images.

2. Background

2.1. *Acoustic Lens Based Multibeam Sonar Image*

The acoustic lens based multibeam sonar can take images in the cloudy water condition, and it can acquire an acoustic video image in real time. It is a forward solution for underwater object detection because it has a longer visual range than optical imaging. However, the image quality of the sonar is lower than the image quality of the optical image. Due to the intrinsic limitations of the acoustic beam, the front-facing acoustic instrument delivers low-quality sound images that has low resolution and high noise. Moreover, its image topology shows different hops by taking height and angle [4], and it can hardly be distinguished from the human eye (Fig. 1). In the end, it is difficult to extract information from image processing technology due to these characteristics.

2.2. *Machine Learning*

The field of image enhancement that uses machine learning is related to the realm of super-resolution. Super-resolution is a technique that artificially enhances the resolution of an image in general, so that information that can not be obtained from the image can be obtained. Several algorithms have been studied, such as restoring already mosaiced faces or attempting to restore a lower resolution image to a larger image. Along with this, the technique of eliminating noise based on machine learning also showed brilliant results. We can construct a neural network that removes noise by itself by learning an image with arbitrary strong noise as an input value and by learning the original image with the expected value.

3. Methodology

We proposed the denoising auto-encoder based image enhancement for high resolution sonar image. We first configured an artificial neural network related to auto-encoder to the sonar image, and then proceeded to create training set images. Next, after sufficient learning, we collected the image enhancement results.

3.1. *Denoising Auto-encoder*

The auto-encoder is a neural network model that has hidden layers [3]. It has deconvolution layers to restore their input size. The artificial neural network has six layers in total and has three convolution processes and three deconvolution processes. The first layer has 32 depths, the second has 64 depths, and the third has 128 depths (Fig. 2). However, since the size of the actual sonar image is larger than 64x64, the structure should be changed slightly after learning. The actual learned values do not need to be re-learned because they are the weights and biases of each convolution and deconvolution. In addition, it is unsupervised machine learning because one image is used for both input and output layers. First, the sonar images are cropped as [64, 64] size. Next, each cropped images artificially gets gaussian-noise and inserts to input layer. Finally, the output data is original cropped image and the model trains a great deal of images.

3.2. *Image Resolution Restore Strategy*

In an auto-encoder network, the resolution is halved by pooling when passing through the convolution layer. It is restored to the deconvolution layers, however the actual result is blurred by the resolution value that was decreased in the previous step. When passing through one layer, the width and height are reduced by half each, four times smaller, and one more layer is passed, so that it becomes 16 times smaller. In order to solve this problem, we artificially increased the image resolution by 16 times and put it into the network for the resolution recovery. Finally, the result is a 16x larger image, which is the last image reduction to make it the same size as the original image.

4. Result

4.1. *Training*

A. Data-set: We trained the total 13,650 images to the model that are randomly cropped by 64x64 from the acoustic lens based multibeam sonar images. All of sonar images were taken from actual sea area by AUV Cyclops [1]. We placed objects such as bricks, tires, cones, and shelters on the surface of the sea, and then captured the sonar image. In addition, the photographing was performed not only in a fixed place but also in a moving situation.

