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Effect of Neural Network on Reduction of Noise for Edge Detection

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EFFECT OF NEURAL NETWORK ON REDUCTION OF NOISE FOR EDGE DETECTION

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ABSTRACT

Processing photographic images is important in many applications, among them the development of automated driver assistance systems (ADAS) and autonomous vehicles. Many techniques are used for processing images, including neural networks, other types of machine learning, and edge detection. One common issue with processing these photos is the presence of noise, whether caused by the camera itself or by physical conditions (e.g., weather conditions or dirt on road signs). In this paper, a neural network is used for noise reduction to improve edge detection results and tested with two kinds of noise, Gaussian and salt & pepper noise, and three different edge detection algorithms, Canny, Sobel, and Zhang. Results showed that the noise reduction process was effective in improving performance of the edge detection process, with the exception of conditions where the noise was originally very minimal.

Keywords: Edge detection, noise reduction

NOMENCLATURE

PR	Pollution Reduction Percentage
R_{IE}	Reference Image Edge
PL_{NE}	Pollution Level of Noised Edge
PL_{RE}	Pollution Level of Restored Edge

1. INTRODUCTION

The problem of determining what is in a particular image is important in many different applications, with one of them being the development of automated driver assistance systems (ADAS) and automated vehicles. In performing a driving task or alerting a driver, there are a variety of different signs need to be detected, including speed limit signs, stop and yield signs, and a variety of directional signs. A variety of approaches have been taken to this detection problem, as noted in Section 2, some of which utilize edge detection algorithms (e.g., [1]). However, one complication in this and other applications of edge detection is the problem of noise in the images. This noise could be caused by the camera's limitations, some kind of corruption of images as they are saved, or it could result from physical conditions in the environment, such as snow, fog, rain, or even dirt on the signs. Therefore, the use of edge detection is complicated by the presence of this noise, which can result in edges being obscured or in edges being detected where they are not actually present. Methods to reduce noise before edge detection, therefore, are necessary.

In this paper, we present the results of implementing a neural network-based noise cancellation algorithm for two different types of noise and three different edge detection algorithms, for a total of six different conditions. We determine the level of noise pollution for the edge detection algorithms for each of the cases when the image has noise added to it, and then the effect when the noise cancellation has been implemented.

The paper is organized as follows: in Section 2, we discuss background information and present a brief literature review. In Section 3, we discuss the specific neural network, types of noise, and edge detection methods used in this paper. Section 4 presents the results of the study, and the conclusion is given in Section 5.

2. BACKGROUND AND LITERATURE REVIEW

A variety of approaches have been taken to the problem of detecting road signs. Some of these approaches have been based on neural networks, in whole or in part, such as [2, 3, 4, 5]. The neural network may be coupled with other approaches, such as a Hough transformation [2], or color thresholding, as in [5]. Other approaches have been used, such as approaches based on edge detection and then on finding the appropriate shapes in the edges, as in [1], or an approach based on polyline extraction and identification of octagons, as in [6]. Other approaches have also been tried, such as a system based on HoG [7].

Any approach to the sign recognition problem, or for that matter any problem of recognizing images, regardless of the techniques used, must account for imperfections in the images. As previously stated, these imperfections can come from many sources; they may result from physical conditions of the objects in the photographs, for example. A traffic sign is exposed to the elements, and can have dirt and debris accumulate on it over time. Weather conditions between the camera and the sign can introduce noise, such as the presence of fog, rain, or snow. Furthermore, the camera itself can introduce noise or imperfections as it captures the images.

The problems of distorted or imperfect images and image denoising have been addressed by a variety of different researchers. In [8], camera noise was one of the issues considered in augmented reality applications. Cross-channel image noise modeling, and the application of this modeling to image de-noising, was considered in [9]. Noise suppression via wavelet transforms was shown in [10], and the type of noise and evaluation of image quality were considered in [11, 12]. The wide range of different approaches, across time, disciplines, and applications, shows the broad scope of the problem and the importance to different applications.

