Fuzzy Filters for Noise Reduction: the Case of Impulse Noise

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Abstract— **Noise reduction is a well-known problem in image processing. The reduction or removal of noise in an image sometimes is as a goal itself (to produce better images), and sometimes is considered as a kind of preprocessing step before other operations are performed on an image (to improve the performance of these operations). Besides the classical filters for noise reduction, quite a lot of fuzzy inspired filters have been proposed during the past years. However, it is very difficult to judge the quality of this wide variety of filters. For which noise types are they designed? How do they perform for those noise types? How do they perform compared to each other? Can we select filters that clearly outperform the others? Is there a difference between numerical and visual results? In this paper, we answer these questions for images that are corrupted with impulse noise.**

Keywords— **Image processing, noise reduction, fuzzy filters, impulse noise.**

I. Introduction

IMAGES are very important information carriers. This information can be of a diverse nature, ranging from commercial to industrial or scientific. The wide availability of images and the easy way to generate them has also increased the interest in image processing in general. In this paper and in [17] we focus on the issue of noise reduction.

In practice, images easily get corrupted with noise, e.g. due to the circumstances of recording (e.g. dust on a lense, electronic noise in cameras and sensors, ...), transmission (e.g. electromagnetic interaction with satellite images, transmission over a channel, ...), storage, copying, scanning, etc. Therefore, it is not surprisingly that different algorithms to deal with that noise have been developed. During the past years, also a lot of fuzzy logic based filters have been introduced. It is now our goal to make a comparative study of the classical and fuzzy logic based noise reduction filters. We have performed such a study in [13], [14], [15] for a limited number of filters. Here, we compare 38 different algorithms on their performance w.r.t. impulse noise in grayscale images.

II. Images and Noise

Grayscale images are mathematically modelled as finite grids of numbers, where the numbers represent gray values. The number of gray values usually is 256 (i.e. the values range between 0 and 255), the number of rows and columns determines the size of the image (e.g. size of 256×256, 512×512, ...). A point in the grid is called a pixel (picture element).

As stated before, images easily get corrupted with noise. In this paper we focus on impulse noise. When an image is corrupted with impulse noise, three things can happen to a pixel: (1) it is replaced by a value p_1; (2) it is replaced by a value p_2; (3) it is left unchanged. Of course, $p_1 \neq p_2$ and both values belong to the set of gray values. Salt and pepper noise is a special case of impulse noise: $p_1 = 0$ and $p_2 = 255$.

It is important to note that images and fuzzy sets can be modelled in the same way. A fuzzy set in a universe X is modelled as a mapping from X into the unit interval $[0, 1]$, i.e. every element x of X is associated with a value in $[0, 1]$ which is called the membership degree of x in the considered fuzzy set. Images are modelled in a similar way: the universe is a finite grid G, and the image can be modelled as a mapping from G into the set $\{0, 1, \ldots, 255\}$. This set can be rescaled by dividing every element by 255, leading to the observation that also an image can be modelled as a mapping from G to $[0, 1]$. Consequently, techniques from fuzzy set theory can be used in image processing, and the past years have shown that they can have an added value.

III. Filters for Noise Reduction

The variety of filters can be divided in three subclasses: (1) classical filters; (2) fuzzy-classical filters, i.e. fuzzy logic based filters that are a modification or extension of classical filters; (3) fuzzy filters, i.e. filters that are purely based on fuzzy logic and have no straightforward connection with classical filters. We will present the studied filters based on this classification. It concerns 38 different algorithms; the fuzzy-classical and fuzzy filters are accompanied by a reference for those readers who want more background information on them.

