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Fixed Valued Impulse Noise Removal using Iterative Adaptive Fuzzy Filter

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***Abstract*—Suppression of impulse noise in images is an important problem in image processing. In this paper, we propose a novel adaptive iterative fuzzy filter for denoising images corrupted by impulse noise. It operates in two stages—detection of noisy pixels with an adaptive fuzzy detector followed by denoising using a weighted mean filter on the "good" pixels in the filter window. Experimental results demonstrate the algorithm to be superior to state-of-the-art filters. The filter is also shown to be robust to very high levels of noise.**

***Index Terms*—Alpha-trimmed mean, fuzzy filter, high-density impulsenoise removal.**

I. Introduction

Digital images may be contaminated by salt-and-pepper noise due to factors such as imperfections in imaging sensors, channel transmission errors, nonideal medium between the scene and the imaging system (factors such as random scattering and absorption), and faulty memory locations in hardware [1].

For most image processing and analysis applications, it is highly desirable to remove impulse noise from the images. It is desired that while removing impulse noise from the image, there is a minimal loss of the useful image detail in the process.

A huge number of techniques have been proposed for solving this problem. Nonlinear filtering techniques, which are based on filters utilizing rank-order information of pixels in a window-wise fashion, are in general better performers than linear filtering techniques. The classical nonlinear filtering technique in the context of impulse noise removal in images is the standard median (SM) filter [2]. The SM filter is not good at preserving image detail, and moreover fails at high levels of corruption. To overcome these limitations, a number of modifications to the filter have been proposed over the years, including the weighted median filter (WMF) [3], [4] and the center-weighted median filter (CWMF) [5]. These filters give more weight to some pixels in the filtering window, but while being more detail preserving than the traditional median filter, they do not deal efficiently with higher levels of noise

Two-staged soft computing approaches have been formulated as well. Russo *et al.* [9] developed a two-step fuzzy filter with better detail-preserving capabilities. Fuzzy inference rules by else-action filters were proposed in [10] to better maintain edge details. Choi *et al.* [11] pro-posed a technique where three filters (based on fuzzy least squares method) were combined based on a set of fuzzy rules. In [12], a switching median filter is proposed on a fuzzy-set framework. Schulte *et al.* introduced a two-stage nonlinear filtering technique based onfuzzy logic [13]. In [14], a filter based on adaptive neuro-fuzzy infer-ence systems was proposed that was effective for the high levels of noise.

The fuzzy filters are usually simpler and quite efficient, especially when used in an adaptive setting. In [27], an adaptive fuzzy mean filter is proposed for impulse noise denoising. Apart from applications in image proccessing, there has been recent interest in applying fuzzy filters to more general signal processing problems as well [16]–[18].

II. PROPOSED Algorithm

We propose a two-stage iterative adaptive fuzzy filter for denoising images corrupted by impulse noise.

The α-trimmed mean is more effective as a measure of central tendency than the classical mean or median measures in the context of impulse noise removal. We rewrite the measure in a form more relevant to our algorithm and call this the mean of k-middle.
The α-trimmed mean computes the mean of a set of elements after trimming the top and bottom α/2 elements of the set

Algorithm for Detection and Denoising of Noisy Pixels

Since we approach the particular problem of salt-and-pepper noise, if a pixel intensity is not fully dark or fully bright, we need not run further checks and its current intensity value is retained as it is. Otherwise, we need to check if it is a corrupt pixel.

The key stages of our algorithm are as follows.

1) *Initialization of parameters:* For denoising, we shall require N "good" pixels in a window. The number of noisy pixels being detected per iteration will be used for the stopping criterion of our iterative algorithm, and so we set a variable d_m to hold this value for the mth run. The window half-size parameter M is set initially to 1, which implies a window size of 3 × 3. and are the initial upper and lower bounds for T , an adaptive threshold for the Gaussian membership function.

2) *Detection of noisy and "good" pixels:* If the center pixel in awindow p_{ij} is not at an extreme intensity, we retain its value. Otherwise, we need to determine whether p_{ij} is a corrupted pixel or not.

a)Safe distance: We expect that pixels lying far away fromp_{ij}donot have much influence on the intensity of p_{ij} , so we introduce a variable S_{max} , which serves as an upper bound on M . As a last resort, we will increase our window size beyond the safe distance, but our priority is to avoid going beyond this size. This will ensure our preference for using nearer pixels for estimating denoised values as far as possible.

b)Gaussian membership function: We compute the param-etersμ^{M}_{ij} and σ_{ij}^{M} of the Gaussian membership function .If it turns out that the deviation σ_{ij}^{M} is below a very low threshold (_), i.e., the window consists of pixels with intensities very close to that of p_{ij} , then we simply set the value of p_{ij} to μ^{M}_{ij}. This also avoids division by zero errors that may arise if theregion is of a uniform intensity which would result in σ_{ij}^{M} being 0. If the degree of membership of p_{ij} ,$m_{Ui}M_j$ (p_{ij}), is above the threshold T , then p_{ij} is deemed to be uncorrupt, and we retain that value of p_{ij} (see Fig. 1).

c) "Good" Set G: If$m_{Ui}M_j(p_{ij}) \leq T$, then$p_{ij}$is likely tobe noisy. Hence, we need to estimate an intensity value from the surrounding pixels. For this, we need to develop a set $G \subseteq R_{ij}^{M}$of neighboring uncorrupted pixels.