The goal of the abovementioned research is to improve the accuracy of feature extraction from images. Feature extraction or pattern recognition is often accomplished using edge detection methods to preserve structural information of an object while suppressing non-structural details. Noised images present challenges to edge detectors in that noise with certain light intensity may be mistaken as structural information in an image.

This research proposes a solution by de-noising the images using a noise cancellation mechanism prior to edge detection. This mechanism can be viewed as a "pre-processing" stage aimed at improving the performances of various edge detectors. The evaluation of the performance results will help determine the level of improvement for each edge detector investigated.

In this work, the approach to noise cancellation based on a neural network is used. This neural network, as indicated in Section 3, is available to the public through github, and has been used for image restoration as described in [13].

3. METHODS AND TECHNIQUES USED

In order to determine and quantify the usefulness of the noise cancellation method for improving edge detection, two results are compared for each case, as shown in Figure 1. Edge detection is implemented on the original image and the results are used as references, on an image that has had noise added but no noise cancellation implemented (Figure 1b), and on an image that has had noise added and then had the noise cancellation implemented prior to edge detection (Figure 1c).

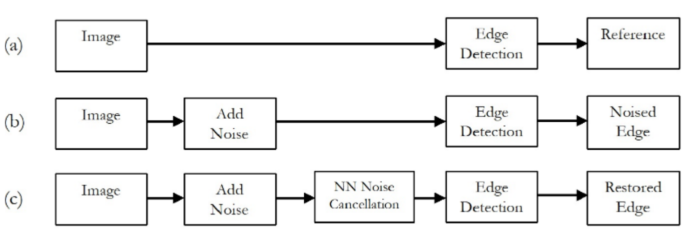

FIGURE 1: IMAGE PROCESSING DIAGRAM [14]

By comparing the Noised Edge (Figure 1b) with the reference (Figure 1a), it is possible to determine a pollution level for the noisy image. This pollution level is determined by counting the number of pixels that are different between the two edge maps, or (PL_{NE} – R_{IE}). Similarly, the pollution level can be determined for the restored edge by comparing the pixels in the original reference edge detection and the edges found from the restored edge maps, or (PL_{RE} – R_{IE}). The difference between these two measurements, or (PL_{NE} - PL_{RE}), provides a means of evaluating whether the noise cancellation neural network helps improve the performance of the edge detectors. To normalize this evaluation parameter, we define the pollution reduction percentage (PR) as:

$$\mathrm{PR} = \frac{PL_{NE} - PL_{RE}}{PL_{NE}} \quad (1)$$

Using this relationship, it is possible to compare the results of the noise reduction method for differing levels and types of noise for three different edge detection algorithms. The noise reduction method, types of noise, and edge detection methods are described below.

3.1 Noise Reduction Method

In this work, the noise reduction is accomplished by means of a neural network. The neural network chosen is a pre-trained network provided by NVIDIA Research [15]. This network was compared to other noise cancellation methods in [13], and was found to perform well; therefore, we are building on that success by applying it with a variety of types of noise and edge detection algorithms.

3.2 Types of Image Noise

Two types of noise were applied to the images used. One was Gaussian noise, with a mean value of 0 and a standard deviation ranging from 5 std to 150 std, with an increment of 5 std used.

The other type of noise applied was salt & pepper noise, with a range of noise density from 0.05 to 0.8. An increment of 0.05 was used for the tests.

In both cases, the noise was applied to a standard set of images, the Kodak Lossless True Color Image Suite dataset [16]. This image set was chosen due to good image quality, which reduces the likelihood of unexpected variables and results in a good quality of reference images.

3.3 Edge Detection Methods

Three edge detection methods were used. These three methods have previously been compared in [1], for use in stop sign detection, with a variety of images studied. Those images included various elements such as snow, but did not account explicitly for the possibility of noise in the images.

The three methods compared are the Canny edge detection algorithm [17],; the Sobel edge detection method [18]; and a method of edge detection developed by Zhang et al. [19], based on a linear predictor.

