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# A Comparative Study of Classical and Fuzzy Filters for Impulse Noise Reduction

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***Abstract***: Different types of noise frequently contaminate images. Impulsive noise is one such noise, which may affect images at the time of acquisition due to noisy sensors or at the time of transmission due to channel errors or in storage media due to faulty hardware. Removing or reducing impulse noise is a very active research area in image processing. In this paper we present the results of a comparative study of classical and fuzzy filters for all type of impulse noise reduction. The discussed fuzzy filters are classified and their performance is compared with classical filters and evaluated by numerical and visual experiments.

***Keywords:*** Fuzzy filter, image processing, impulse noise, membership functions, noise reduction.

## I. INTRODUCTION

Image denoising is a key issue in all image processing researches. It is the first preprocessing step in dealing with image processing where the overall system quality should be improved. Generally, the quality of an image could be corrupted by a lot of noise due to the undesired conditions of image acquisition phase or during the transmission. The great challenge of image denoising is how to preserve the edges and all fine details of an image when reducing the noise. In this article, a comparative study of image denoising techniques is presented. Subjective and objective evaluation methods are used to judge the efficiency of different types of filters applied to different types of noise.

Noise can be systematically introduced into digital images during acquisition and/or transmission of images. A fundamental problem of image processing is to effectively reduce noise from a digital image while keeping its features intact.

The structure of the paper is as follows. The introduction presents the definition of impulse noise. The evaluation of the performance of classical and fuzzy filters for impulse noise will be supported by numerical and visual experiments in section II. Amongst other things, we will investigate whether fuzzy filters perform better than classical filters and whether good numerical results are also confirmed by good visual results. Noise reduction is an important issue in image processing. Several classical and fuzzy filters for image noise reduction have already been developed; cfr.[1] and [2] for an extensive overview.

## II. AN OVERVIEW OF CLASSICAL FILTERS

### A. *Linear filters:*

A linear filter replaces the gray-value of a pixel (i,j) by a linear combination of the gray-values in a (2N+1)×(2N+1) neighbourhood of that pixel:

$$A^1(i,j) = \sum_{k=-N}^{N} \sum_{l=-N}^{N} w(k,l) \cdot A(i-k, j-l).$$

The coefficients w(k,l) are independent of the processed pixel (i,j). In the early development of image processing, linear filters were the primary tools. Their mathematical simplicity with satisfactory performance in many applications made them easy to design and implement.

However, in the presence of noise the performance of linear filters is poor. In image processing applications they tend to blur edges, do not remove impulsive noise effectively, and do not perform well in the presence of signal dependent noise [6].

### B. *Non-Linear filters:*

#### a. *Adaptive weighted mean filter:*

The Adaptive weighted mean filter replaces the gray-value of a pixel (i,j) by a weighted average of the gray-values in a (2N+1)×(2N+1) neighbourhood of that pixel. Note that in this case the weights depend upon the processed pixel:

$$A'(i,j) = \frac{\sum_{k=-N}^{N} \sum_{l=-N}^{N} w_{i,j}(k,l) \cdot A(i-k, j-l)}{\sum_{k=-N}^{N} \sum_{l=-N}^{N} w_{i,j}(k,l)}$$

The choice of the weights $w_{ij}(k,l)$ is based on the gray-value differences $|A(i,j) - A(i-k, j-l)|$ : if this difference exceeds a certain threshold, one assumes that the corresponding pixel is a noise pixel (or that the pixeel belongs to another homogeneous region in the image) and one defines $w_{i,j}(k,l)=0$; in the other case $w_{i,j}(k,l)=1$.

One of the drawbacks of the adaptive weighted mean filter is that it will make the original image more blurred.

#### b. *Standard Median Filter (SMF):*

Median filter is the non-linear filter which changes the image intensity mean value if the spatial noise distribution in the image is not symmetrical within the window. Median filter reduce is the variance of the intensities in the image. Median filter is a spatial filtering operation, so it uses a 2-D mask that is applied to each pixel in the input image. To apply the mask means to centre it in a pixel, evaluating the covered pixel brightness and determining which brightness value is the median value.

#### c. *Adaptive Wiener Filter (AWF):*

Adaptive Wiener Filter (AWF) changes its behavior based on the statistical characteristics of the image inside the filter window. Adaptive filter performance is usually superior to non-adaptive counterparts. But the improved performance is at the cost of added filter complexity. Mean and variance are two important statistical measures using which adaptive filters can be designed.