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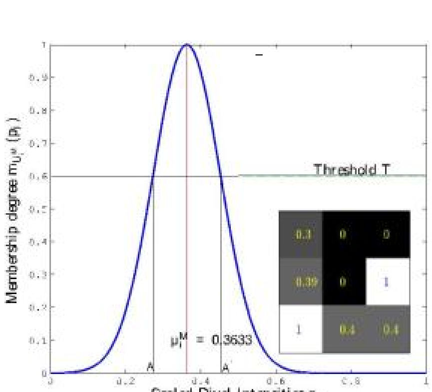


Fig. 1. Gaussian membership function for a sample 3 × 3 window (inset). Pixel intensity values lying within A and A^- (with a Gaussian membership degree above T) or are not in {0, 1} are "good" pixels.

d) Adaptive slackening of parameters: If the cardinality of theset of "good" pixels $|G|$ is below N , the minimum number of required "good" pixels, we slacken our initially demanding parameterswhich order are guided by a set of rules. Christo Ananth et al. [22] discussed about Improved Particle Swarm Optimization. The fuzzy filter based on particle swarm optimization is used to remove the high density image impulse noise, which occur during the transmission, data acquisition and processing. The proposed system has a fuzzy filter which has the parallel fuzzy inference mechanism, fuzzy mean process, and a fuzzy composition process. In particular, by using no-reference Q metric, the particle swarm optimization learning is sufficient to optimize the parameter necessitated by the particle swarm optimization based fuzzy filter, therefore the proposed fuzzy filter can cope with particle situation where the assumption of existence of "ground-truth" reference does not hold. The merging of the particle swarm optimization with the fuzzy filter helps to build an auto tuning mechanism for the fuzzy filter without any prior knowledge regarding the noise and the true image. Thus the reference measures are not need for removing the noise and in restoring the image. The final output image (Restored image) confirm that the fuzzy filter based on particle swarm optimization attain the excellent quality of restored images in term of peak signal-to-noise ratio, mean absolute error and mean square error even when the noise rate is above 0.5 and without having any reference measures.

Thus, we now enumerate the three slackening rules.

Rule 1: If we are unable to find N uncorrupted pixels in thewindow, we first slacken the membership threshold T from its initial value of T_{max} down to T_{min} in a stepwise manner. (The stepsizeα may be varied.) We stop if the criterion |G| ≥N is reached, as we then have our minimum number of "good" pixels required to perform denoising of p_{ij} .

Rule 2: If |G| is still less than N , we increase the windowhalf-size parameter M such that the window size increases from 3×3upto($2S_{max}$ + 1) × ($2S_{max}$ + 1) in a stepwise manner, stopping if the criterion |G| ≥N is reached.

Rule 3: If |G| is still below N, we decrease our parameter N in a stepwise manner. If the iterative process results in N falling below 1, we increase S_{ma} by unity, setting N permanently to 1 for denoising p_{ij} .

3) Denoising noisy pixels: We estimate the denoised pixel intensityfrom the pixel intensities in the "good" set G. We weight the elements of G by a simple inverse distance weighting function that assigns lower weights to pixels far from p_{ij} and higher weights to pixels that are closer.

4) Iterations and stopping criterion: Algorithm I is run iteratively,with the following stopping criterion. We find the difference of the number of noisy pixel detections d_m in succeeding iterations of the algorithm. We terminate iterations when d_m falls below a small threshold. We set the threshold at 0.05% of the total number of pixels in the image