A. Classical Filters

- MF: Median Filter
- WF: Weighted Filter
- AWF: Adaptive Weighted Filter
- WIENER: Wiener Filter
- GAUS: Gaussian Filter
- EMF: Extended Median Filter

B. Fuzzy-Classical Filters

- FMF: Fuzzy Median Filter [1], [2]
- TMED: Symmetrical Triangle Fuzzy Filter with median center [9]
- ATMED: Asymmetrical Triangle Fuzzy Filter with median center [9]
- GMED: Gaussian Filter with Median Center [9]
- FIDRM: Fuzzy Impulse noise Detection and Reduction Method [22]
- WFM: Weighted Fuzzy Mean Filter [10], [11]
- FWM: Fuzzy Weighted Mean [2]
- AWFM: first Adaptive Weighted Fuzzy Mean Filter [10]
- AWFM2: second Adaptive Weighted Fuzzy Mean Filter [11]
- CK: Choi & Krishnapuram Filter [3]
- FDDF: Fuzzy Decision Directed Filter [12]
- TMAV: Symmetrical Triangle Fuzzy Filter with Moving Average Center [9]
- ATMAV: Asymmetrical Triangle Fuzzy Filter with Moving Average Center [9]
- DWMAV: Decreasing Weight Fuzzy Filter with Moving Average Center [9]
- GMAV: Gausian Fuzzy Filter with Moving Average Center [9]
- MPASS: Multipass fuzzy filter [18], [6]
- FMMF: Fuzzy Multilevel Median Filter [7], [6]

C. Fuzzy Filters

- FIRE: Fuzzy Inference Ruled by Else-action Filter [19]
- DSFIRE: Dual Step Fuzzy Inference Ruled by Else-action Filter [20]
- PWLFIRE1: first (non-adaptive) Piecewise Linear Fuzzy Inference Ruled by Else-action Filter [21]
- PWLFIRE2: second (adaptive) Piecewise Linear Fuzzy Inference Ruled by Else-action Filter [21]
- IFCF: Iterative Fuzzy Control based Filter [5]
- MIFCF: Modified Iterative Fuzzy Control based Filter [5]
- EIFCF: Extended Iterative Fuzzy Control based Filter [5]
- SFCF: Smoothing Fuzzy Control based Filter [4]
- SSFCF: Sharpening Smoothing Fuzzy Control based Filter [5]
- GOA: Gaussian Noise Reduction Filter [27]
- HAF: Histogram Adaptieve Filter [8]
- FSB1: first Fuzzy-Similarity-Based Noise Reduction Filter [23], [24]
- FSB2: second Fuzzy-Similarity-Based Noise Reduction Filter [23], [24]
- FSB1R: first Recursive Fuzzy-Similarity-Based Noise Reduction Filter [23], [24]
- FSB2R: second Recursive Fuzzy-Similarity-Based Noise Reduction Filter [23], [24]

IV. Comparative Study

It is important to note that it is the first time that a comparative study is performed on such a large scale. Usually, when one goes through the literature, a newly introduced filter is compared to just a few other filters. It always turns out that the new filter outperforms those other filters, but because of the limitations of the comparison no sound conclusion w.r.t. the performance of the new filter can be made. This now changes, by comparing nearly 40 different filters at the same time.

The evaluation is carried out on two levels: numerical (based on the MSE values) and visual (based on visual inspection by humans). In order to get a clear idea of the performance w.r.t. the level of impulse noise, experiments have been carried out for 10%, 20%, 30%, 50%, 70% and 90% of impulse noise. Furthermore, the experiments have been carried out on several images, such as the Lena image (256×256), the cameraman image (256×256) and the bridge image (512×512).

A. Numerical evaluation

The numerical results for the Lena image are summarized in Table 1 (10%, 20%, 30%) and Table 2 (50%, 70%, 90%); those for the cameraman and bridge images are not displayed here. We use the Mean Square Error (MSE) as numerical measure. Given two images A and B, and indicating the gray value of the pixel at position (i,j) as $A(i,j)$ and $B(i,j)$, the MSE between the images A and B is defined as:

$$MSE(A,B) = \frac{1}{N}\sum_{i,j}\left(A(i,j) - B(i,j)\right)^2,$$

where N denotes the total number of pixels. Instead, one can also use the Peak Signal to Noise Ratio (PSNR), which is defined as:

$$PSNR(A,B) = 10 \cdot \log_{10}\frac{255^2}{MSE(A,B)}$$

Although these measures have their shortcomings w.r.t. expressing the quality of an image as observed by human beings, they are still widely used in the image processing community. In that regard, we note that we are currently working on the construction of alternative similarity measures to overcome the shortcomings of the MSE (see [25], [26]).