Both Canny and Sobel edge detectors are gradient based edge detection methods. In an image, gradients calculate the light intensity differences between a pixel and its adjacent pixels. The large differences in light intensity represent edges in an image. Both Canny and Sobel edge detectors develop a gradient map of the image and use threshold(s) to extract those pixels with higher light intensity, thus the edges.

Unlike Canny and Sobel detectors, Zhang's method is based on the concept of Linear Predictive Coding (LPC). LPC is a prediction method that was originally developed for audio signal processing. It uses a linear combination of the past samples in a signal to predict the current value. The goal is to minimize the Minimal Mean Squared Error (MMSE) between the actual value and the estimated value. When applied to edge detection, an edge pixel and the surrounding background pixels have a large difference in light intensity, thus the MMSE between the real edge pixel value and the estimated edge pixel value is large. These large prediction errors represent edges in an image. Because LPC uses a linear combination (a moving average) of adjacent pixel values to predict a certain pixel value, this detection method is intrinsically less susceptible to noise [1, 19].

As with all edge detection algorithms, tuning detector parameters can change the performance of these algorithms. In order to accurately assess the effect of the noise cancellation neural network on the edge detectors, once the parameters are set after generating the reference edge maps, these parameters are not changed during the process of generating noised edges and restored edges.

4. RESULTS

When applying the noise cancellation neural network approach for Gaussian noise and using the Canny edge detection method, it was found that the restored edge showed a significant reduction in noise pollution. In Figure 2, the average pollution level is shown for both the noised edge and restored edge, for varying levels of noise applied to the image, as is the pollution reduction due to the noise cancellation. As the level of noise in the image increases, the amount of noise pollution is larger for both the noised image and the restored image; however, the reduction generally is larger, although there are a few anomalies. A negative spike of pollution reduction percentage is found at 35 std, which is due to a drop in the pollution level of the noised edge at 35 std. It is suspected that the reason is the relatively small set of sample images, which is 25 images, in the data set. This could be investigated further with a larger data set.

The reduction in the noise level reaches a plateau of approximately 88% at 125 std. The highest pollution reduction rate is 88.8% at 150 std.

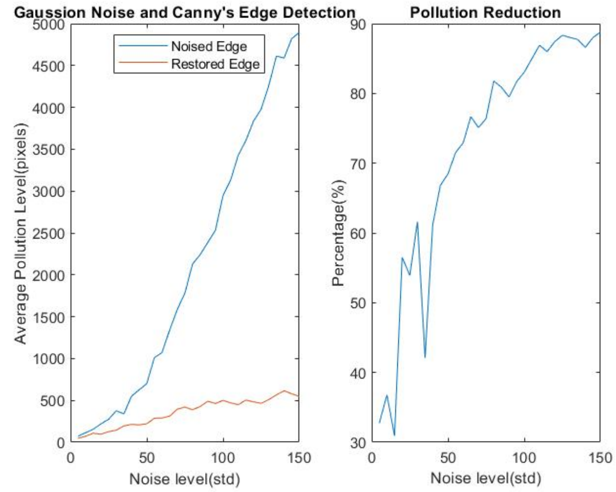

FIGURE 2: COMPARISON OF NOISE POLLUTION IN NOISED AND RESTORED EDGES FOR CANNY EDGE DETECTION ALGORITHM [14]

The effects of the noise reduction can be seen visually in an example, shown in Figure 3. This example shows the impact when the noise level is 120 std, which is near the plateau.

