Modified CPI Filter Algorithm for Removing Salt-and-Pepper Noise in Digital Images

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ABSTRACT

In this paper, the theoretical aspects, implementation issues and performance analysis of a modified CPI filter algorithm will be presented. As the concept of the original CPI algorithm is to identify corrupted pixels by interrogating subimages, and considering the intensity spread of pixel values within the subimage when making a decision, the modified algorithm similarly takes into account of the subimage gray level distribution across the whole gray scale. It works on the assumption that to consider which group in the subimage is corrupted, the multiple-feature histogram representing a subimage gray level distribution must be transformed into a two-feature histogram such that these two features can be mapped onto the two available pixel classes. This transformation is performed by using a 1-sigma decision about the mean intensity of the subimage, which enables pixels that fall inside the sigma bounds be considered as uncorrupted, and the rest corrupted. A performance analysis of the modified CPI, original CPI, average, median and sigma algorithms is given for noisy images corrupted by salt-and-pepper noise of the impulsive and Gaussian nature, and gray noise over the signal-to-noise ratios (SNR) of +50 dB to -50 dB. The results show that similar to the original CPI algorithm, the modified CPI algorithm exhibits a number of desirable features. Firstly, due to its pixel identification property, it has better noise removing capability than the conventional filter algorithms. Secondly, most features in the original image are preserved in the restored image compared with say the median filter. Thirdly, iterative filtering of a noisy image using the CPI algorithm is possible

Keywords: feature preservation, noise removal, salt-and-pepper noise, corrupted pixel identification, performance evaluation, mean square error.

1. INTRODUCTION

Noise removal is a technique commonly employed in many digital image processing applications where the images are degraded by randomly populated strong, spikelike or Gaussian components in the spatial domain. The existence of such additive random noise in an image is often the consequence of poor input sampling and/or interference from an external source[1]. Conveniently, the additive random nature of these popular noise distributions enables the noisy image to be represented as a summation of the original image and a noise distribution as given by equation (1) where g(x,y) denotes the noisy image, f(x,y) denotes the original image and $\eta(x,y)$ denotes the additive noise term[2].

$$g(x,y) = f(x,y) + \eta(x,y) \qquad (1)$$

Given the noisy image g(x,y), and a priori knowledge of the statistical nature of $\eta(x,y)$, an estimation of f(x,y) can be determined, of which in the ideal case, equals to f(x,y). In practice, the estimated f(x,y) will be somewhat different from the original f(x,y) due to the errors introduced as a result of the estimation algorithm. If the original image is a known quantity, the quality of the estimation may be evaluated against an error criterion such as the magnitude error, maximum error or mean-square error, as well as subjectively (visually). Broadly, the objective evaluation measures the degree of deviation of the estimated image from the original image based on a certain error criterion, whereas the subjective evaluation is a visual inspection of the estimated image to see if it is acceptable. Based on these two methods of evaluation, the usefulness of noise removal algorithms could be measured.

Over the years, many noise filtering algorithms have been developed which work either in the spatial domain or frequency domain[3]. Typical examples of spatial filters are the median filter and its variants, averaging filter, sigma filter and box filter[4,5,6]. These filter algorithms are mostly designed for removing a specific type of noise distributions, for example, median filter is for removing impulsive noise, and sigma filter is for removing Gaussian noise. Of these filter algorithms, two characteristics are common. The first is that every single pixel in the image is subjected to the same filtering process disregarding the nature of the pixels. This philosophy of "processing without discrimination" is commonly employed in spatial filtering and other enhancement operations and has been proven effective in removing additive random noise but is also capable of introducing a smoothing or blurring effect to the restored image. The reason is that these algorithms do not consider which high spatial frequency component is noise and which is not. All pixels are considered equally and treated in exactly the same way. This effect is not entirely undesirable if fine details in the image are to be removed, or small gaps in lines or curves are to be filled. However, such distortion may be unacceptable as it can reduce the sharpness of lines, edges and boundaries. Secondly, indiscriminately processing the whole image wastes a significant amount of computing resources and may become critical in real-time applications. Obviously, if the corrupted pixels can be identified and only this selected subset of pixels is processed, then there would be at least two advantages: image features will not be subjected to filtering and considerable saving in computation would be expected if the algorithmic overhead for identifying the selected subset is smaller than processing all the other uncorrupted pixels.

Due to this feature preserving requirement, another class of filter algorithms emerges, with the aim of preserving the image features while possessing an effective noise removal capability. This class of algorithm focuses on the assumption that if the corrupted pixels can be identified at an acceptable overhead, then its subsequent filtering can be performed on the corrupted pixels only, leaving the major image feature untouched. In Kundu-Mitra-Vaidyanathan[7], they identified the corrupted pixels by interrogating every pixel in the image using a 'thresholding and complementation' technique, which is effective but time-consuming. On the other hand, Yung and Lai[8] took a different approach by interrogating the subimages which resulted in a substantial saving in computing time. In addition, they proved that the Corrupted-Pixel-Identification (CPI) algorithm generally out-performs the well established median and sigma filters in noise removal capability and feature preserving ability for white or black impulse and Gaussian noise[9]. However, when both salt (white) and pepper (black) noise are present in the image, the original CPI algorithm fails to perform as in other cases.