The numbers shown in Table 1 and Table 2 are the MSE between the noise-free Lena image and the noisy or filtered Lena images.

We can summarize our conclusions w.r.t. the numerical results, based on experiments with the Lena image and other images, as follows:

- The FIDRM filter performs best for all levels of impulse noise. In the case of the Lena image it reduces the MSE by a factor 143 for low levels (10%) and by a factor 57 for very high levels (90%). For the other images these factors range between 68 to 77 and 37 to 40, respectively. These are remarkable results.
- For low noise levels (10%, 20% and 30%) the EMF filter nearly always is the second best performing filter (an exception is its forth place when the Lena image is

TABLE I
NUMERICAL RESULTS FOR 10%, 20% AND 30% IMPULSE NOISE (LENA IMAGE).

	10%	20%	30%
Noisy	1731.4	3309.4	4719.34
MF	80.93	127.17	232.86
WF	305.2	540.48	758.05
AWF	1734.06	3287.44	4679.23
WIENER	1857.91	1819.8	2002.45
GAUS	1714.73	3276.44	4670.75
EMF	13.24	44.48	118.23
FMF	40.01	102.31	212.53
TMED	83.74	134.85	248.44
ATMED	95.95	116.29	145.58
GMED	81.73	128.03	348.88
FIDRM	12.1	30.57	51.1
WFM	130.03	136.42	146.13
FWM	550.88	907.78	1292.56
AWFM	121.96	130.7	139.64
AWFM2	69.32	74.96	84.46
CK	1489.27	2954.2	4313.4
FDDF	843.04	2146.31	3510.19
TMAV	87.49	144.76	267.64
ATMAV	133.19	144.57	145.82
DWMAV	305.2	540.48	758.05
GMAV	3441.11	5669.26	508.46
MPASS	123.37	211.66	376.51
FMMF	996.78	1981.24	3033.74
FIRE	88.7	258.42	560.76
DSFIRE	269.61	296.72	344.26
PWLFIRE1	112.32	385.29	798.03
PWLFIRE2	49.76	263.57	603.99
IFCF	92.97	137.41	217.4
MIFCF	95.62	167.65	292.64
EIFCF	93.2	141.43	224.32
SFCF	111.68	214.79	419.16
SSFCF	104.52	199.16	401.28
GOA	265.46	411.51	536.37
HAF	89.4	94.76	101.72
FSB1	87.64	137.34	253.14
FSB2	88.52	136.2	258.41
FSB1R	107.2	134.53	177.57
FSB2R	130.63	154.86	193.94

TABLE II
NUMERICAL RESULTS FOR 50%, 70% AND 90% IMPULSE NOISE (LENA IMAGE).

	50%	70%	90%
Noisy	7255.23	9132.95	10886.41
MF	855.3	1989.81	3650.08
WF	1238.59	1602.51	2008.21
AWF	7197.47	9066.02	10822.86
WIENER	2434.87	2906.8	3014.26
GAUS	7180.67	9040.4	10779.22
EMF	540.66	1398.47	2768.66
FMF	750.16	1519.45	2594.85
TMED	834.26	1832.87	3299.04
ATMED	308.93	575.01	959.29
GMED	855.96	1990.28	2646.36
FIDRM	94.48	134.69	188.97
WFM	160.22	211.3	382.42
FWM	2070.48	2784.3	3553.19
AWFM	154.47	207.93	389.55
AWFM2	94.94	136.18	279.8
CK	6838.37	8735.7	10539.86
FDDF	6268.35	8366.59	10368.52
TMAV	810.92	1604.01	2695.1
ATMAV	152.13	187.86	351.35
DWMAV	1238.59	1602.51	2008.21
GMAV	9506.29	10776.45	2133.11
MPASS	1215.41	2440.86	4294.19
FMMF	5205.66	7062.8	8811.14
FIRE	1633.8	2949.94	4480.83
DSFIRE	672.95	1375.31	2559.15
PWLFIRE1	2300.26	4068.43	6100.48
PWLFIRE2	1999.38	3663.34	5659.72
IFCF	534.88	1008.59	1725.39
MIFCF	832.49	1622.25	2713.46
EIFCF	563.66	1081.09	1869.79
SFCF	1201.87	2216.87	3393.82
SSFCF	1262.51	2454.71	3893.14
GOA	835.54	1042.59	1303.42
HAF	119.04	162.74	343.03
FSB1	930.83	2146.04	3872.48
FSB2	936.37	2140.53	3862.51
FSB1R	335.63	581.64	1069.37
FSB2R	324.46	493.22	787.78