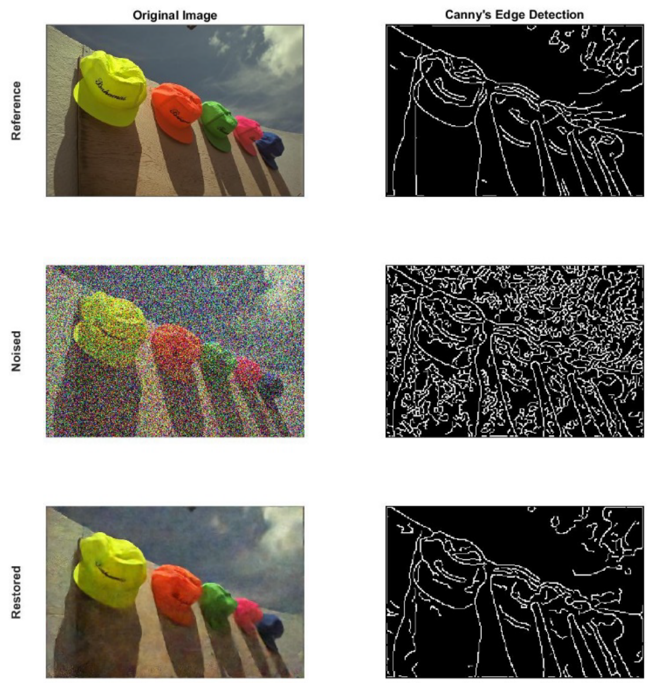

FIGURE 3*:* VISUAL COMPARISON OF EDGE DETECTION FOR ORIGINAL, NOISED, AND RESTORED EDGES FOR CANNY EDGE DETECTION ALGORITHM (120 std) [14]

Similar trends are seen when Gaussian noise is present and the Sobel edge detection is used, although there are some differences in the trends at higher noise levels. As shown in Figure 4, the average pollution level in the restored edges increases with noise level, as one might expect. The restored edge does always exhibit some reduction, but the level of pollution reduction actually drops after a certain noise level is reached. The peak pollution reduction occurs at 75 std, after which the reduction is less pronounced.

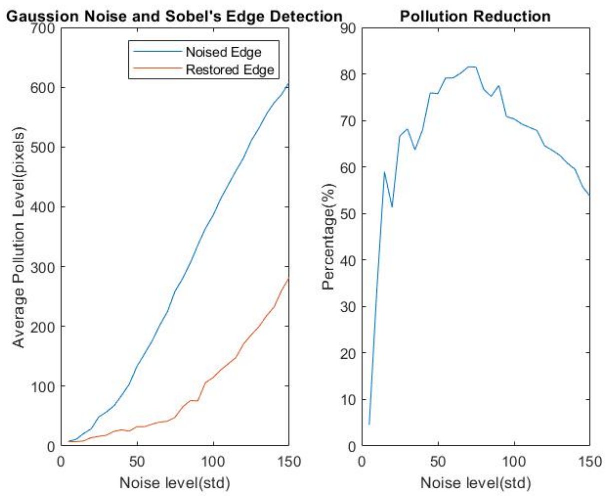

FIGURE 4: COMPARISON OF NOISE POLLUTION IN NOISED AND RESTORED EDGES FOR SOBEL EDGE DETECTION ALGORITHM [14]

When looking at the rate at which noise pollution increased, it is evident that the Sobel edge detection method is less sensitive to the Gaussian noise than the Canny method. This can be seen, visually, in Figure 5, which shows the results for 120 std Gaussian noise for the Sobel edge detection. Comparing the noised image, in particular, shows much less pollution than was seen in Figure 3 for the Canny method.

Note, also, that while the level of pollution reduction was much higher for the Canny method, the restored edge pollution level for the Canny method was still higher than the restored edge pollution level for the Sobel method. Using the Canny method, the average pollution level for the restored edge situation is in the range of about 500 pixels at the highest point, while for the Sobel method, it is approximately 300 at its maximum value for the restored edge.