In this paper, the theoretical aspects, implementation issues and performance analysis of a modified CPI filter algorithm will be presented. Based on the original CPI concept, a modified algorithm was developed to remove noise that are either impulsive or Gaussian in nature with both salt (white) and pepper (black) components. As the concept of the original CPI algorithm is to identify corrupted pixels by interrogating subimages, and considering the intensity spread of pixel values within the subimage when making a decision, the modified algorithm similarly takes into account of the subimage gray level distribution across the whole gray scale. It works on the assumption that to consider which group in the subimage is corrupted, the multiple-feature histogram representing a subimage gray level distribution must be transformed to a two-feature histogram such that these two features can be mapped onto the two available pixel classes: corrupted and uncorrupted. This transformation is performed by using a 1-sigma decision about the mean intensity of the subimage, which enables pixels that fall inside the sigma bounds be considered as uncorrupted, and the rest corrupted. A comprehensive performance analysis between the modified CPI, original CPI, average, median and sigma algorithms were conducted for noisy images corrupted by salt-and-pepper noise of the impulsive and Gaussian nature, and gray level noise over signal-to-noise ratios (SNR) of +50 dB to -50 dB. The results show that similar to the original CPI algorithm, the modified CPI algorithm exhibits a number of desirable features. Firstly, due to its pixel identification property, it has better noise removing capability than the conventional filter algorithms. Secondly, most features in the original image are preserved in the restored image compared with say median filter. Thirdly, iterative filtering of a noisy image using the CPI algorithm is possible. This is not possible for conventional filters as their smoothing effect will gradually degrade the original features of the image over even a small number of iterations.

This paper is organized in the following manner: Section 2 - Gives a brief overview of the original CPI algorithm, and an appraisal of the algorithm. Section 3 - Outlines the approach taken in modifying the CPI algorithm and the basis of deriving the new decision function. Section 4 - Presents the performance evaluation of the modified CPI algorithm. The evaluation will be focused on the removal of the salt-and-pepper impulse noise, salt-and-pepper Gaussian noise, gray impulse noise and the iterative applications of the modified CPI algorithms. Comparisons are made between the original CPI algorithm, modified CPI algorithm, median filter, sigma filter and averaging filter in terms of their mean-square-error (MSE), and their visual qualities are also presented. Section 5 - Concludes the merits and pitfalls of the modified CPI algorithm.

2. ORIGINAL CPI ALGORITHM

2.1 Overview

The concept of the original CPI algorithm is depicted in Figure 1[8,9]. Assuming the noise pixels are in minority, the idea of the CPI algorithm is to first divide the image g(x,y) into subimages of which each subimage is tested if the intensity spread satisfies a condition. This condition is that if the variation in intensity within the subimage is large, then no decision should be made and further sub-division is required, otherwise a decision can be made by calculating the mean intensity within the subimage and threshold the subimage into black and white. After the subimage has been thresholded, the pixels (black or white) that are in minority are considered corrupted, and a list identifying these pixels are generated. The subimage lists are combined when all the pixels have been interrogated in this way. The combined list of corrupted pixels are then passed to the filter stage where the pixels in the noisy image are filtered selectively according to the list. In other words, only the pixels identified as corrupted are filtered, whereas other pixels are simply left along. The decision functions for the subimage division and pixel identification of the original CPI algorithm are given by equations (2) and (3).

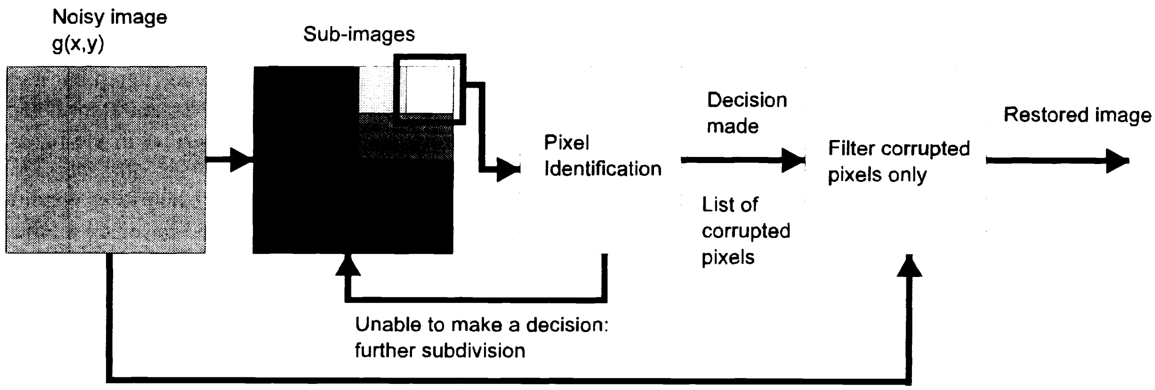


Figure 1: Original CPI Algorithm

Subimage division:

$$I_i(m,n) = \max_{\substack{x=0\\y=0}}^{\substack{y=n-1\\x=m-1}}\{g(x+x_i,y+y_i)\} - \min_{\substack{x=0\\y=0}}^{\substack{y=n-1\\x=m-1}}\{g(x+x_i,y+y_i)\} \tag{2}$$

where $I_i(m,n)$ is the intensity spread of subimage $S_i(m,n)$, and m, n are the dimension of the subimage. If $I_i(m,n)$ is greater than a pre-defined maximum intensity spread and the size of subimage, $S_i(m,n)$ is greater than the minimum subimage size, $S(m_o,n_o)$ then divide $S_i(m,n)$ into two equal but smaller subimages according to: If $m \geq n$ then $S_{i+1}(m/2,n)$ else $S_{i+1}(m,n/2)$.