### *d. Gaussian Filter (GF):*

Gaussian low pass filter is the filter which is impulse responsive, Gaussian filters are designed to give no overshoot to a step function input while minimizing the rise and fall time. Gaussian is smoothing filter in the 2D convolution operation that is used to remove noise and blur from image.

## III. AN OVERVIEW OF FUZZY FILTERS

### *A. The fuzzy weighted mean filter:*

The fuzzy weighted mean filter [9] is an extension of the adaptive weighted mean filter. The idea behind the FWM filter is that weights should take values in [0,1] instead of only the crisp values 0 and 1, and that the weights should not depend on a threshold value, but should be determined by means of fuzzy rules.

### *B. Fuzzy median filter:*

The fuzzy median filter [5], [7] is an extension of the classical median filter, and is designed for the reduction of impulse noise. A drawback of the classical median filter is that it makes the image more blurred, because every pixel is filtered independent of the fact whether the pixel is a noise pixel or not. The idea of the fuzzy median filter is to "tune" the classical median filter by using fuzzy rules that determine the degree to which a pixel is a noise pixel or not.

### *C. The weighted fuzzy mean filter:*

The weighted fuzzy mean filter [8], [9] can be seen as a fuzzy adaptive weighted mean filter. The difference with the fuzzy weighted mean filter is the way in which the weights are determined. Here, the detection of noise pixels is based on the observation that a noise pixel in a homogeneous region contrasts with the homogeneous gray-value of that region. If for instance most of the pixels in a region are dark, then a noise pixel will not be dark and consequently will be characterized by a small membership degree in a fuzzy set dark, then a noise pixel will not be dark and consequently will be characterized by a small membership degree in a fuzzy set dark. Therefore, the membership degrees can be used as weights in the calculation of the weighted mean. This is not only done for dark, but also for the features median and bright.

### *a. The first adaptive weighted fuzzy mean filter:*

The first adaptive weighted fuzzy mean filter (AWFM1)[8] is an extension of the WFM filter. Instead of choosing fixed membership functions are determined adaptively. For each class of images(e.g. human faces), this is done by selecting a noise-free source image, from which the typical fuzzy sets describing the intensity features dark, median and bright are derived.

When performing experiments, one can easily construct an optimal AWFM1 filter. Indeed, given an original image and a corresponding noise image one can use the original to adaptively calculate the fuzzy sets dark median and bright.

### *b. The second adaptive weighted fuzzy mean filter:*

The second adaptive weighted fuzzy mean filter (AWFM2) [9]is also an extension of the WFM filter; it was designed because experiments with impulse noise showed that the WFM filter performs bad when the noise probability is low. Besides the adaptive construction of the membership functions, the filter consists of two extra mechanisms, namely fuzzy detectors and a dynamic selector, to cope with the drawbacks of the WFM filter.

### *D. The FDD filter:*

The fuzzy decision directed filter [10] is designed for the removal of impulse noise. The filter is based on the observation that classical filters subject each pixel to the filtering process *in the same degree*, despite the fact wether the corresponding pixel is a noise pixel or not. Since also noise-free pixels are filtered, this degrades the image quality. The idea behind the FDDF filter is to make the impact of a classical filter dependent on the degree in which a pixel is considered as a noise pixel. In this sense, the FDDF filter can be seen as a fine tuner of classical filters.

### *E. Fuzzy inference ruled by else-action (FIRE) filter:*

Using inference ruled by else-action(FIRE) filter, effective removal of salt-and-pepper noise can be achieved by using a fuzzy rule base and employing fuzzy sets, although the FIRE filter itself still could not properly remove noise present at objects' edge. This class of filters removes salt-and-pepper noise by estimating a correction term based on a set of fuzzy rule base[11]. The rule base consists of different patterns for evaluating a pixel neighborhood in processing, but not all the neighboring pixels at a time. The rules fired will determine the degree to which a pixel is noisy based on the fuzzy membership value calculated from the fuzzy sets used. An appropriate correction term is then calculated to replace the noisy pixel

## IV. PERFORMANCE OF CLASSICAL AND FUZZY FILTERS

### *A. Numerical and visual results:*

The considered classical and fuzzy filters [1],[2] have been evaluated by several experiments. Different types of impulse noise and different noise levels have been considered. The evaluations have been carried out on two levels: the numerical level and the visual level. An extract of the obtained numerical results has shown in Table I; visual result can be found in Figs. 1(salt & pepper noise)

The numbers given in Table I are the *mean square errors* (MSE): given an original image A and another (noisy or filtered) image B, the MSE of these images is defined as

$$\text{MSE(A,B)}=\frac{1}{M_1 \cdot M_2}\sum_{i=1}^{M_1}\sum_{j=1}^{M_2}[A(i,j)-B(i,j)]^2,$$

where (i,j) are the image pixels, $1 \le i \le M_1$ and $1 \le j \le M_2$ ($M_1, M_2$ in $\mathbb{N} \backslash \{0\}$).