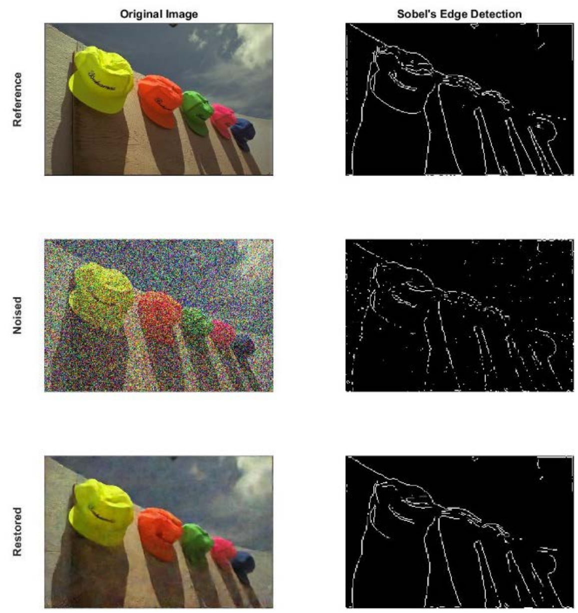

FIGURE 5: VISUAL COMPARISON OF EDGE DETECTION FOR ORIGINAL, NOISED, AND RESTORED EDGES FOR SOBEL EDGE DETECTION ALGORITHM [14]

In the case of Gaussian noise and Zhang's edge detection method, it can be seen that the level of noise pollution in the noised edge is also much less than the case of Canny edge detection. The level of pollution is also less than in the Sobel method, as shown in Figure 6. As with the Sobel method, there appears to be a point after which the pollution reduction decreases, although the decrease is less pronounced.

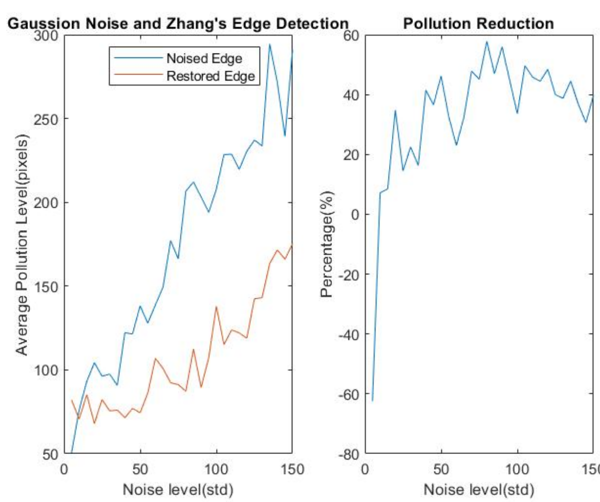

FIGURE 6: COMPARISON OF NOISE POLLUTION IN NOISED AND RESTORED EDGES FOR ZHANG EDGE DETECTION ALGORITHM [14]

Visual inspection of the results of the edge detection, again at 120 std, show a similar appearance to the results shown for the Sobel method. Figure 7 shows this result, and while the calculations of the noise pollution show a definite difference, it is not easily detected visually.

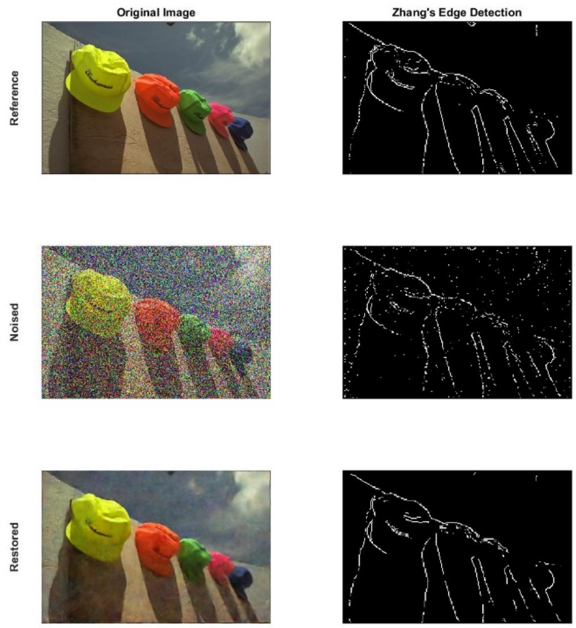

FIGURE 7: VISUAL COMPARISON OF EDGE DETECTION FOR ORIGINAL, NOISED, AND RESTORED EDGES FOR SOBEL EDGE DETECTION ALGORITHM [14]

The same method was carried out with salt & pepper noise, and again it was seen that when using the Canny edge detection method, the neural network's noise cancellation did result in a significantly improved image. The level of noise pollution of both the noised edge and restored edge increased as the noise level in the image increased, with less noise pollution in the restored edge, as shown in Figure 8.