Pixel Identification:

$$\bar{g}(x+x_i,y+y_i) = \begin{cases} 1 & g(x+x_i,y+y_i) > M_i(m,n) \\ 0 & g(x+x_i,y+y_i) \leq M_i(m,n) \end{cases} \quad \text{for x=0,..,m-1 and y=0,..,n-1.} \tag{3a}$$

$$\text{Corrupted Pixels} = \begin{cases} g(x+x_i,y+y_i) \text{ where } \bar{g}(x+x_i,y+y_i) = 0 \text{ when } \sum_{y=0}^{n-1}\sum_{x=0}^{m-1} \bar{g}(x+x_i,y+y_i) \geq \frac{mn}{2} \\ g(x+x_i,y+y_i) \text{ where } \bar{g}(x+x_i,y+y_i) = 1 \text{ when } \sum_{y=0}^{n-1}\sum_{x=0}^{m-1} \bar{g}(x+x_i,y+y_i) < \frac{mn}{2} \end{cases} \tag{3b}$$

where $M_i(m,n)$ denotes the mean intensity within the subimage and the other variables have their usual definitions[9].

2.2 Merits and Drawbacks

There are a number of merits due to the original CPI algorithm. First, it preserves high frequency image features which other conventional or non-selective filters smooth out. This is a desirable property as in applications such as video phone, the restored image is best to be as close to the original as possible. Second, when white or black impulse or Gaussian noise is concerned, the CPI algorithm has the best noise removal performance among filters such as the median and sigma filters. The measure of the MSE and visual inspection consistently point to the superiority of the algorithm. Third, the computing resource requirement of the CPI algorithm is lower than the other filters both theoretically and practically. In theory, the CPI performs better than the median filter for (2N+1)>3. In practice, the CPI is 1.6 times faster than the median filter. Fourth, due to the feature preservation property of the CPI algorithm, it can be applied iteratively when the noisy image has very low SNR. Extensive evaluation of this particular property shows that the best result can be obtained after two or three iterations[9].

However, there are a number of drawbacks associated with the CPI algorithm as well. Firstly, if both black and white noise appear in the image, as both the black and white pixels have similar probability of being the corrupted pixels, the decision function in determining the majority pixels could wrongly identify either the black or white pixels as the uncorrupted pixels. Secondly, although the subimage approach is relatively fast compared with the conventional approaches, it was reported recently that the pixel identification process introduces unavoidable errors in two aspects: (1) pixels that are corrupted but identified as not corrupted; and (2) pixels that are not corrupted but being identified as corrupted[10]. These errors are significant if the SNR of the noisy image is high, and less so if the SNR is low. Nevertheless, these errors are translated into errors in the restored image as corrupted pixels that are not processed (noise pixels remain), and uncorrupted pixels that are processed (unnecessary smoothing). Thirdly, the filtering stage is performed by a conventional filter operator (median) and while the median filter window is centered on a corrupted pixel, every pixel within that window is considered, meaning the median is calculated based on all the pixels in the window, disregarding whether these neighboring pixels are corrupted or not. Since the knowledge of which pixel is corrupted is a priori, there is no reason why the filtering should not be carried out on a selective basis, for example, in the median case, only the uncorrupted pixels are included in the calculation of the median. Preliminary results obtained indicate that substantial improvement is possible if the knowledge of pixel type is considered appropriately[11].

3. MODIFIED CPI ALGORITHM

The modified CPI algorithm was developed to tackle the cases where the noise distribution is either impulsive or Gaussian with both black and white noise pixels. It is also desirable that the algorithm has the possibility of removing gray noise. The major difference between the original and modified CPI algorithms lies with the decision process of which are the corrupted pixels. With reference to the two decision functions: subimage division and pixel identification, the subimage division criterion can be employed in exactly the same way. Therefore, the focus is on the decision function governing the pixel identification within a subimage. In the original CPI algorithm, we assume the histogram of the subimage consists of two distributions: original image and noise. By assuming the noise is in minority, a decision can be made by counting the pixel numbers. In the case of the salt-and-pepper noise, a subimage histogram probably consists of more than two prominent features representing the black noise, white noise and the original image feature. As our final pixel classes are still two, the multiple-feature histogram in this case has to be transformed into a two-feature histogram for mapping onto the two classes of pixels. To achieve that, we consider the statistical property of the histogram and use it as a basis for our decision. In essence, the mean and standard deviation (sigma) of the histogram is calculated and the pixel values that fall within the 1-sigma region are considered as uncorrupted. Any pixel values that lie outside the 1-sigma region are considered corrupted.