Results

Simulation results for images

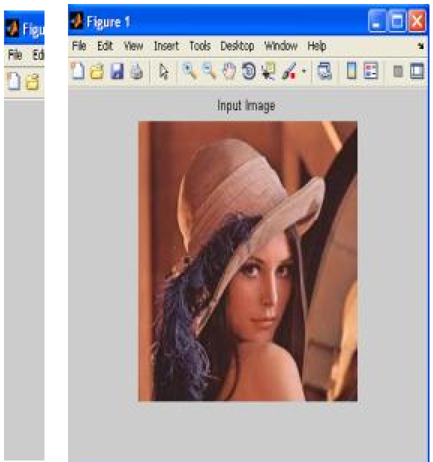


Fig.2 Input image Fig.5 Input Image

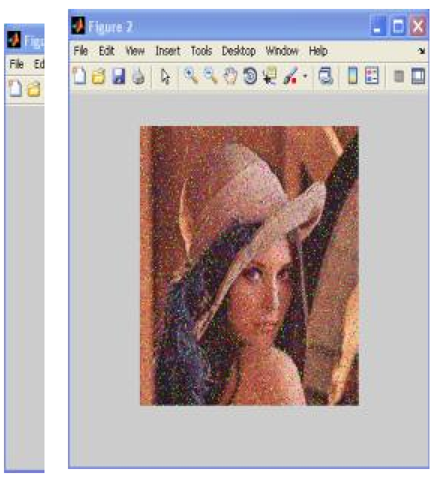
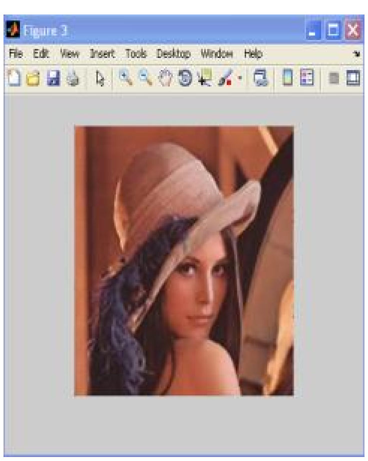


Fig.3 Noisy ImageFig.6 Denoised Image



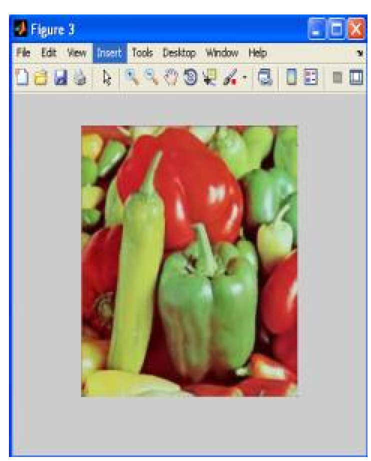


Fig.4 Denoised Image Fig.7 Denoised Image

Table.1.comparison of PSNR and MSE values of Lena image

NOISE DENSITY	CMF		VMF		SMF		MSMF		AMFATM (proposed work)	
	MSE	PSNR	MSE	PSNR	MSE	PSNR	MSE	PSNR	MSE	PSNR
10	293.63	23.45	317.22	23.12	364.13	22.80	361.71	22.83	20.24	35.07
20	294.54	23.44	319.02	23.10	366.52	22.77	363.02	22.81	20.95	34.92
30	293.94	23.45	319.95	23.08	369.74	22.73	364.35	22.79	21.96	34.72
40	296.05	23.42	318.14	23.10	371.71	22.71	365.21	22.77	22.44	34.62
50	295.74	23.42	320.07	23.08	373.61	22.68	368.36	22.75	23.63	34.40
60	294.10	23.45	323.06	23.08	375.97	22.65	368.45	22.74	24.61	34.22
70	297.40	23.40	326.95	22.99	376.84	22.65	368.86	22.74	25.41	34.08
80	297.78	23.39	326.30	22.99	379.46	22.61	370.59	22.71	28.99	33.51
90	297.83	23.39	328.15	22.97	380.51	22.60	371.66	22.69	29.94	33.37

Table.2.comparison of PSNR and MSE values of Pepper image

NOISE DENSITY	CMF		VMF		SMF		MSMF		AFFATM (proposed work)	
	MSE	PSNR	MSE	PSNR	MSE	PSNR	MSE	PSNR	MSE	PSNR
10	661.93	19.92	706.26	19.64	576.51	20.70	572.56	20.73	18.83	35.38
20	662.62	19.92	708.62	19.63	577.37	20.69	572.62	20.73	18.74	35.40
30	665.80	19.90	715.13	19.59	583.98	20.65	577.55	20.70	20.97	34.91
40	665.16	19.90	713.67	19.59	583.21	20.64	575.85	20.70	21.64	34.77
50	664.65	19.90	716.12	19.58	589.03	20.60	580.68	20.67	24.89	34.17
60	668.75	19.88	716.07	19.58	591.84	20.57	580.77	20.66	24.56	34.23
70	670.79	19.86	724.79	19.53	594.97	20.56	582.87	20.65	26.75	33.86
80	668.38	19.88	726.55	19.52	584.42	20.54	584.42	20.64	29.09	33.49
90	665.23	19.90	737.10	19.46	603.93	20.48	591.22	20.58	32.34	33.03

CONCLUSION

A two-stage filter for denoising images corrupted with salt-and-pepper noise is proposed. In the first stage, an adaptive fuzzy filter is used for the detection of noisy pixels. In the second stage, denoising is performed on noisy pixels, by performing a weighted mean filtering operation on nearby uncorrupt pixels. We have done a comparison of the proposed method's PSNR and MSE with the previous methods.

In comparison with median filters, mean filters, center mean filter, vector median filter, standard median filter, multi stage median filter, the proposed iterative adaptive fuzzy filter with alpha trimmed mean shows effective denoising results.

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