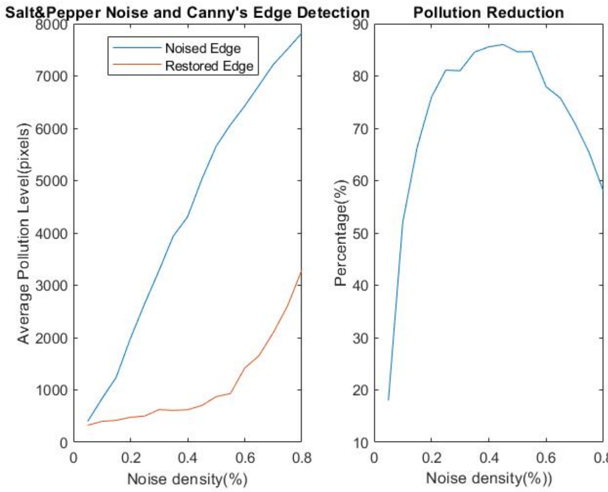

FIGURE 8: COMPARISON OF NOISE POLLUTION IN NOISED AND RESTORED EDGES FOR CANNY EDGE DETECTION ALGORITHM [14]

It can be seen in Figure 8 that the pollution reduction increased as the noise density increased, then began to decrease at higher levels of noise. The graph shows a peak of pollution reduction occurring at approximately 0.45 noise density, with a reduction of 86%.

The results of the noise cancellation can be seen visually in Figure 9, for a noise density of 0.5. Similar to the case of Gaussian noise, it can be seen that there is a high level of visible noise pollution.

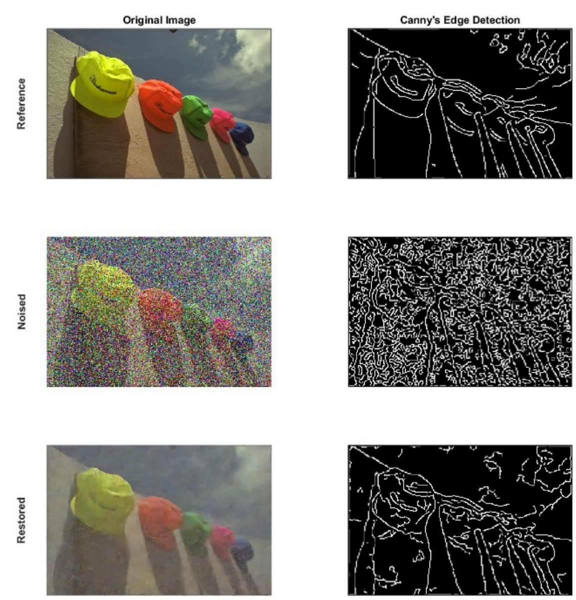

FIGURE 9 VISUAL COMPARISON OF EDGE DETECTION FOR ORIGINAL, NOISED, AND RESTORED EDGES FOR CANNY EDGE DETECTION ALGORITHM [14]

In the case of Sobel's edge detection method, there is a similar trend, as seen in Figure 10. The restored edge exhibits less pollution than the noised edge, and both show a trend of increasing noise pollution with the level of noise in the original image. However, the pollution reduction peaks as it does for the Canny method. The peak occurs earlier and at a lower level of pollution reduction.