Mathematically, a pixel may be considered corrupted if $g(x+x_i,y+y_i) > \mu + \sigma$ or $g(x+x_i,y+y_i) < \mu - \sigma$, where μ is the mean of the subimage $S_i(m,n)$, and σ is the standard deviation of $S_i(m,n)$ given by equation (4a) and (4b), respectively.

$$\mu = \frac{1}{m.n} \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} g(x+x_i, y+y_i) \tag{4a}$$

$$\sigma = \sqrt{\frac{1}{m.n}\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}\left[g(x+x_i, y+y_i) - \mu\right]^2} \tag{4b}$$

The new decision function is given by equation (5). This is also illustrated in Figure 2 by a typical subimage histogram having three prominent features. The corrupted pixels are identified as those to the left of 'mean-sigma' and to the right of 'mean+sigma'.

$$\text{Corrupted Pixel } = g(x+x_i, y+y_i) \text{ if } g(x+x_i,\ y+y_i) \le \mu - \sigma \text{ or } g(x+x_i,\ y+y_i) \ge \mu + \sigma \tag{5}$$

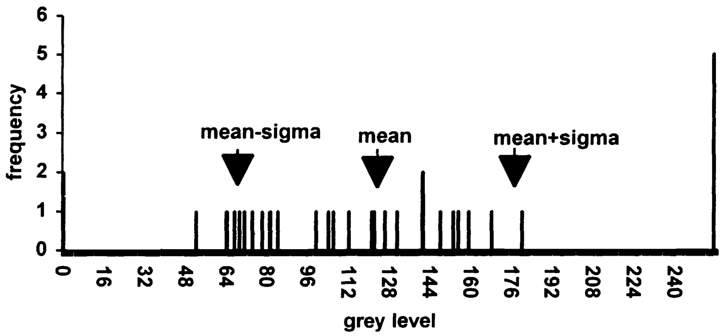


Figure 2: Typical histogram of a subimage

4. PERFORMANCE EVALUATION

The performance evaluation of the modified CPI algorithm given in this section is based on measuring the mean square error between the restored image, $\hat{f}(x,y)$ and the original image *f(x,y)* over an SNR range of +50 dB to -50 dB. All the images evaluated are the image of a "Mickey mouse" key-ring having 256 gray levels from 0 (black) to 255 (white); and a spatial dimension of 205 by 441. The characteristics of this image are that the key-ring itself has sharp lines and edges, and well-defined regions against a relatively smooth background. In summary, the evaluation is focused on the aspects of

- filtering images that are degraded by salt-and-pepper impulse noise;
- filtering images that are degraded by salt-and-pepper Gaussian noise;
- filtering images that are degraded by gray impulse noise; and
- the iterative applications of the CPI and modified CPI algorithm.

Comparisons are made between the modified CPI algorithm, CPI algorithm, median filter, averaging filter and sigma filter. A window size of 5 x 5 is used in all cases, and a 5 x 5 median filter is used as the filter core of both the CPI and modified CPI algorithms, as well as a MIS = 32.

4.1 Salt-and-Pepper Impulse Noise

As can be seen from Figures 3 and 4, all the noise removal algorithms under consideration here removes noise to some extent at varying degrees. When comparing the MSE of the five algorithms over the entire SNR range, a number of observations can be made. Firstly, all the error functions are monotonic increasing with decreasing SNR. Secondly, the averaging filter performs poorly compares with all the other algorithms with the exception of the original CPI algorithm at SNR less than 10 dB. Thirdly, the original CPI performs better than the sigma and median filters at SNR above 30 dB. Below this, the MSE of the CPI algorithm increases rapidly and becomes worst below 10 dB. This could be reasoned as a large number of pixels have been identified incorrectly, and therefore, high MSE as a result. Fourthly, the performance of the median and sigma filters is very similar throughout, and the sigma filter is consistently better by a small margin. This is consistent with earlier results given in Yung & Lai[9]. Fifthly, the MSE of the modified CPI is the smallest over the entire range.

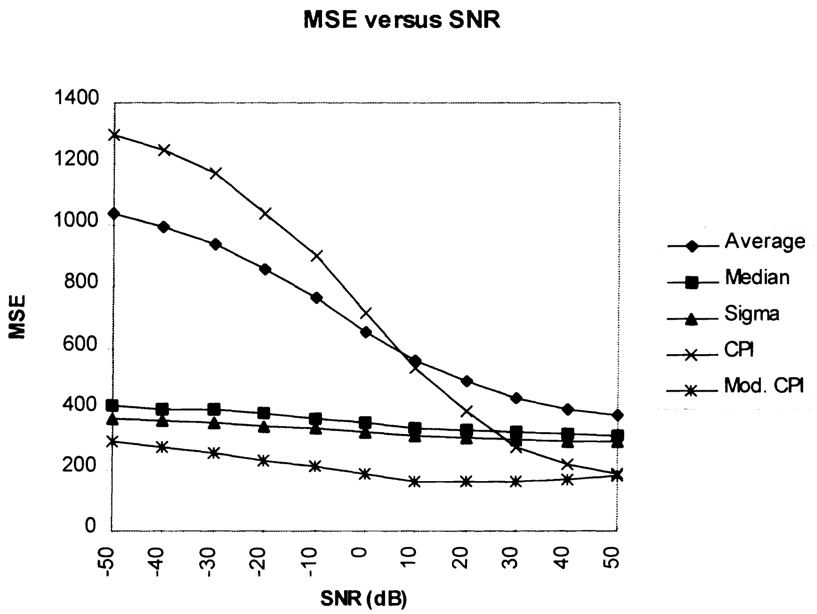
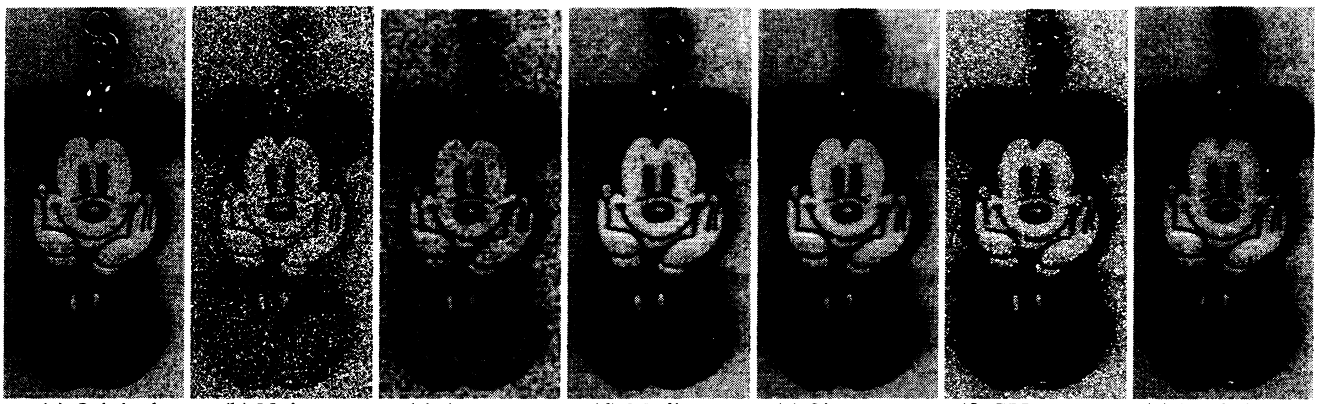