The evaluation of both numerical and visual results is summarized in Table II. Note that this table is based on a much larger set of experiments than those reported in this paper; cfr. [3].

### *B. Discussion:*

Regarding salt & pepper noise, the best filters are always fuzzy filters (DS-FIRE and PWL-FIRE for low noise levels, AWFM2 for higher noise levels). They clearly outperform the considered classical filters.

The best performing classical filter is, not surprisingly, the median filter. Note however that the fuzzy median filter(FM) performs much better than its classical counterpart, certainly for lower noise levels.

From the visual point of view, we have the following results:

a. for low noise levels, most filters perform good, except the FWM, GOA, FDD, CK, mean, wiener and Gaussian filters;
b. for higher noise levels, the best visual results are obtained by the WFM, AWFM1, AWFM2, FM, DS-FIRE and PWL-FIRE and median filters.Using the Template

Table I; numerical results (mse-values) for impulse noise and different noise levels.

| FILTER | Salt & Pepper | | |
|---|---|---|---|
| | 3% | 15% | 30% |
| Noise image | 578.06 | 2779.61 | 5612.34 |
| FWM | 317.92 | 902.13 | 1735.24 |
| FM | 22.60 | 71.88 | 347.17 |
| WFM | 133.29 | 137.08 | 154.08 |
| AWFM1 | 124.05 | 130.82 | 147.93 |
| AWFM2 | 65.48 | 74.76 | 89.46 |
| FIRE | 39.62 | 174.13 | 837.14 |
| DS-FIRE | 15.43 | 37.40 | 177.42 |
| PWL-FIRE | 8.74 | 154.80 | 1012.22 |
| IFC | 60.35 | 119.74 | 323.48 |
| MIFC | 60.73 | 123.37 | 318.74 |
| EIFC | 61.11 | 120.95 | 325.04 |
| SFC | 34.00 | 139.73 | 625.43 |
| SSFC | 34.60 | 128.67 | 604.08 |
| GOA | 138.73 | 325.25 | 609.01 |
| FDD | 190.34 | 1635.83 | 4487.98 |
| CK | 479.72 | 2536.76 | 5257.25 |
| median | 71.59 | 101.10 | 367.19 |
| mean | 164.33 | 455.09 | 935.65 |
| wiener | 378.29 | 888.96 | 1379.43 |
| gaussian | 257.61 | 1199.04 | 2481.37 |

Fig. 1. Salt & Pepper noise (15%). Top row: original image, noise image; middle row: results of AWFM2 and DS-FIRE filter; bottom row: results of IFC and median filter

## V. CONCLUSION

The existing fuzzy filters have been classified, based on 5 different criteria. This classification gives us a good insight in the technical differences between the considered filters, and can be a useful tool in selection procedures.

On the application level it follows from the experiments that, both from a numerical and visual point of view, the best performing filters are fuzzy filters. This clearly illustrates the usefulness of a fuzzy approach in the construction of filters for image noise reduction.

The comparative study also reveals topics for further research. For example, there is need for (fuzzy) filters that can cope with other types of noise than only salt & pepper noise (e.g. speckle noise).necessary peripheral observations in the text (within parentheses, if you prefer, as in this sentence).

Table 2 Experimental Results: Best Performing Filters

| | **Salt & Pepper** | |
|---|---|---|
| | **Low** | **high** |
| Numerical<br>(top 5) | PWL-FIRE<br>DS-FIRE<br>FM<br>SFC<br>SSFC | AWFM2<br>AWFM1<br>WFM<br>DS-FIRE<br>IFC |
| Visual<br>(top 5) | Most filters perform very good | AWFM2<br>AWFM1<br>WFM<br>DS-FIRE<br>median |
| Global<br>(top 3) | AWFM2<br>DS-FIRE<br>median | |

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