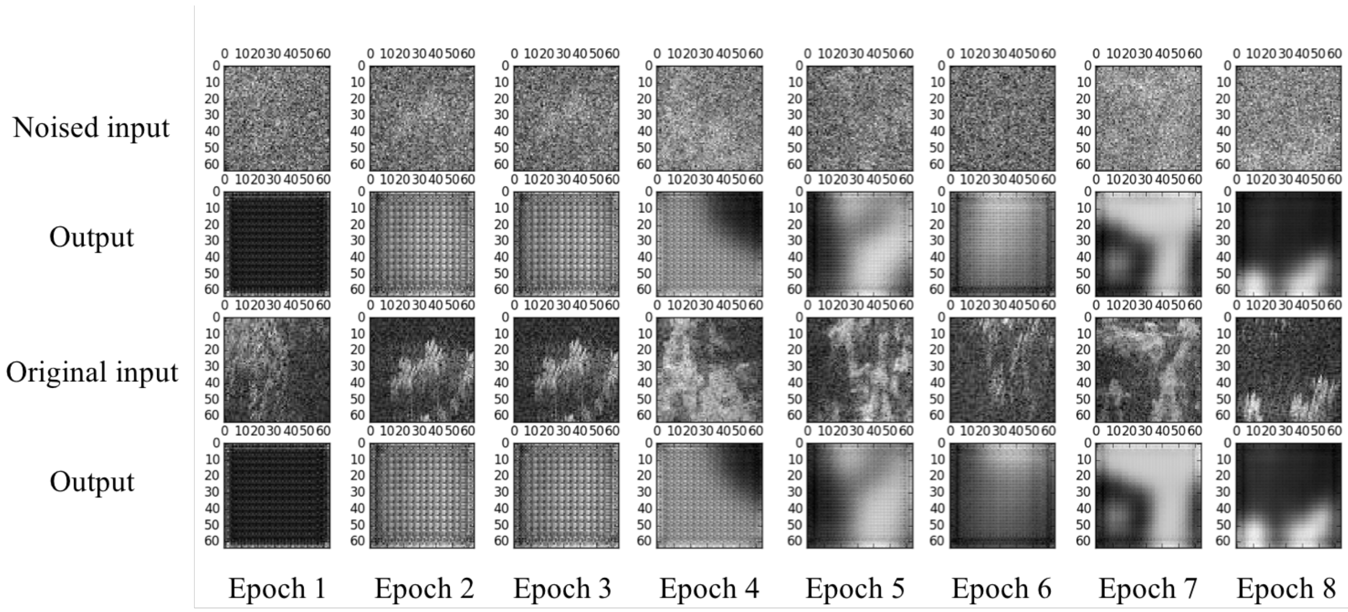

Fig. 3. The progress of the output images in each training epochs.

B. Loss Function: The gaussian-noise added images are put into the network's input. Then we train the model for the output of the original images. We can check the training progress by the loss value (Fig. 4). With the decreasing saturation of graph tendency, we can check the learning influence. We used a deep-running library Tensorflow with GPU acceleration. We used the GPU called Titan X Pascal and it took a long time to learn despite its high speed and high parallelism. It took about thirty minutes to finish the training.

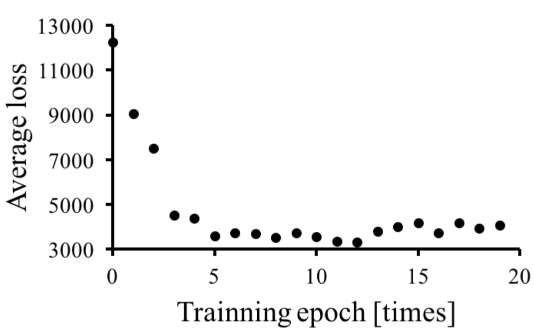

Fig. 4. The average loss function value of training.

C. Training Process: In each epochs, we can check the reducing noise performance (Fig. 3). The first row shows the training input images that are gaussian-noise added images. This shows a partial area of the sonar images that are invisible to the human eye, it is not identified at all. The output columns shows the output of neural network. In progress of epochs, the output images are gradually similar to original images. The third line shows the partial area of the original image, and the last line shows the output image of the model according to the partial area input of the original image. These two lines also show similar pattern trends according to the progress of the epoch.

Fig. 5. The optical image of traffic cone and tire.

4.2. Whole Image Result

After the training finished, we tested the whole sonar images. The original denoising auto-encoder lowers the resolution six teen times by dropout of pixel data. For this reason, we made higher the resolution six teen times and conducted noise reduction. The output images show the nice image enhancement (Fig. 6, Fig. 7). In addition the highlight section far stand out as the high contrast. As a comparison target, five multi-frame Gaussian filters were superimposed [5]. However, this algorithm has the disadvantage that the afterimage remains and the filtering is not performed properly unless the object is locked-on.