Figure 3: Salt-and-pepper impulse noise: MSE versus SNR



(a) Original (b) Noisy (c) Average (d) Median (e) Sigma (f) CPI (g) Mod. CPI

Figure 4: "Mickey" image heavily degraded by salt-and-pepper impulse noise

Figure 4 depicts the images where the original is heavily degraded by the salt-and-pepper impulse noise (SNR = -50 dB). The averaged image looks blur and patchy. Such visual appearance reflects the poor MSE of the average filter. On the other hand, the median and sigma filtered images are very similar with most of the noise successfully removed, but at the same time, it should be noted that the restored images are also smoothed as well as a very small number of noise pixels are still remained in the restored images. This is not surprising as according to their mathematical description, they are particularly suited for noise with both black and white components. For the original CPI, the reason for the high MSE is because of the black and white noise pixels that have not been identified and therefore not removed particularly around the edges. This is clearly shown in the restored image. As for the modified CPI, the restored image looks sharp but a small number of black and white noise pixels are still evident in the image, but tolerable as a whole.

4.2 Salt-and Pepper Gaussian Noise

Figure 5 depicts the MSE behaviours of the filter algorithms in concern and Figure 6 displays the restored images of the heavily corrupted case for visual inspection. From Figure 5, these functions behave similarly to the impulse case with a number of fine distinctions. First, the average, median and sigma filters all perform similarly as before. When the actual numbers are considered, their MSE in this case are slightly higher than the impulse case. Second, the MSE of the original CPI is not rising as high as the previous case but the difference is minor. Third, the MSE of the modified CPI are slightly higher than the impulse case and this becomes more obvious at low SNR values. In general, the modified CPI algorithm scores the lowest MSE among all the other algorithms considered here.

From Figure 6, the averaged image is of very poor quality, with severe loss of edge and line information. This again agrees with its high MSE. Both the median and sigma images are of reasonable quality although blurring and some isolated noise pixels are evident in both cases. This is still very much in line with the expected performance of these two algorithms. The quality of the CPI image is also poor as a large number of black and white noise pixels are left in the image. These are mainly noise pixels that have not been identified as corrupted during the pixel identification decision process. This simply underlines the inadequacy of the original decision function in handling salt-and-pepper noise. As for the modified CPI image, its visual quality is acceptable although there is still a small number of noise pixels remaining in the image. The clear difference between the modified CPI image and the median image say, is that the former does not suffer as much blurring as the latter, but the former also has more noise pixels remain in the image.