corrupted with 30% impulse noise). Also the FMF filter has a good performance: it always is in the top-3 or top-4 of best performing filters. Other filters that perform good for low noise levels are the PWLFIRE2 filter (top-4 for 10% impulse noise), the AWFM2 filter (which performance increases when the noise rate gets higher), the HAF filter (same remark), the ATMED filter (top-5 for 20% impulse noise on the cameraman image and for 30% impulse noise on the bridge image), and the AWFM filter (top-5 for 30% impulse noise on the camera and Lena images).

- For high noise levels (50%, 70% and 90%) the top-5 of best performing filters always consists of the same set, namely the FIDRM filter (always performs best), the AWFM2 filter (nearly always is the second best performing filter), and the HAF, ATMAV and AWFM filters.

We could also make the following specific observations:

- For noise levels around 10% the EMF filter produces a MSE that is very close to the MSE of the FIDRM filter; the MSE values of the other top-5 filters for this noise level are at least three times as high. A similar observation holds for the other images.
- For noise levels around 20% and 30% the second best filters have an MSE value that is around 30% to 50%

higher than the MSE value of the FIDRM filter, which confirms the very good result of the latter.

- The higher the noise level, the better the numerical performance of the AWFM2 filter. This is clearly illustrated for the Lena image: for noise levels of 30% and higher it always is the second best performing filter.

In general, our conclusion based on the numerical evaluation of the filters is that the FIDRM filter outperforms the rest. For noise levels around 10% to 30% the EMF and FMF filters are respectable contestors. For higher noise levels, it is clear that the AWFM2, HAF, ATMAV and AWFM filters constitute the top-5 of best performing filters.

We can also clearly see that several filters are not designed to deal with impulse noise. For example, the classical WIENER and GAUS filters are specifically designed for gaussian noise and fail w.r.t. impulse noise.

B. Visual evaluation

Since it is not possible to show all visual results of our experiments, we have made a selection. For each of the considered noise levels, we show an original noisy image and the result of the three best performing filters for that specific noise level and that specific image. The captions of the figures only mention the noise level (the corresponding image is always shown in the first row on the left) and the name of the applied filters (the first filter is shown in the first row on the right, the second filter is shown on the second row on the left, and the third filter is shown on the second row on the right). The original noise-free images are shown in Figure 1.

Fig. 1. The original noise-free camera, Lena, and bridge images

We can summarize our conclusions w.r.t. the visual results as follows:

Fig. 2. 10% impulse noise, FIDRM, EMF and PWLFIRE2.

- The visual results of all three best performing filters is in general very good for all considered noise levels. This confirms the good numerical performance of these filters.
- For the higher noise levels (70% and 90%) the second and third best performing filters show an increasing number of black and white dots, which does not occur with the FIDRM filter.
- For all noise levels the HAF filter produces a more blurry picture than the FIDRM and AWFM2 filters. In other words, the FIDRM and AWFM2 filter have the property that they keep the sharpness of the image. This observation is important for the higher noise levels, since then these filters all are in the top-5 w.r.t. their numerical performance.
- In a similar context, we found that for the lower noise levels (e.g. 30%) the FIDRM filter gives slightly sharper results than the AWFM2 filter, while for the higher noise levels (e.g. 70%) the AWFM2 filter gives slightly sharper results than the FIDRM filter.

In general, our conclusion based on the visual evaluation of the filters is that all top-3 best performing filters produce good results, even when the level of impulse noise is very high.