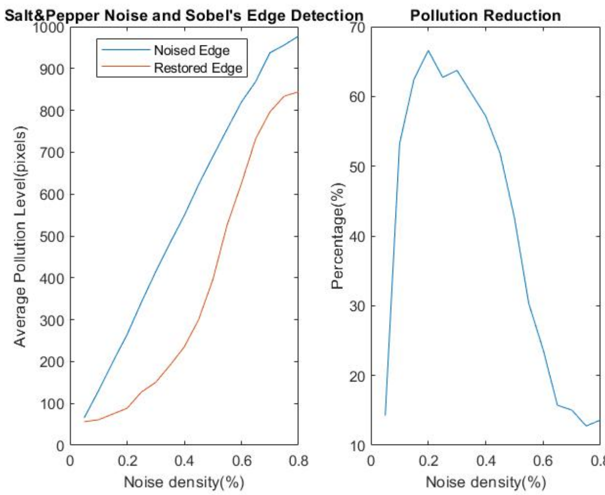

FIGURE 10: COMPARISON OF NOISE POLLUTION IN NOISED AND RESTORED EDGES FOR SOBEL EDGE DETECTION ALGORITHM [14]

The results of this can be seen visually in Figure 11; as with Figure 9, it shows the results at a noise density of 0.5. Comparing it to Figure 9, it is evident that there is less noise pollution in the edges, and therefore it is not altogether surprising that the level of improvement from noise cancellation is lower.

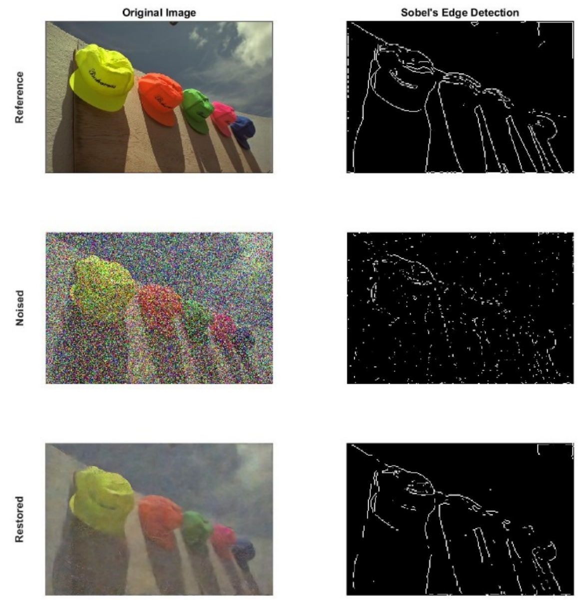

Figure 11: VISUAL COMPARISON OF EDGE DETECTION FOR ORIGINAL, NOISED, AND RESTORED EDGES FOR SOBEL EDGE DETECTION ALGORITHM [14]

Finally, the same method was applied with Zhang's edge detection method, with results shown in Figure 12. In this case, it is interesting to note that there is actually a range in which the restored edge exhibits a higher level of noise pollution than the noised edge, with the pollution reduction generally decreasing with the noise level. This indicates that the combination of the neural network for noise cancellation and the use of Zhang's edge detection method is not necessarily appropriate, when the noise that is present is expected to be salt & pepper noise.

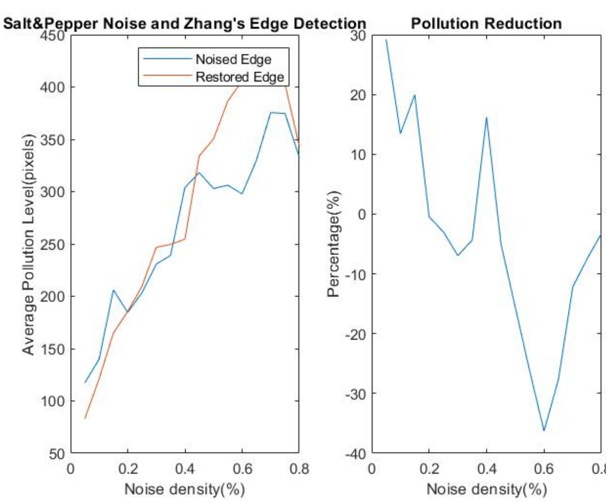

FIGURE 12: COMPARISON OF NOISE POLLUTION IN NOISED AND RESTORED EDGES FOR SOBEL EDGE DETECTION ALGORITHM [14]

The results of using this method are shown visually in Figure 13, for a noise density of 0.5. This looks very similar, visually, to the results for the Sobel method, although close inspection shows that there are some areas where an edge is more “broken” in the image from the Zhang edge detection than the Sobel detection.