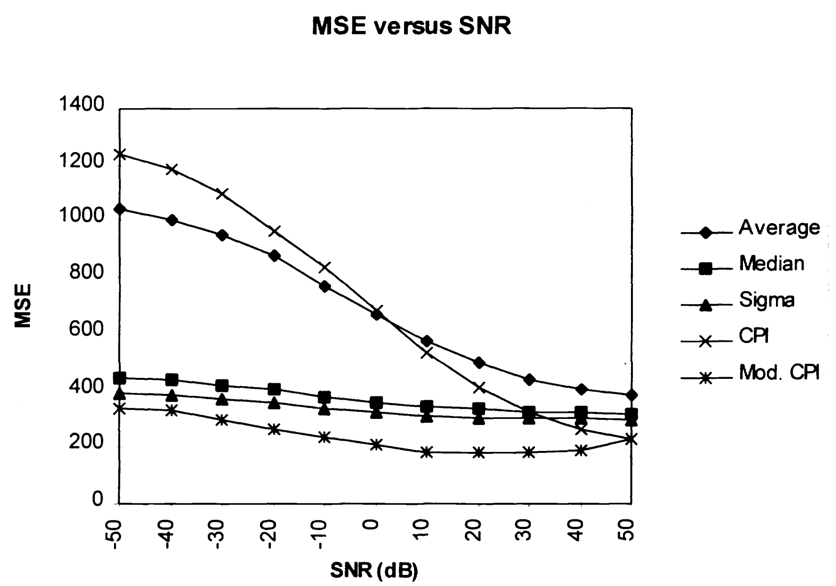
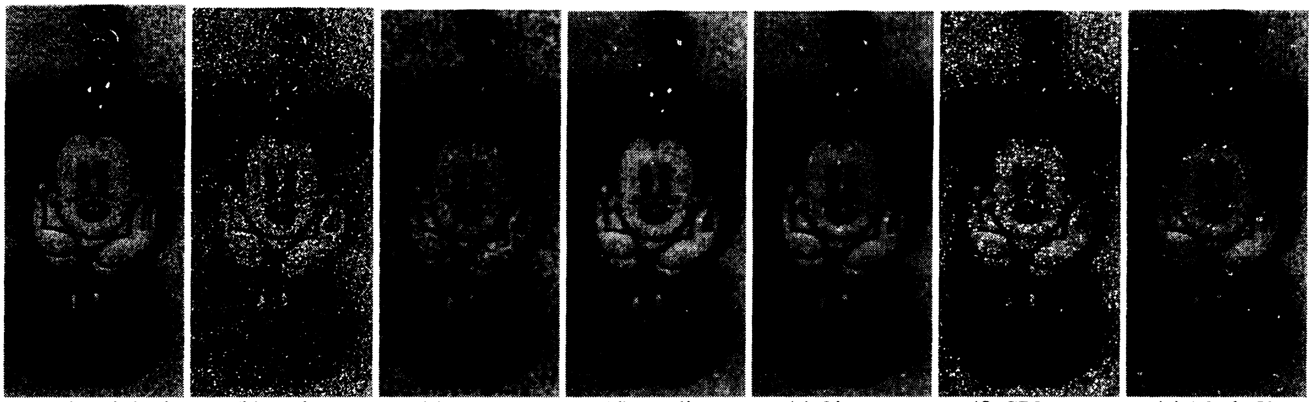


Figure 5 : Salt-and-pepper Gaussian noise: MSE versus SNR



(a) Original (b) Noisy (c) Average (d) Median (e) Sigma (f) CPI (g) Mod. CPI

Figure 6: "Mickey" image heavily degraded by salt-and-pepper Gaussian noise

4.3 Gray Impulse Noise

In this case, the noise pixels are impulsive in nature but are no longer white or black. The pixel values of these noise components are randomly generated over the entire gray scale, presenting a rather different case of noise degradation altogether. As can be seen in Figure 7, the average filter gives a slight improvement at the low SNR, but its general MSE performance has not changed much. For the median and sigma filters, their MSE are almost the same as in the Gaussian case at the SNR above 10 dB. At the SNR less than that, their MSE begin to rise but not substantially. It also seems that the MSE of the median filter rises more than the sigma filter, and the better performance of the sigma filter is consistent with the other cases presented here. For the CPI algorithms, the original CPI has an improved MSE compared with all the other cases at SNR > 0 dB. However, it starts to deteriorate rapidly for the SNR below 0 dB and becomes roughly 20 % worse than the median filter at -50 dB. In the case of the modified CPI, its general performance is acceptable for high SNR: better than both the sigma and median filters. At the low SNR (< -10 dB), the MSE of the modified CPI are comparable with the sigma and median filters. At -50 dB, the sigma filter is the best performed filter.

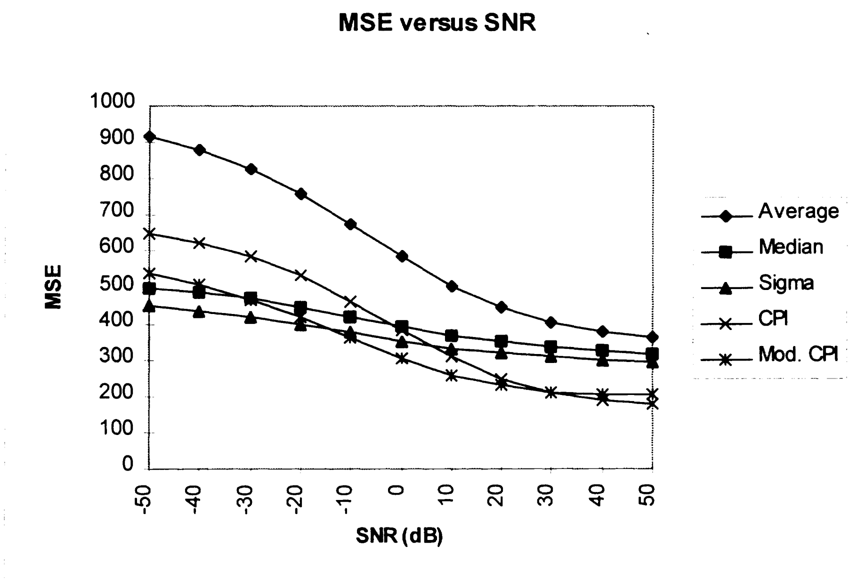
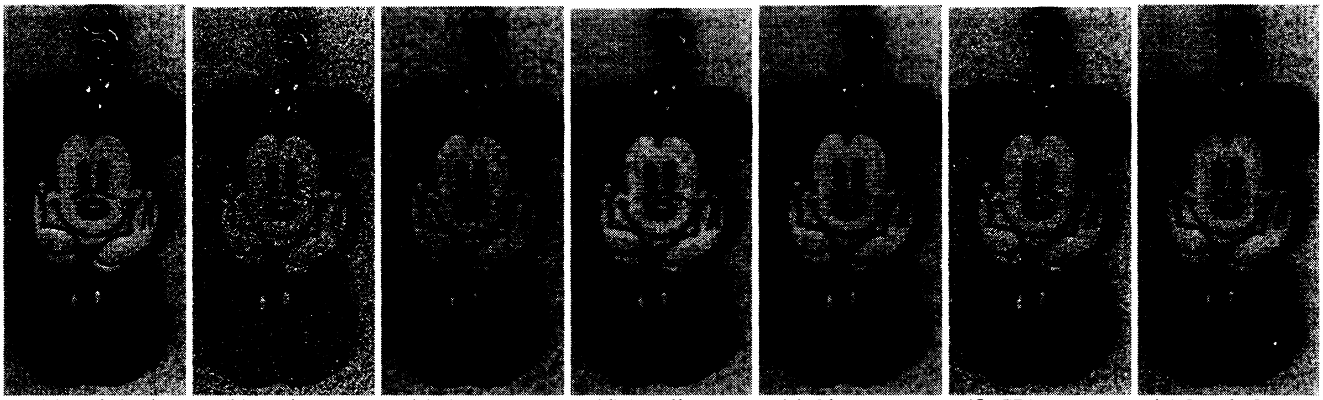