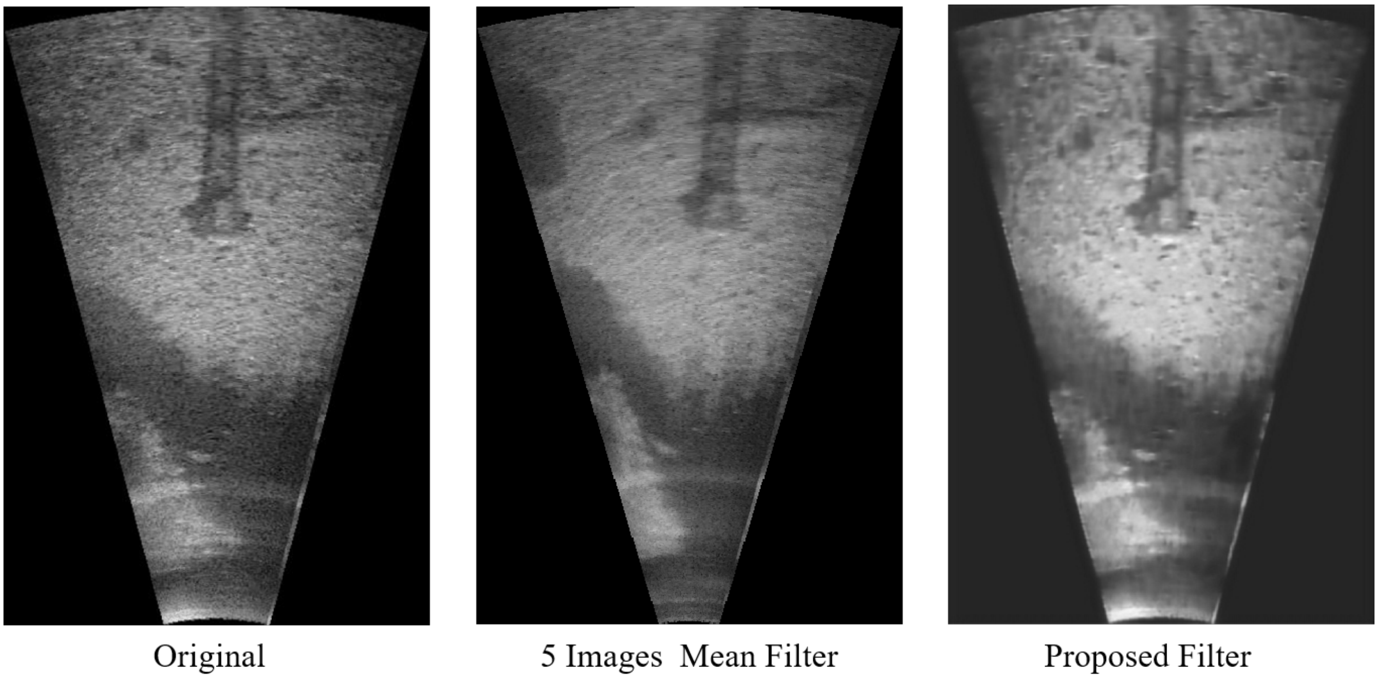

Fig. 6. The result of image enhancement of high resolution sonar images. This is traffic cone.

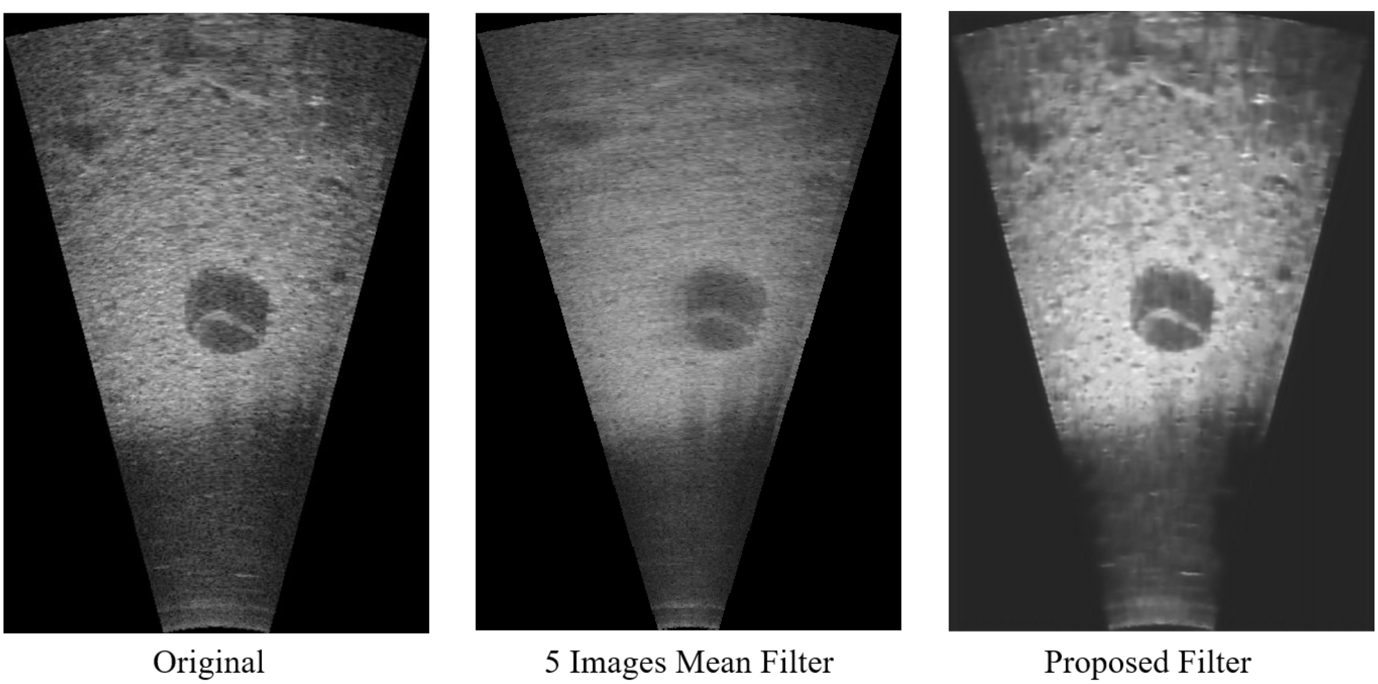

Fig. 7. The result of image enhancement of high resolution sonar images. This is tire.

5. Conclusion

This study verified the results of denoising auto-encoder based image enhancement of the acoustic lens based multi-beam sonar images. We generated custom data-set and conduct the auto-encoder neural network algorithm. Then, The data set was learned in the model and the image enhancement results were obtained while maintaining the resolution. We found that the proposed algorithm is very excellent noise rejection filter role. Finally, it shows applying machine learning algorithms on processing sonar image is greatly effective.

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