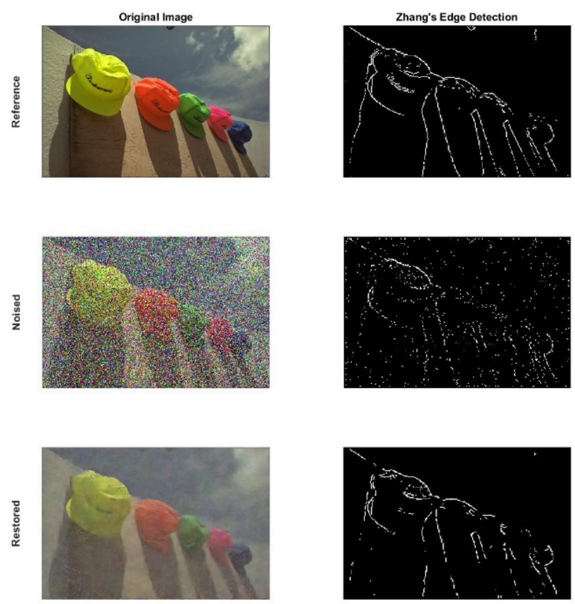

FIGURE 13: VISUAL COMPARISON OF EDGE DETECTION FOR ORIGINAL, NOISED, AND RESTORED EDGES FOR SOBEL EDGE DETECTION ALGORITHM [14]

These results suggest that, if the Canny method is used for edge detection, the application of noise reduction using a method such as the neural network noise cancellation algorithm is highly desirable. However, given the lower levels of noise pollution seen for the Sobel and Zhang edge detection methods, even without noise cancellation, either of them may be a better choice in practice. If noise cancellation is used, then the type of noise present should be carefully considered, due to the increases in noise pollution seen when the Zhang edge detection and the noise cancellation were combined in the case of salt & pepper noise.

5. CONCLUSION AND DISCUSSION

The results of testing the combination of a neural-network based noise reduction algorithm and different edge detection methods show that the noise cancellation does improve the performance of all edge detection methods. However, the level of improvement varies significantly depending on the detection method used.

The most prominent improvement is on the Canny edge detector. This is expected due to the construction of Canny detection algorithm. Canny detector first smoothies the image using a Gaussian filter (Gaussian blur) before the detection process. The Gaussian filter may effectively remove noise from an image but at the same time, it also blurs the edge points in that image, which in turn causes the loss of some edges that are polluted by noise. Therefore, using a pre-denoised image as the input to a Canny edge detector will see significant improvement of the detection outcome.

Noise cancellation also improves the performances of both Sobel and Zhang’s methods, as evidenced by the restored edges compared with noised edges shown in the results section. However, the level of improvement is not as significant as that when a Canny detector is employed. In the case of Sobel detection, it uses a 3x3 kernel to calculate local gradients around a pixel; In the case of Zhang’s method, it calculates the weighted running averages of the adjacent pixel values to estimate a pixel value of interest. Both operations work locally without suffering from smoothing procedure that was used in Canny’s method.

Pollution Reduction reaches a plateau and then decreases in almost all cases except using Zhang’s method in Salt & Pepper noise. This demonstrates that when noise level (or density) reaches a certain level, all edge detector performances will degrade even after denoising by the neural network.

In the case of using Zhang’s method in Salt & Pepper noise, it shows a negative Pollution Reduction when the noise density increases. This is simply due to the fact that high-density noise has caused loss of real edges (more “broken” as described in the results section). This loss of real edges causes (PL_{NE} - PL_{RE}) to be negative. Therefore, it results in a negative PR.

This research has demonstrated the concept of improving edge detection using a noise cancellation neural network prior to edge detectors. Further investigation on a large database will help better characterize the effects of this process on various edge detectors. Furthermore, because this researched is aimed at an application in autonomous driving, computational time of each combination presented in this research needs to be investigated to determine the suitability for the targeted application.

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