Figure 7 : Gray impulse noise : MSE versus SNR

Figure 8 depicts the case of gray level noise at SNR = -50 dB. It can be seen that the average image still has very poor visual quality and would be considered unusable. Both the median and sigma images are of reasonable quality but the blurring effect is more severe, and some isolated noise components are also evident. In fact, it is almost impossible to separate the two visually. For the original CPI image, the blurring effect is obviously less severe, but the restored image looks more grainy than the others with a substantial number of noise pixels still remaining. As for the modified CPI image, the degree of blurring is minor and the majority of the noise pixels are removed. However, a considerable number of noise pixels still remained in the image causing it to look grainy, although not as severe as the original CPI image. This explains the high SNR for the modified CPI algorithm as depicted in Figure 7. On the other hand, as the noise pixels are neither black nor white, the visual appearance can still be considered as acceptable.



(a) Original (b) Noisy (c) Average (d) Median (e) Sigma (f) CPI (g) Mod. CPI

Figure 8: "Mickey" image heavily degraded by gray impulse noise

4.4 Iteractive Applications of CPI and Modified CPI Algorithm

In practice, conventional filter algorithms are seldom used iteratively in processing a noisy image because of the line and edge distortion introduced as the result of filtering. Further subjecting the restored image to the filtering would only worsen the distortion. However, as the class of CPI algorithms exhibit feature preservation property, it is likely that even if the CPI algorithms are applied iteratively to a noisy image, the resultant line and edge distortion would probably be tolerable.

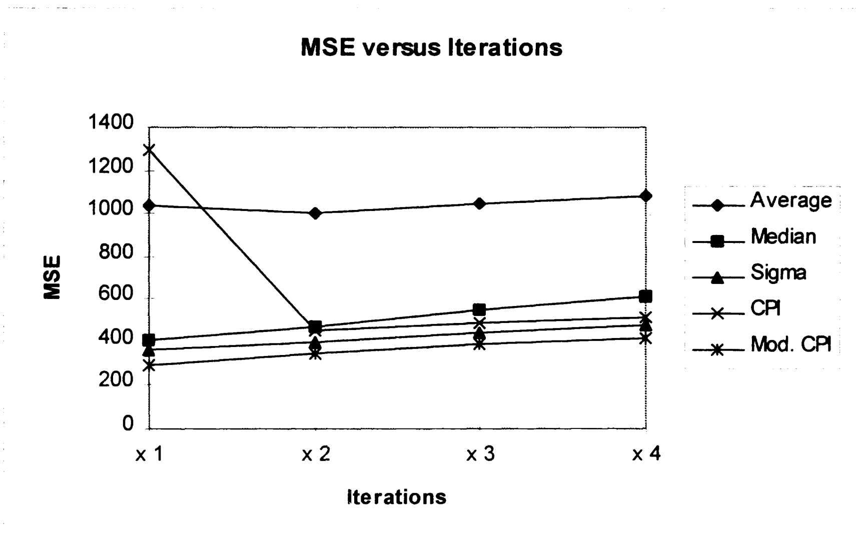
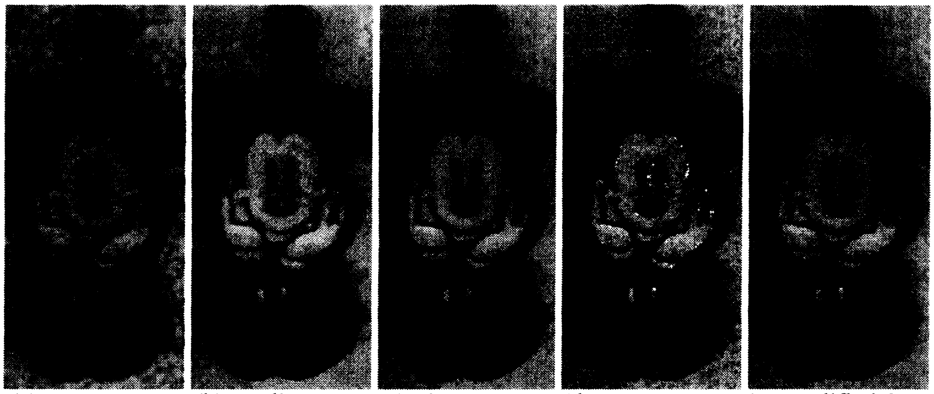