C. Conclusion

The numerical and visual experiments confirm each other: the FIDRM filter performs best for all noise levels, followed by the classical EMF filter for low noise levels, and the AWFM2 filter for high noise levels. These results also show that the use of fuzzy techniques in image processing can have an added value. Indeed, except for the EMF filter all best performing filters belong to the class of fuzzy-classical or purely fuzzy filters.

Fig. 3. 20% impulse noise, FIDRM, EMF and AWFM2.

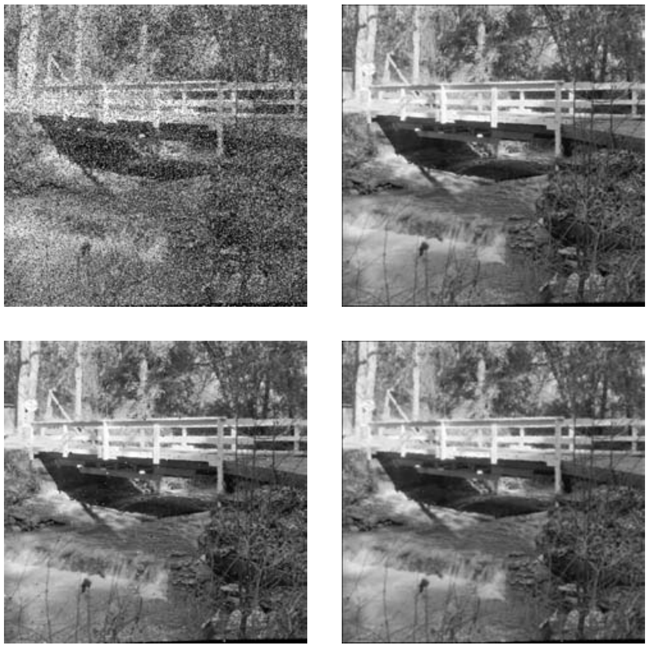

Fig. 4. 30% impulse noise, FIDRM, EMF and HAF.

V. Final Note

We found that, among the 38 evaluated filters, the FIDRM filter performs best on the numerical level, which was also confirmed by visual experiments. We could also select the EMF filter (for low noise levels) and the AWFM2 filter as very good performing filters.

Finally, we note that our comparative study focused on grayscale images corrupted with impulse noise. In [17] these filters will be compared w.r.t. the reduction of gaussian noise in grayscale images. We are currently preparing similar comparative studies for color images as well.

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Fig. 5. 50% impulse noise, FIDRM, AWFM2 and AWFM.

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Fig. 6. 70% impulse noise, FIDRM, AWFM2 and HAF.

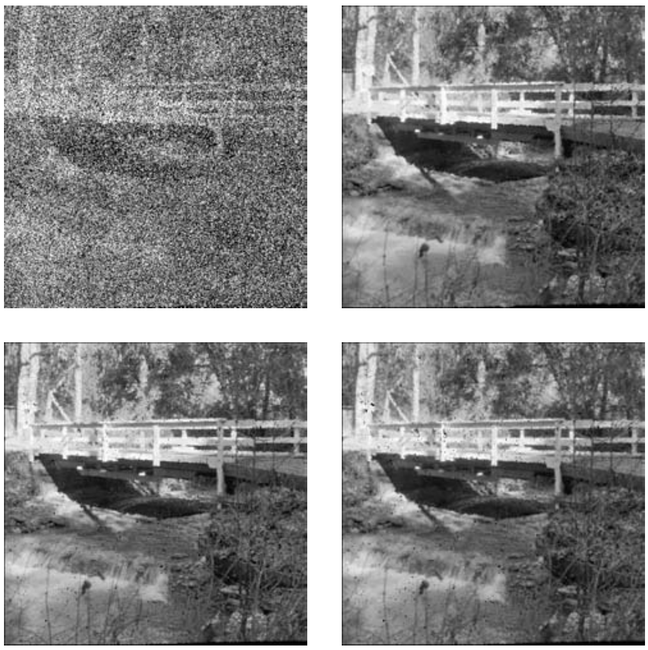

Fig. 7. 90% impulse noise, FIDRM, AWFM2 and ATMAV.