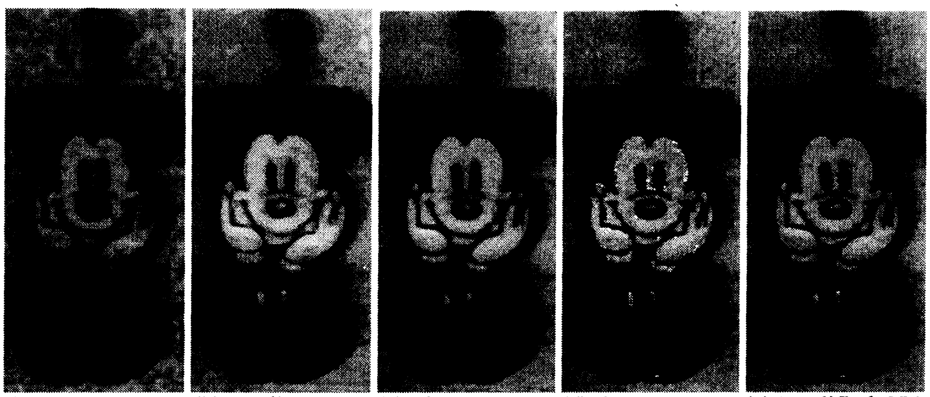
Figure 9: Salt-and-pepper impulse noise at SNR = -50 dB: MSE versus Iterations

Figure 9 depicts the variations of the MSE for all the five algorithms under the effect of iteratively applying the algorithms to the same image. In the figure, we can see that the MSE of the non-CPI algorithms generally increase slightly with respect to the number of iterations. This can be explained as the filtered images do not have many noise pixels left after the first filtering, and therefore, subsequent applications of the same filter algorithm only introduce more distortion. Similarly, for the CPI algorithms, if the noise content after the first iteration is small, further iterations would not have much improvement, but the distortion is also expected to be small. A distinction between the modified CPI algorithm and the non-CPI algorithms is that the rate of increase in the MSE due to an increase number of iterations is smaller in the CPI case. However, if the noise content after the first iteration is still high, further iteration would improve its MSE. This is shown by the case of the original CPI in which the large number of noise pixels remained in the image after the first iteration are being removed when the algorithm is applied again. This is highlighted by the sharp drop in the MSE. Subsequent applications of the CPI algorithm in fact raise the MSE slightly. This can also be seen in Figure 10 that at the second iteration, the average, median and sigma images are blurred further, whereas the original CPI image looks to have a lot less noise pixels and the modified CPI image has even less noise pixels. At the third iteration as shown in Figure 11, this effect becomes even clearer, which further proves that iterative application of the CPI algorithm will improve the image quality.



(a) Average (b) Median (c) Sigma (d) CPI (e) Modified CPI

Figure 10: Iterative filtering of noisy image at -50 dB - *TWO* times



(a) Average (b) Median (c) Sigma (d) CPI (e) Modified CPI

Figure 11: Iterative filtering of noisy image at -50 dB - *THREE* times

5. CONCLUSION

In conclusion, the whole concept of identifying corrupted pixels first before filtering can be extended and applied to removing salt-and-pepper noise as well as just black or white Gaussian or impulse noise. The modified CPI algorithm presented in this paper uses a 1-sigma decision function which proves to be effective in fulfilling this requirement. The performance evaluation of the algorithm over images degraded by salt-and-pepper impulse, salt-and-pepper Gaussian noise and gray impulse shows that the modified CPI algorithm has the lowest MSE in the first two cases and in the gray impulse case at high SNR, and an MSE comparable with the median filter in the gray impulse case at very low SNR. This objective performance is in line with the original CPI algorithm over white impulse or Gaussian noise reported previously. In addition, subjective evaluation shows that the image restored by the modified CPI algorithm generally has less line/edge distortion than the other conventional algorithms, however, certain amount of noise components can still be found in the restored image as a result of inaccurate pixel identification. These noise components are not excessive and therefore can be considered tolerable in all three cases considered here. On the other hand, because of the feature preserving property of CPI algorithms, the modified CPI algorithm can be applied iteratively to a noisy image until both the MSE and visual quality are acceptable. This is demonstrated in the last part of the performance evaluation that the remaining noise components can be removed effectively without introducing much distortion, and the MSE can be maintained at a low level. If the conventional filters are applied iteratively, the smoothing effect will dominate the noise removing effect, which will cause the visual quality of the restored image to deteriorate and the MSE to increase. In terms of computing requirement, the modified CPI is roughly 1.6 times faster than a median filter. Even if the modified CPI algorithm has to be applied twice comparing with applying the median filter only once say, the improvement in visual quality and low MSE still favour the modified CPI algorithm. Future investigation into the accuracy of the pixel identification process (i.e. the decision function and its rate of success) and the consideration of the a priori knowledge of corrupted pixels at the filtering stage (i.e. only the corrupted or uncorrupted pixels are considered when filtering) will probably improve the performance of the CPI algorithm further.

6. REFERENCES

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